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Integrating Topology Optimization and Aesthetic Design Preferences through Interactive User-Sketched Input

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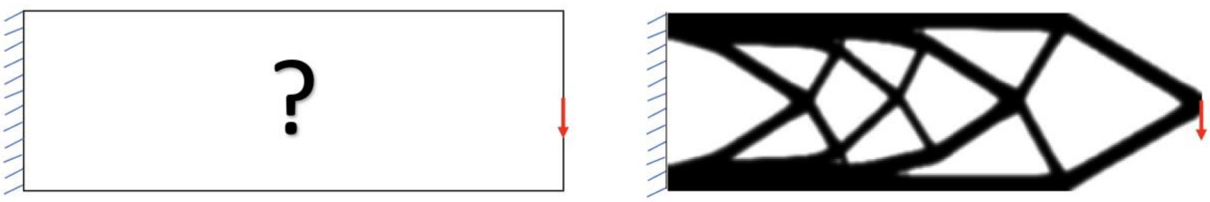
Abstract

Topology-optimized designs can leverage the new, rapidly developing fabrication possibilities and identify new, more efficient structural solutions. Most existing topology optimization frameworks are fully automated such that the design generation and evolution are driven exclusively by a machine. Input by a human design engineer is only needed to initialize the design and judge the quality of the final output. This makes it difficult for a designer to implement aesthetic design intentions as the design is generated. This work introduces a new topology optimization design technology that relies on human-machine collaboration to drive design generation. Using two different approaches, the user is enabled to interactively select regions where they want to alter geometric features by drawing sketches they wish to see replicated in the final design. The new technology uses density-based topology optimization as the backbone of the design algorithm and solves a compliance minimization problem with a gradient-based optimizer. The two approaches for sketch incorporation are demonstrated in an example design case and shown to alter the aesthetics of the final designs based on the user input while optimizing the structural performance.

Keywords: Topology optimization, interactive, human-in-the-loop design, geometric control, appearance constraint

1. Introduction

Topology optimization is a computational design tool that generates high-performing, lightweight structures uniquely suited to a user's design goals in terms of structural performance (Figure 1). The classic formulation of topology optimization aims to minimize compliance (often equivalent to maximizing stiffness) subject to a user-inputted volume fraction, equilibrium, and solid (1) or void (0) material bounds [1]. The process is fully automated such that the designer only initiates the design generation process and assesses the final quality of the design. The resulting optimized designs use less material than traditional designs, thereby reducing embodied carbon and material demand.



(a) (b)

Figure 1: Conceptual schematic of using topology optimization to design a long cantilever beam where (a) shows how the designer selects a design domain with applied loads and boundary conditions and (b) gives the automatically generated topology-optimized design results with compliance c = 216.8.

Interactive topology optimization presents exciting opportunities for users to embed their engineering expertise or graphical intentions into the computational design generation. Interactive approaches overcome a critical obstacle to the widespread use of topology optimization by granting users the flexibility to modify the design as it converges and ensure the result conforms to *both* aesthetic and performance goals. Mid-optimization interaction allows for the improvement of these metrics while avoiding the reduction in performance that can result from ad-hoc post-processing modifications to the converged design [3]. This paper introduces aesthetic applications of the two methods presented in previous work by the authors [2] by incorporating a user-drawn pattern into topology optimization: first through a passive implementation and second through an appearance constraint. The passive implementation exactly replicates the drawn pattern by prescribing elements as solid or void in accordance with the user's drawing. The appearance constraint, derived from computer graphics patch-based analysis, balances replication of the drawing with minimizing the objective function. Both methods follow the workflow shown in Figure 2, where 50 iterations of traditional topology optimization are run (a), after which the user draws a geometric pattern (b) and region where they wish to see the sketch replicated, (c) in which the algorithm takes this into consideration when generating the final optimized design (d).

(a) (b) (c) (d)

Figure 2: (a) Traditional topology optimization is run for 50 iterations, after which (b) the user draws an input and (c) region of interest to locate the drawing. (d) The interactive algorithm resumes with the user's drawing replicated in the region of interest. Reproduced from [2].

