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Sketch driven machine-learning based topology optimization

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Abstract

Sketch design plays a very important role in model design. In order to improve the efficiency of existing design models that rely on computer-aided and human experience guidance, this work proposes a sketch driven machine-learning based topology optimization method. It helps designers directly design hand-drawn sketches to obtain topology-optimized structures that conform to sketching experience. The proposed method uses neural style transfer technique, and can compensate for the lack of design experience to obtain optimized structures without the need of multiple computational simulation interactions. Specific structural shapes and design styles according to the design requirements also can be obtained. In contrast to the approach of specifying the undesignable domain and initial layout, similarity constraints between sketches and structures are constructed to quantify the degree of inheritance of different sketches. Both 2D and 3D problems are solved to illustrate the effectiveness of the proposed approach.

Keywords: sketch driven, topology optimization, machine-learning, Neural style transfer, VGG-19 model, hand-drawn sketch.

1 Introduction

As an assisting technique for structural design, sketch is a basic tool for intuitively expressing design intent and conveying a priori knowledge. For example, designers can draw sketch schemes with basic concepts and element layouts based on design requirements and experience, and continuously refine them on this basis to achieve the purpose of stimulating creativity and rapid design. Therefore, the sketch not only can quickly and accurately reflect the design ideas and structural forms, making the subsequent process more simplified and efficient, but also has the potential to combine with topology optimization to directly guide the optimization of design [1,2]. Enno et al. [3,4] proposed an assisted topology optimization method for designers to communicate intuitively with artificial intelligence tools to help designers improve their initial sketches. The method generates structures that match the drawing load profile by training an artificial neural network. Xie et al. propose a topology optimization method SP-BESO that takes into account the designer's subjective preferences (SP). It introduces subjective scoring and a texture-based drawing system into the bi-directional evolutionary structural optimization (BESO) technique. It allows the designer to add subjective preferences, iterate and interact continuously to create topologically different and structurally efficient solutions [5]. Denk et al. established a sketch-based reverse engineering to reconstruct the 2D sketch shape obtained from topology optimization into a subdivision surface control mesh for 3D redesign, which is evaluated by finite element analysis [6]. In addition, sketch-guided topology optimization functionality has been integrated in several commercial software. SketchOpt [7] introduces an automated design generation system that takes as input a sketch of the basic plane and as output a parametric model prepared for multi-objective building optimization. It helps designers explore multiple performance-based layout plans in the early stages of the design process. DreamSketch [8] software uses a new design workflow that allows designers to express their design intent through sketching, while the computer uses methods such as topology optimization to help designers explore additional solutions with better performance. These solutions are enhanced as 3D objects in a sketching environment. Users can interact with the scene to select and modify within the generated solutions.

Although the above-mentioned research on topology optimization combined with sketching has improved the efficiency of structural design, it is still mostly based on the idea of mutual correction of sketching and topology optimization. This may cause the following problems: 1) The features of sketch are difficult to be controlled explicitly in topology optimization. Too strong sketch features tend to destroy the optimized mechanical structure, while too weak sketch features cannot represent the existed design experience; 2) The mutual correction method has the potential to cause repeated iterations of the design. Since the sketches are not effectively integrated into the topology optimization, the sketches need to be constantly revised according to the optimization results to meet the design requirements. The above analysis shows that there is an urgent need for a deep integration method of sketching and topology optimization to realize sketch-driven topology optimization. In this paper, we propose a sketch-driven topology optimization method based on machine learning for a priori knowledge-guided structural topology optimization design problems. In this approach, CAD descriptions or even hand-drawn sketches can be directly used to guide topology optimization and to make real-time corrections according to design requirements. In the SIMP topology optimization framework [9], unlike the traditional method of specifying the undesignable domain and initial layout [10,11], this paper defines sketch data in the topology optimization column equation based on machine learning techniques. This allows the topology optimization results to explicitly control the extent to which the sketch is presented. Using this approach, the designer can quickly communicate the design intent in the topology optimization and obtain an optimized structure that meets the design requirements.

2 Methods

In this study, style transfer technique [12] is used. The purpose of style transfer is to blend the content image and the reference image together. For the content transfer, the technique extracts the content of the reference image and imports it into the target image.

