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Machine-learning assisted topology optimization with structural gene inheritance

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Abstract

A machine-learning assisted topology optimization approach is proposed for structural design with structural gene inheritance. This work establishes a novel framework to systematically integrate structural topology optimization with subjective human design preferences. To embed the structural gene into the design, neural style transfer technique is adopted to measure and generate the prior knowledge from a reference image with the concerned structural gene (such as biological characteristic, artistic flavor and manufacturing requirement, etc.). By using different convolutional layers in the VGG-19 model-based CNN, both the style and content of the structural gene can be constructed from low to high levels of abstraction. The measured knowledge can then be integrated into pixel-based topology optimization as a formal similarity constraint. Both 2D and 3D problems are solved to illustrate the effectiveness of the proposed approach where the inheritance of the structural gene can be achieved in a systematic manner.

Keywords: topology optimization, structural gene, bio-inspired structure, machine-learning, neural style transfer, VGG-19 model.

1 Introduction

In traditional topology optimization-based approaches, only structural properties can be considered in the optimization process. Aesthetic side, is often handled manually by trial and error or post-processing. As discussed in [1], there is an urgent need for the sound integration of artistry and function in the final design. The second issue is that it is difficult for the topology optimization to inherit prior design knowledge, which could make it possible to achieve desired innovative structural forms. For example, the style of nature structures, such as trees, are usually considered to have excellent ornamental forms. Obviously, taking these styles into topology optimization can expand the design space to explore more design options. However, most research studies can only achieve the replication of existing nature structures or using biomimetic initial structure with post-processing treatment to improve the structure. Therefore, integrating the treatment into the optimization problem is highly required. Last but not least, the optimization result lacks diversity. It means once the optimization model is defined, the optimal architectural structure is also determined. Therefore, the designer has to go through the process of trial-corrections (such as changing the boundary conditions of the problem) to obtain satisfactory results. Obviously, this treatment has great limitations and is unreliable.

To improve the details of structural features in design, machine learning is widely sought after recently. Similar to the shape matching and object recognition idea [2,3], Li [4] and Han [5] pointed out that artistic shapes can be recognized by machine learning through style transfer methods. One of the very first attempts can be found in [6], where ImageNet classification with deep convolutional neural networks (CNN) is proposed. Then, the rapid development of deep learning [7–9] technique provides inspiration for topology optimization with artistic flavor. With the use of deep learning technique, the graphical features of neural networks provide a possibility to define the measurement of the similarity between the reference images and the optimized structures. Unlike the artistic shape recognition, neural style transfer uses images derived from CNN to display high-level information. This idea can separate and recombine the content and style of the images [10]. In [11] Vulimiri et al. tried, with use of a pre-trained neural network, to achieve the combination of reference image and optimized structure. In their study, they showed how to preliminarily quantify the desired geometric style of the optimized design. Furthermore, texture guided approach [12–14] also has the capability of combining the graphic features with topology optimization. Excellent results of synthesized textural structures have been also proposed [13,14] However, the approaches mainly focus on the concrete geometric similarity. When the similarity requirement for abstract structural style or form is concerned, the approaches could face some challenges.

In the present work, a machine-learning assisted topology optimization approach is proposed for structural design with structural gene inheritance. In this approach the structural gene, including structural feature, structural shape and even structure type and form can all be taken into consideration in the optimization. The approach is developed under the SIMP (solid isotropic material with penalization) framework [15]. Unlike the traditional approaches where trial techniques or hypothesis initial structures are adopted for promoting structures to produce structural gene, the machine-learning technique is introduced to define and measure the structural gene mathematically. In this work, the structural gene can be controlled as a formal similarity constraint which makes explicit control of the structural gene possible in topology optimization. Since the structural topology and geometry are described by a set of pixels in SIMP, analytical sensitivity of the similarity constraint can also be easily obtained. With the use of this approach, architectural structures can be designed with relatively good structural performance blended with various structural gene.