2. Background

Topology optimization is a flexible computational design method that allows users to generate designs optimized designs that seek to reach their design goals, which can be engineering performance-centric or aesthetics-related. In theory, gradient-based topology optimization can accommodate any objective function if the derivatives of the function can be calculated with respect to the design variables. Examples of alternative engineering related objective functions include minimizing stress, maximizing buckling load, improving manufacturability, or optimizing shell-infill structures that will be additively manufactured. On the other end of the spectrum, aesthetics-focused topology optimization incorporates graphical design intentions into the converged results while still maximizing the objective function and satisfying constraints. These approaches generally rely upon interaction by the user to input their design intentions. An algorithm that accomplishes this in the evolutionary optimization space is iBESO: a Bi-directional Evolutionary Structural Optimization (BESO) algorithm that prompts users to draw a feature that is replicated in the optimized design [4]. The two interactive topology optimization methods presented in this paper accomplish a similar goal of incorporating human-drawn graphical inputs but using two different methods that rely on gradient-based topology optimization. The contributions in this paper build on previous work by the authors on Human informed Topology Optimization (HiTop) that allows users to interactively specify regions where the minimum solid or void feature sizes [5] and/or maximum solid feature sizes are changed [6]. This work extends this idea by enabling human-drawn preferences to guide the design generation process using two separate strategies: a passive element approach and an appearance constrained method.

When implementing a passive element design approach for user-provided drawings, as detailed in Section 3.2, the user sketch will define solid or void regions where the design cannot be changed. Identifying passive solid and void regions is common practice when initializing topology optimization design problems where voids can be used to prescribe structural openings and solids, for example, are prescribed where structural supports will be applied. However, in this work, rather than predefining elemental densities before running the optimization, the user is enabled to draw an outline of elements that will be prescribed as solid or void after assessing a quick, initial design. The second approach in this work uses an appearance constraint and originates from a computer graphics-based image analysis called Patch Match, which uses nearest neighbor matches between patches of a source and target image to complete or manipulate the target image [7], [8]. Patch Match relies upon the calculation of the Euclidean distance between pixels of images, minimizing the distance to replicate the source image in the target image [7], [8]. Recent work explores using Patch Match in aesthetics-motivated topology optimization by formulating an appearance constraint that minimizes the distance between the source image and the optimized design [9]. The algorithm presented in Section 3.3 builds upon these works' use of appearance constraints in topology optimization but is novel in its interactive component, where the user manually draws the graphical source image and selects where in the design to place the source image [2].

3. Methodology and results

3.1 Optimization formulation

Topology optimization with interactive graphic input follows the classic topology optimization formulation aiming to minimize compliance subject to static equilibrium, a user-inputted volume constraint, and solid or void material bounds [1].

$$\begin{aligned} \min_{\boldsymbol{x}} \quad & c(\boldsymbol{\rho}) = \mathbf{U}^{\mathrm{T}}\mathbf{K}\mathbf{U} \\ \text{s.t.:} \quad & \mathbf{K}(\boldsymbol{\rho})\mathbf{U} = \mathbf{F} \\ & \frac{V(\boldsymbol{\rho})}{V_0} \leq f \\ & 0 \leq x_e \leq 1 \qquad \forall\, e \in \boldsymbol{\Omega}. \end{aligned} \tag{1}$$

Where c is compliance as a function of $\boldsymbol{\rho}$, the vector of physical elemental densities, $\boldsymbol{x}$ is the vector of design variables, $\mathbf{U}$ is the vector of elemental displacements, $\mathbf{K}$ is the assembled stiffness matrix, $V(\boldsymbol{\rho})$ is the volume of design, V_0 is the fully solid design volume, f is the relative volume fraction constraint, and $\boldsymbol{\Omega}$ is the design domain. To penalize intermediate densities and generate a clear, manufacturable solution, the Solid Isotropic Material Penalization (SIMP) method is implemented, as shown below [10].

$$E(\rho_e) = E_{min} + (\rho_e)^{\eta}(E_0 - E_{min}) \quad \forall\, e \in \boldsymbol{\Omega}. \tag{2}$$