The difference of content between a target structure and a reference sketch can be measured by function L_{diff}:

$$L_{diff}(\boldsymbol{x},\boldsymbol{a}) = L_{content}(\boldsymbol{x},\boldsymbol{a}) + L_{tv}(\boldsymbol{x}), \tag{1a}$$

where

$$L_{content}(\boldsymbol{x},\boldsymbol{a}) = \sum_{l=1}^{L} w_c^l E_c, \tag{1b}$$

$$L_{tv}(\boldsymbol{x}) = w_{tv} E_{tv} \tag{1c}$$

with

$$E_c(\boldsymbol{x},\boldsymbol{a},l) = \frac{1}{2}\sum_{m,k}\left(F_{mk}^l - S_{mk}^l\right)^2, \tag{1d}$$

$$E_{tv}(\boldsymbol{x}) = \sum\left((\nabla_x \boldsymbol{x})^2 + \left(\nabla_y \boldsymbol{x}\right)^2\right)^{1.25} \tag{1e}$$

In Equation (1), the vectors $\boldsymbol{a}$ and $\boldsymbol{x}$ represent the image data associated with the sketch and the optimized structure (target image), respectively. They consist of the optical primary colors R^c, G^c, and B^c. The symbol l denotes the number of layers of the VGG-19 model network. $L_{content}$ is the function that calculates the difference in content between the sketch and the optimized structure. This function is able to process the image and calculate the mathematical description of the content. L_{tv} is the total variable loss, which serves to enhance the spatial smoothness of the generated image and avoid the results of over-pixelation. The symbols w_c and w_{tv} are the weighting coefficients. $E_s(\boldsymbol{x},\boldsymbol{a},l)$ is the content contribution of the l-th convolutional layer to the total loss, and E_{tv} is the total variable contribution. The filters with size of $3 \times 3 \times C$ are applied to the convolutional layers of the used network. Each layer can be considered as a nonlinear filter bank whose activation in response to the image forms a set of feature maps. The symbol C is the number of total channels, i.e., in the

RGB color image, $C = 3$. These feature maps are stored in the matrix $\mathbf{F}^l, \boldsymbol{S}^l \in \mathcal{R}^{N_l \times M_l}$, where F_{mk}^l and S_{mk}^l are the activations of the m-th filter in the l-th layer layer at position $k \in M_l$; N_l is the number of different filters, which means that there are N_l feature maps whose vectorized size is M_l in the l-th layer.

In this paper, topology optimization is performed in the density-based SIMP framework. In the SIMP framework, a set of continuously varying densities is used to describe the structural topology and geometric structure. The similarity constraint function can be naturally introduced into the SIMP-based optimization column, due to the fact that both the sketch in deep learning and the structural topology in SIMP are described in terms of pixels. Thus, the problem can be formulated as in Equation (2):

$$\begin{aligned}
&\text{Find} \quad \boldsymbol{\rho}^{\mathrm{T}}, \boldsymbol{u} \\
&\text{Minimize} \quad J = \boldsymbol{f}^{\mathrm{T}} \boldsymbol{u} \\
\text{S.t.} \quad & \\
&\mathbf{K}(\boldsymbol{\rho})\boldsymbol{u} = \boldsymbol{f}, \\
&g_1(\boldsymbol{\rho}) = L_{diff}(\boldsymbol{\rho}; \boldsymbol{a}) \leq \varepsilon, \\
&g_2 = \sum_{e=1}^{n} \rho_e \, v_e \leq \bar{V}, \\
&\boldsymbol{u} = \bar{\boldsymbol{u}}, \qquad \text{on } \Gamma_u, \\
&\rho_i \in [0,1] \; \forall \, i \in \Omega,
\end{aligned} \tag{2}$$

where ε is a constant to control the similarity. It is worth noting that the density field $\boldsymbol{\rho}$ should be replaced by $\widetilde{\boldsymbol{\rho}} = \mathbf{T} \times \boldsymbol{\rho}^{\mathrm{T}}$ in the calculation of g_1. The symbol $\widetilde{\boldsymbol{\rho}}$ represents the image data (composed of optical primary colors) converted from the grayscale described by the densities of the optimized structure, where $\mathbf{T}$ denotes the conversion matrix to extend the dimension of $\boldsymbol{\rho}$.