2 Methods

In the present work, the style transfer technique [10] is adopted to measure the style of a reference image. Actually, neural style transfer is a significant development in the field of deep-learning-driven image modification. The aim of style transfer is to blend a content image and a reference image together. It consists of two steps, i.e., extracting the style of a reference image and importing it into a target image while preserving the style and content. Obviously, the style extraction process, which measures a pattern from feature, texture, shape, form and style aspects, can be used to define the structural gene.

Generally, the difference of a target structure and a reference pattern can be measured by function L_{diff} expressed as:

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

where

$$L_{style}(\boldsymbol{x},\boldsymbol{a}) = \sum_{l=1}^{L} w_s^l E_s, \tag{1b}$$

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

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

with

$$E_s(\boldsymbol{x},\boldsymbol{a},l) = \frac{1}{4C^2 N_l^2 M_l^2} \sum_{m,n} (G_{mn}^l - A_{mn}^l)^2, \tag{1e}$$

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

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

and

$$G_{mn}^l(\boldsymbol{x},l) = \sum_k F_{mk}^l F_{nk}^l, \tag{1h}$$

$$A_{mn}^l(\boldsymbol{a},l) = \sum_k S_{mk}^l S_{nk}^l. \tag{1i}$$

In Equation (1), the vectors $\boldsymbol{a}$ and $\boldsymbol{x}$ denote the data associated with the reference image and the optimized structure (target image), respectively. They are composed of R^c, G^c, and B^c, which represent the optical primary colors. The symbol l represents the number of the layer of the network (total number L). L_{style} and $L_{content}$ are the functions that calculate the discrepancies of style and content between the reference pattern and the optimized structure, respectively. Here, the style represents the abstract pattern features while the content represents the concrete pattern features. The two functions have the ability to process an image and compute the mathematical description of its style and content. L_{tv} represents the total variation loss. It plays a role to enforce the spatial smoothness of the produced images and avoiding overly pixelated results. The symbols w_s, w_c and w_{tv} are the weight coefficients. The symbol $E_s(\boldsymbol{x}, \boldsymbol{a}, l)$ is defined as the style contribution of the l-th convolutional layer to the total loss; E_c and E_{tv} are the content contribution and total variation contribution, respectively. The filters with size of $3 \times 3 \times C$ are also applied to the convolutional layers in the adopted network. So, each layer can be seen as a nonlinear filter bank, whose activations in response to an image form a set of feature maps. The symbol C is the number of total channels, that is, in RGB color images, $C = 3$; N_l is the number of the distinct filters, which means that there are N_l feature maps whose vectorized size is M_l in the l-th layer; $\mathbf{G}^l$ and $\mathbf{A}^l$ are the gram matrixes which calculate the inner product (G_{mn}^l and A_{mn}^l) of the m-th and n-th feature maps in the l-th layer ($m, n \in N_l$); these feature maps are stored in matrixes $\mathbf{F}^l, \mathbf{S}^l \in \mathcal{R}^{N_l \times M_l}$, where F_{mk}^l and S_{mk}^l are the activation of the m-th filter at position $k \in M_l$ in the l-th layer. The corresponding detail expressions of $\mathbf{F}^l$ and $\mathbf{S}^l$ are provided in the subsequent subsection.

Since the goal is to optimize various structures that exhibit excellent mechanical performance and simultaneously possess certain artistic content and style associating with a reference image, the topology optimization formulations for 2D and 3D cases can be expressed as follows.

For 2D case, the similarity constraint can be introduced into the SIMP-based optimization formulation in a natural way. This is because both the artistic style in deep-learning and structural topology in SIMP are described by pixels in a similar way. Thus, Equation (2) can be restated as follows:

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

where ε is a constant to control the similarity; n is the total numer of elements and $\bar{V}$ is the upper bound of the volume of available solid material. It is worth noting that the density field $\boldsymbol{\rho}$ should be replaced by $\widetilde{\boldsymbol{\rho}} = \mathbf{T} \times \boldsymbol{\rho}^{\mathsf{T}}$ 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 $\boldsymbol{\rho}$.