Where $E(\rho_e)$ is the elemental Young's modulus as a function of the density value, η is a user-inputted penalization factor, E_0 is the initial Young's modulus and E_{min} is a small number to ensure the stiffness matrix is positive definite. For this work $E_0 = 1$, $E_{min} = 1 \times 10^{-9}$, and $\eta = 3$. In addition to SIMP, a density filter is used to impose a minimum feature size in the optimization. Equation (3) calculates the filtered elemental density, and Equation (4) constructs $\boldsymbol{H_{ei}}$, the matrix of weighting factors based on the user-inputted minimum feature size radius, r_{min} [1].

$$\tilde{x}_e = \frac{\sum_{i \in \boldsymbol{N_e}} \boldsymbol{H_{ei}} \cdot x_i}{\sum_{i \in \boldsymbol{N_e}} \boldsymbol{H_{ei}}} \quad \forall\, e \in \boldsymbol{\Omega}, \tag{3}$$

$$\boldsymbol{H_{ei}} = max\left(0, r_{min} - \Delta(e,i)\right) \forall\, e \in \boldsymbol{\Omega}, \forall\, i \in \boldsymbol{N_e}. \tag{4}$$

Where $\boldsymbol{N_e}$ is the neighbourhood of elements within r_{min} of element e, and x_i is the elemental design variable. This classic density filter prevents checkerboarding that results from the SIMP method. Finally, the filtered density is weighted with a Heaviside's function to further push all values towards 0 or 1 [11].

$$\rho_e(\tilde{x}_e) = 1 - e^{-\beta \cdot \tilde{x}_e} + \tilde{x}_e e^{-\beta} \;\forall\, e \in \boldsymbol{\Omega}, \tag{5}$$

where ρ_e is the physical elemental density and β is the steepness factor that is set to 5 in this work.

3.2. Passive implementation

The passive implementation of interactive topology optimization with graphical input follows the formulation outlined in 3.1. The passive approach is demonstrated on the long cantilever shown in Figure 1a, where the beam is fixed on the left side and subject to a downward force at the midpoint of the right side. The number of elements in the x and y-direction are 300 and 100, respectively, and the volume fraction $f = 0.4$.

The optimization initializes and runs an initial 50 iterations. At the 50th iteration, the user is prompted to make changes if desired. For the current example, the user requests to make changes within the red shape highlighted in Figure 3a. The user subsequently draws the outline of a flower within the selected region, as shown in Figure 3b.

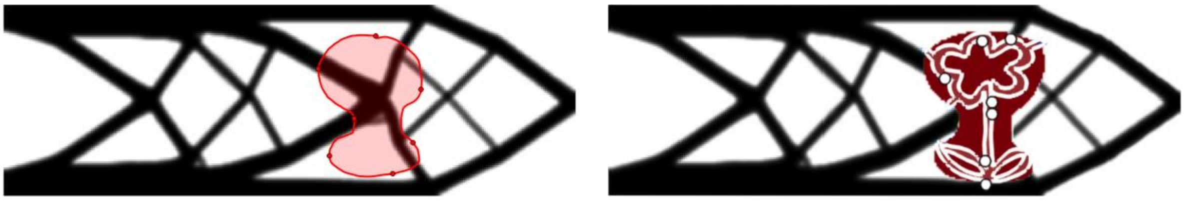


Figure 3: (a) The user draws a region in which the drawing will be located, and (b) shows the graphical input desired within the selected region, here shown in red.

The algorithm passively prescribes solid and void elements within the drawn flower as either solid (1) or void (0) and resumes the optimization. Note here the user *must* include connection points to their drawing to generate continuous, manufacturable designs that fulfill the equilibrium constraint in Equation (1).

Figure 4: Optimized passive design with user-drawn flower with c = 242.1.

The final converged design is shown in Figure 4, where the flower drawing is exactly replicated in the final output and has a compliance of 242.1. The 12% increase in compliance compared to the fully automated design in Figure 1b is not surprising since the design in Figure 4 is inherently more restricted in its exploration. The structural shape near the tip of the cantilever beam is seen to have changed significantly to accommodate the user input such that the tip is no longer symmetric. Some intermediate densities are observed near the edges of the drawing due to difficulty in connecting the passive drawing to the rest of the actively generated structural layout. This difficulty arises since the users must decide where the drawing will connect at 50 iterations when they do not know of how the material will be distributed in the final converged design.