The transfer learning model used in this paper is the VGG-19 model. Before importing into the model, the sketch $\boldsymbol{a}$ will be divided into two parts (i.e., Ω^{s_i} denotes the sketch area and the void area). Here, we define Ω^{s_1} and Ω^{s_2} as the areas occupied by the sketch and the void, respectively. Then $\boldsymbol{x}'$ and $\boldsymbol{a}'$ are defined as Equation (3):

$$\boldsymbol{x}' = \begin{cases} \boldsymbol{x}, \text{if } \boldsymbol{x} \in \Omega^{s_1} \\ 0, \text{if } \boldsymbol{x} \in \Omega^{s_2} \end{cases}, \boldsymbol{x} = \widetilde{\boldsymbol{\rho}}, \tag{3a}$$

$$\boldsymbol{a}' = \boldsymbol{a} + \mathbf{T} \times (\boldsymbol{ones} - (\frac{\boldsymbol{\rho}'^{\mathrm{T}}}{\boldsymbol{\rho}'^{\mathrm{T}}_{max}})^3), \tag{3b}$$

with

$$\boldsymbol{\rho}' = \begin{cases} \boldsymbol{\rho}, \text{if } \boldsymbol{\rho} \in \Omega^{s_1}, \\ 0, \text{if } \boldsymbol{\rho} \in \Omega^{s_2}, \end{cases} \tag{3c}$$

where $\boldsymbol{ones}$ is the unit matrix of the same size as $\boldsymbol{\rho}'$. The sketch $\boldsymbol{a}$ is improved to the trivial penalty in Equation (3a). The significance is that it enables the similarity constraint to prioritize the less dense regions of Ω^{s_1} at the beginning of the iteration to prevent being optimized to void material by the objective function. Normalization as a numerical trick can weaken the constraint strength of the sketch, allowing the structure to adjust the sketch guided by the stiffness, and the latter term of Equation ($3c$) will be infinitely close to 0 in the late iteration.

3 Results

According to numerical experience, only Conv3_2 is considered in the calculation of g_1 in this paper. Due to the influence of down-sampling, Conv1_2 and Conv2_2 can be considered if the structure size is too small, and Conv4_2 can be considered if the structure size is too large. Conv5_2 is not suitable for sketch inheritance.

In this section, a cantilever beam design with dolphin shape topology optimization example shown in Figure 1. We will illustrate the adaptability of the proposed approach to sketch-driven topology optimization design. With volume constraints and machine learning assisted similarity constraints, the objective is to minimize the compliance of the structure, allowing simultaneous optimization of sketch experience and structural stiffness. Figure 2 shows the design domain, loads and boundary conditions for a cantilever beam structure. The design domain is a 1×1 (discrete to 400×400) area subjected to a downward concentrated force load in the lower right corner. The volume constraint is $\mathrm{V} \leq 0.2|D|$. The result of the pure compliance minimization result is shown in Figure $2b$ ($I = 178.518$), where the main beam is concentrated at the upper left corner where the constraint is located and the lower part of the structure is the downward extension arm of the beam.

In the topology optimization while considering the sketch Figure $2a$, the head of the dolphin plays a role of supporting. The extension arm in the lower right corner is replaced by the caudal fin, and the pectoral fin is taken into account to make the dolphin shape more abundant. The sketch is broken at the connection of the line to verify the stability of the algorithm, and secondly, the dorsal fin is in the inefficient force transfer region of the structure in order to make the algorithm optimization more difficult.