3 Results

An example is explored in this section to demonstrate the effectiveness of the proposed approach in structural design with structural gene inheritance. For the performance testing of the numerical approach, compliance minimization problem for both 2D and 3D structures are considered. All used data are chosen as dimensionless, that is, the Young's modulus of material is $E = 1.0$ and Poisson's ratio is $\nu = 0.3$. If not otherwise specified, the upper bound of the similarity constraint is set to $\varepsilon = \frac{1}{3}\varepsilon_0$, where ε_0 is the difference in the structural gene between the initial structure (pure gray structure) and the reference image in Figure 2*d*-*e* (the smaller the value of ε, the more similar of the style and contents of the two images). Additionally, only Conv2_1 and Conv3_1 in L_{style} and Conv5_2 in $L_{content}$ are active for the calculation of g_1 in the present work (i.e., there are 16 layers in the neural network). Under this circumstance, only $w_s^{\text{Conv2\_1,Conv3\_1}}$ and $w_c^{\text{Conv5\_2}}$ are nonzero weight coefficients. The total variation loss w_{tv} is set to be $w_{tv} = \min\left(w_s^{\text{Conv2\_1,Conv3\_1}}, w_c^{\text{Conv5\_2}}\right)/10$. Furthermore, the method of moving asymptotes (MMA) is adopted for solving the optimized solutions of problems. All examples are solved with use of a computer with 8 cores 2.30 GHz Intel Core i7 – 11800H CPU and NVIDIA GeForce GTX 3080 Laptop GPU whose CUDA cores is 6144 with 16 GB memory.

In this section, a tall high-rise building topology optimization example shown in Figure 1 is examined to investigate the capability of the proposed method for topology optimization with structural gene. The design domain is a 1×6 rectangle discretized by a 200×1200 finite element mesh. The outer frame is defined as undesignable region as indicated in Figure 1. The graded distribution loads are imposed on the left and right sides. The bottom side of the design domain is clamped. The constraint of available solid material is set to $g_2 \leq 0.7|D|$. The pure compliance result without similarity constraint is given in Figure 2*a*. The corresponding value of structural compliance is $I = 212.029$. Some crossed beams can be observed in the structure. Since the available solid material is relatively high, the bottom region is almost completely filled with solid material. Closed to the top region, the distribution of material becomes sparse and only several thin beams can be found. This time, Figure 2*d*-*e* are appointed as the references to be associated with topology optimization. Figure 2*d* is a nature structure, i.e., the microstructure of bamboo. The heterogeneous microstructure is often considered of having good mechanical properties, such as good tensile and flexural strength. If the tall high-rise building is designed inspired by bamboo, besides the increase in the complexity of the design, the improvement in anti-seismic property is also possible to be improved. In Figure 2*e*, a typical Baroque pattern of waves, which is deemed to have highly decorative and theatrical style, is described. If the Baroque style can be integrated into the building topology optimization, the obtained design may be more decorated and dramatic. We also hope to find elements of Renaissance architecture (the basic elements in Baroque style) in the final design. Inspired by the previous example, $L_{style}(\boldsymbol{x}, \boldsymbol{a})$ is adopted as similarity constraint directly (this treatment may increase the solution space of the optimization problem).

Then, the topology optimization is carried out with considering structural gene using similarity constraint. Figure 2b-c shows the corresponding optimized structures with structural gene ($I = 216.003$ and $I = 216.910$, respectively). In both results, the supporting beams closed to the left and right sides are very strong to resist the bending loads. However, some regions originally filled with pure solid material are replaced by very complicated lattice patterns. In Figure 2b, the voids existing in the structure are almost in circular shape, which are consistent with the microstructure of bamboo. Due to the existence of image style (i.e. $L_{style}(\boldsymbol{x}, \boldsymbol{a})$) term in the similarity constraint, the circular voids are not evenly distributed throughout the structure. They keep the trend of graded decrease from bottom to top. In Figure 2c, quite different structural topology can be observed. The inside region is filled with reticulated structures, whose features are very similar to the wave pattern. In the optimization result, some strong beams are generated in the high strain energy regions to produce excellent structural stiffness as main loading paths (the locations of these beams are also consistent with these in Figure 2a). In other regions where relatively low strain energy exists, the original strong beams are replaced by tiny beams in wave shape. It is worth noting that even though the sizes and shapes of these beams are affected by the style of Figure 2e, the distribution and form of the beams still conform to the mechanics principle. It can be observed that apart from the pure mechanical design in Figure 2a, the expected structural gene are clearly reflected in the optimization results.