3.3. Appearance constraint

Appearance-constrained interactive topology optimization follows the classic minimum compliance formulation outlined in Section 3.1; however, it also includes the appearance constraint shown in Equation (6).

$$A(\boldsymbol{\rho}) \leq 1. \tag{6}$$

Here $A(\boldsymbol{\rho})$ is a function of the relative physical elemental density and is defined by Equation (7).

$$A(\boldsymbol{D}) = \frac{1}{A^*|\Omega_{\mathrm{ROI}}|} \sum_{e \in \boldsymbol{\Omega}_{\mathbf{ROI}}} D_e(\boldsymbol{\rho}, \boldsymbol{\alpha}), \tag{7}$$

where $\boldsymbol{\Omega}_{\mathbf{ROI}}$ is the set of elements included in the drawn input and $D_e(\boldsymbol{\rho}, \boldsymbol{\alpha})$ is the difference between the density value of the optimized design, $\boldsymbol{\rho}$, and the drawn graphical input, $\boldsymbol{\alpha}$, for every element e in the selected region. A^* is a parameter controlling how strictly the appearance constraint is applied where a lower A^* enforces a more exact replication of the user's sketch. In this work, the distance D_e is calculated using the sum of squared differences between the optimized design and graphical input, as shown in Equation (8).

$$D_e(\boldsymbol{\rho}, \boldsymbol{\alpha}) = \frac{\sum_{j \in \omega_e} (\rho_{e,j} - \alpha_{e,j})^2}{|\boldsymbol{\omega_e}|} \, \forall \, e \in \boldsymbol{\Omega_{\mathrm{ROI}}}. \tag{8}$$

In Equation (8), $\boldsymbol{\omega_e}$ is the set of j elements $\rho_{e,j}$ within the neighborhood of element e, and $\alpha_{e,j}$ is the corresponding element in the source image. The distance value for each element is weighted by the distances for the surrounding elements to ensure continuity across the boundary of the selected region where a design sketch is provided and the rest of the design space.

The appearance-constrained interactive topology optimization workflow is similar to the passive implementation. A quick initial design is generated, and after 50 iterations, the user is prompted to provide input if desired. The initial 50 iterations directly solve Equation (1), and the appearance constraint in Equation (6) is thus not initially applied. The order of the graphical input is slightly different from before. The user first draws the graphical input, which is then overlaid with the 50-iteration initial structural layout to make it easier for the user to decide where the sketch should be replicated within the structure. This is shown in Figure 5 for the same flower example within a cantilever beam as above.

(a) (b)

Figure 5: (a) The user draws a graphical input, and (b) the input is repeated across the design domain and overlaid with the 50-iteration optimized design to draw the region shown in red.

As in the passive implementation, the appearance-constrained topology optimization resumes with the elements in the red region, and the sketch is used to seed the elements that are either solid (1) or void (0) in accordance with the user's drawing. When the optimization resumes, the appearance constraint in Equation (6) is made active such that the provided sketch will be replicated in the selected region.

Figure 6: Optimized appearance-constrained design with user-drawn flower with c = 233.0.

Figure 6 shows the final design, which has a compliance of 233.0. This is only a 7% increase compared to the design result in Figure 1b. The cantilever's topology is seen to have features that resemble the sketched flower. However, the algorithm has made slight modifications to the material distribution within the flower to improve the cantilever beam's mechanical performance. The slight modifications to the flower have allowed the exterior bars of the cantilever tip to appear more symmetric. Consequently, the appearance-constrained design in Figure 6 has a 4% lower compliance value than the passive design in Figure 4.

4. Conclusions

Interactive topology optimization presents new opportunities for users to guide computational design to fit their desired engineering performance metrics and aesthetic intentions. This paper has presented two approaches, passive and appearance-constrained, that follow the minimum compliance optimization formulation and allow users to interactively draw regions of interest in which they will place a drawn graphical input. The passive approach directly replicates the input, while the appearance-constrained result resembles the input while redistributing material to improve the structural performance. As with any interactive method, the performance of the optimized designs depends upon intuitive and compatible user selections and graphical input drawings. For the herein-discussed algorithms, this is especially important for how the sketches and structural topologies integrate. Future work will explore the extension of passive and appearance-constrained interactive topology optimization to 3D, as well as further investigate the most beneficial timing of user interventions.

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