To compare the algorithm in this work with the method of setting undesignable domain, Figure 2c ($I = 221.850$) shows the optimization results of setting the sketch part to the undesignable domain. It can be observed that the dorsal fin is completely preserved and the pectoral and caudal fins have lines separate from the structure. The structure is not optimal, part of the material loses performance and does not contribute to the compliance. When considering setting the sketch part as the initial layout for the first step of the topology optimization iteration, as shown in Figure 2d ($I = 187.907$). In the initial material distribution, the density of the sketch part is set to be $\boldsymbol{\rho} = 1, \boldsymbol{\rho} \in \Omega^{s_1}$ and the rest of the part is weak material $\boldsymbol{\rho} = 0.01, \boldsymbol{\rho} \in \Omega^{s_2}$, it can be observed that the presence of the jawed part of the sketch makes the structure different from the pure compliance result in the constrained region. Secondly, since the sketch is concentrated on the upper right side, the final optimization results are also distributed so that the thin short beam in the lower left part disappears.

Using the algorithm of this paper, the upper limit of the similarity constraint is set to a very strong $\varepsilon = 0.035\varepsilon_0$, and the corresponding optimized structure is shown in

Figure 2e ($I = 209.165$). ε_0 is the difference in the sketch inheritance between the initial structure (pure gray structure) and the reference sketch. In contrast to setting the undesignable domain method, there is no material distribution in the structure that contributes to 0, although the dorsal fin also remains. To make the structure optimal under this strength constraint, the structure changes from a longer beam to a combination of many shorter beams with a better objective function. When the upper limit of similarity constraint is set to $\varepsilon = 0.15\varepsilon_0$, the corresponding optimized structure is shown in Fig. 2f ($I = 196.821$), and the dorsal fin is degraded to the existing structure. To make the structural connectivity preserved, many short beams serve as interconnections, and the number is smaller relative to the $\varepsilon = 0.035\varepsilon_0$ result. Many detailed parts of the dolphin sketch are modified by the stiffness, but it also clearly reflects the presence of the dolphin structure.

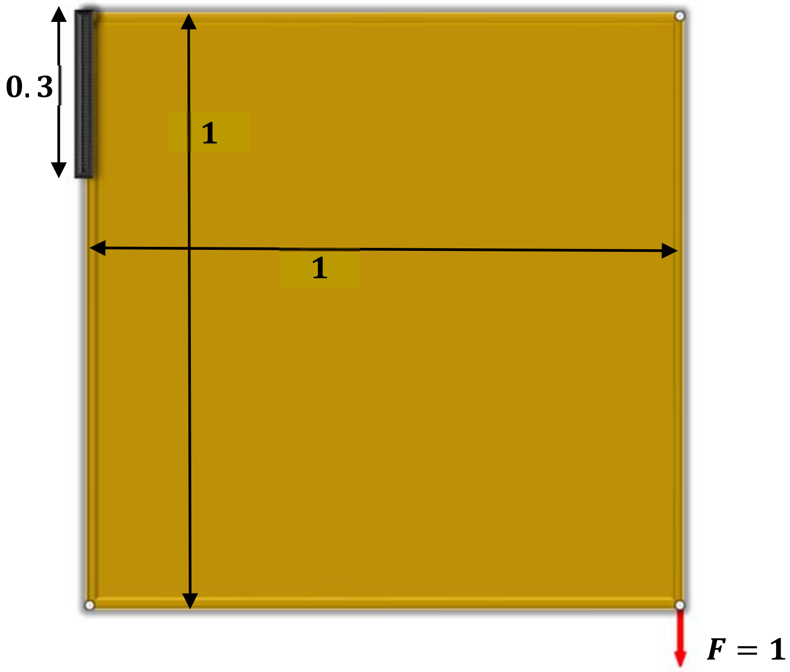

Figure 1: A dolphin beam example.

4 Conclusions and Contributions

In the present work, a novel topology optimization approach is proposed for sketch inheritance. To achieve this approach, the content difference between the sketch and the structure is defined as an explicit control in the SIMP framework. Machine learning techniques are used to measure the values of the features quantified by the content. The optimization results can well inherit the regions of the sketch that contribute more to the structural stiffness and assist in the modification of the regions that contribute less. Numerical calculations show that the method can design an optimization structure inherited to the essence of the sketch, making the connection between the designer and the mechanics deepen. Corresponding studies and results will be reported in the future