4 Conclusions and Contributions

In the present work, a novel topology optimization approach is proposed for structural design with structural gene inheritance. To achieve this purpose, the structural gene is defined as a formal similarity constraint under the SIMP framework. Machine-learning technique is adopted to measure the structural gene of a reference image in constraint calculation. Unlike the post-processing treatments, the structural gene can be controlled in the optimization process in an explicit way. Therefore, the concerned structural gene can be produced along with reasonably excellent structural performance. Compared with the existing approaches, the distinctive feature of the present machine learning assisted approach is that it has the capability of generating both abstract style and concrete content, rather than simple copy of the geometrical patterns. The provided numerical examples illustrate the fact that the proposed approach has the capability of designing structure with desired structural gene, which may create innovative structural forms and increase the diversity of the design. Actually, the same approach can also be extended to topology optimization for nature inspired design, which may bring some unanticipated performance with use of traditional topology optimization formulation. Corresponding research and results will be reported in the future.

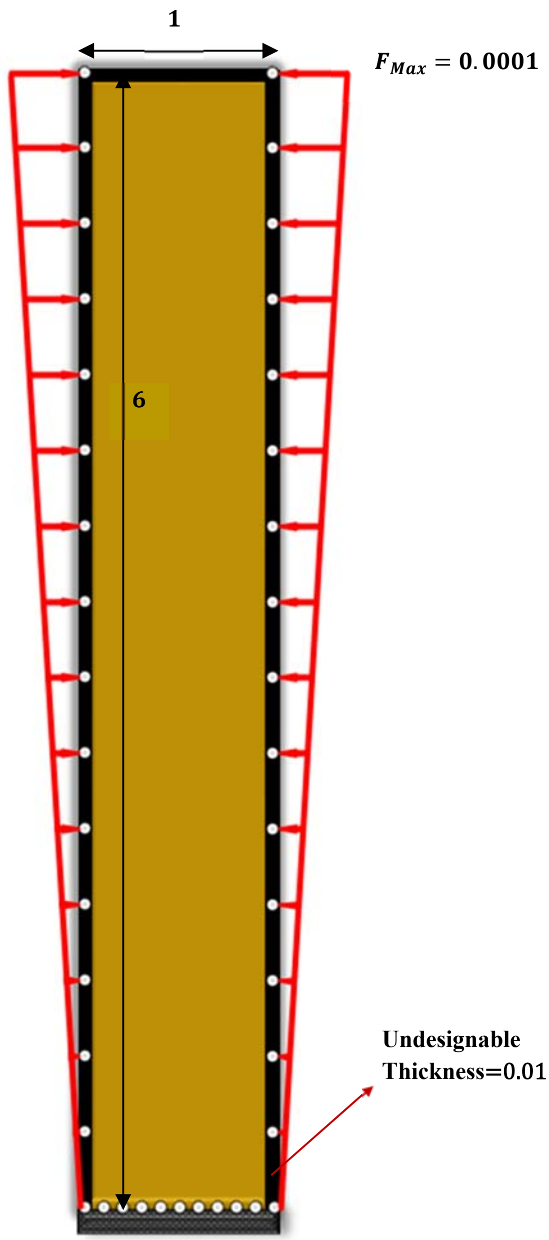

Figure 1: A tall high-rise building example.