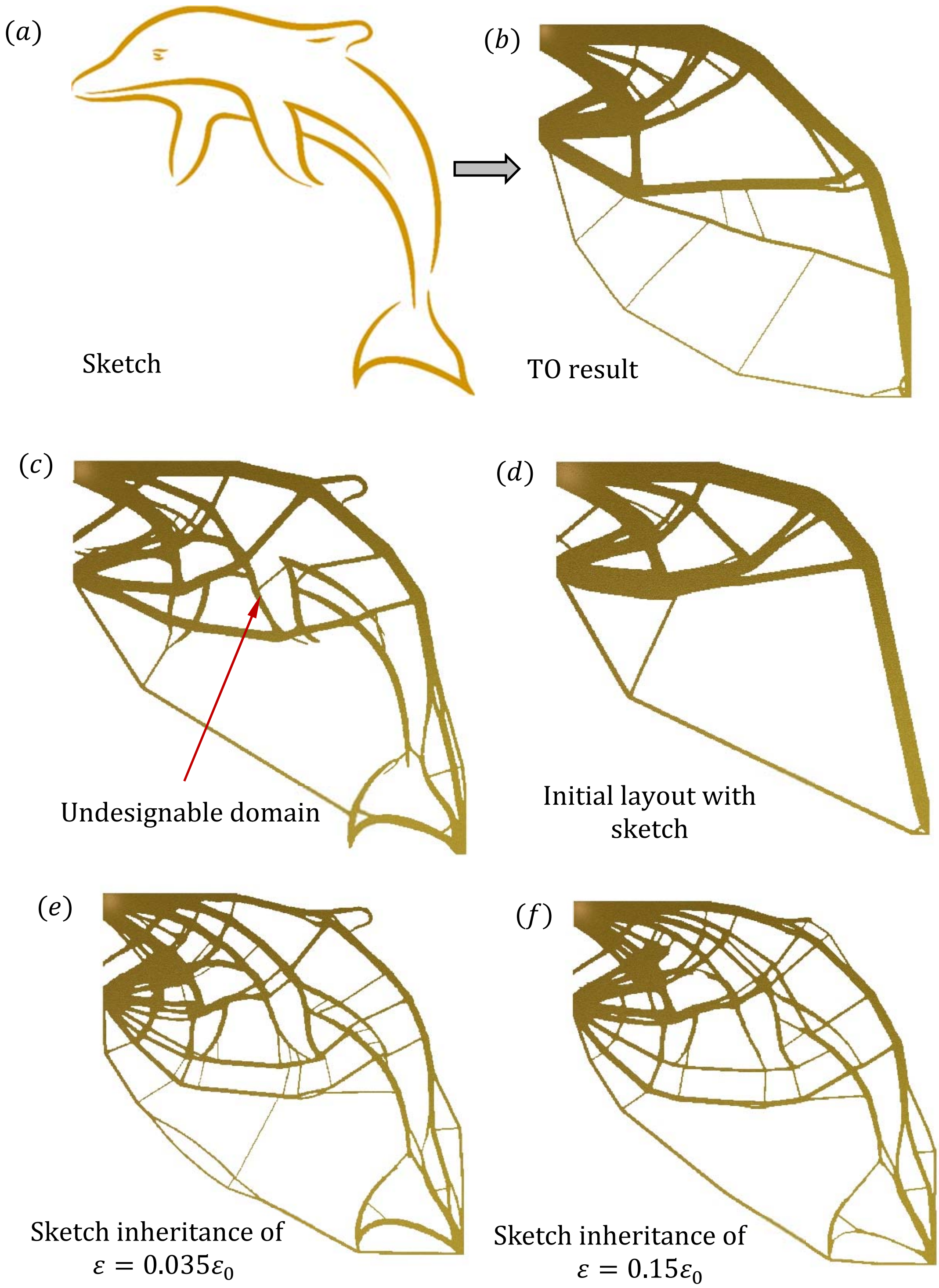

Figure 2: The optimized design of dolphin beam example.(*a*) Sketch; (*b*) The pure compliance minimization result; (*c*) The pure compliance minimization result with undesignable domain of sketch; (*d*) The pure compliance minimization result with initial layout of sketch; (*e*) The optimized design referring to the sketch with $\varepsilon = 0.035\varepsilon_0$; (*f*) The optimized design referring to the sketch with $\varepsilon = 0.15\varepsilon_0$.

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