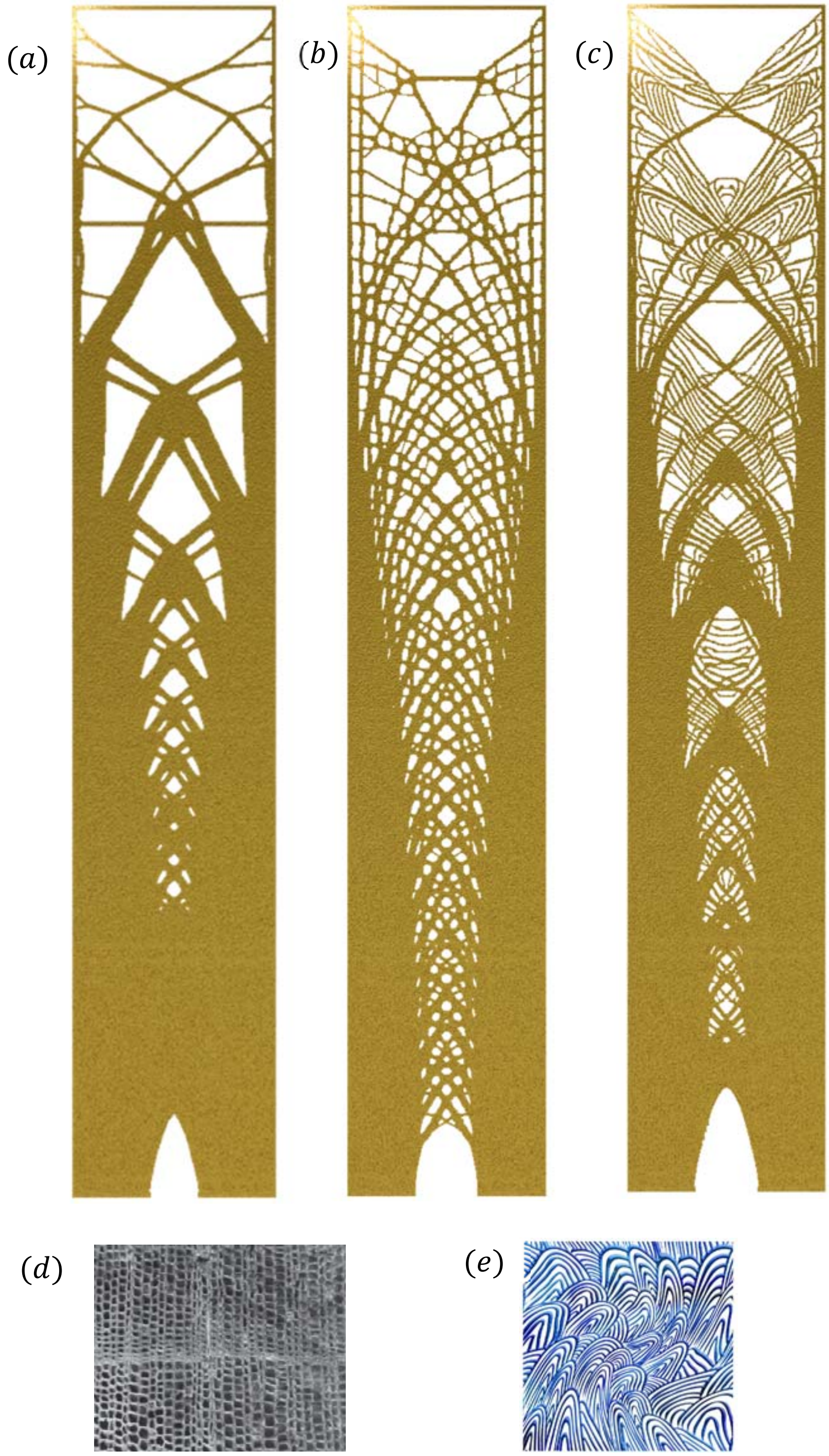

Figure 2: The optimized design of the tall high-rise building with similarity constraint. (a) The pure compliance optimized design of the tall high-rise building. (b) The optimized design referring to the style of Figure 2(d); (c) The optimized design referring to the style of Figure 2(e); (d) Microstructure of bamboo; (e) Baroque pattern of waves.

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