Convergence Study of 3D Porous Infill Optimization using Stress Tensor Visualization

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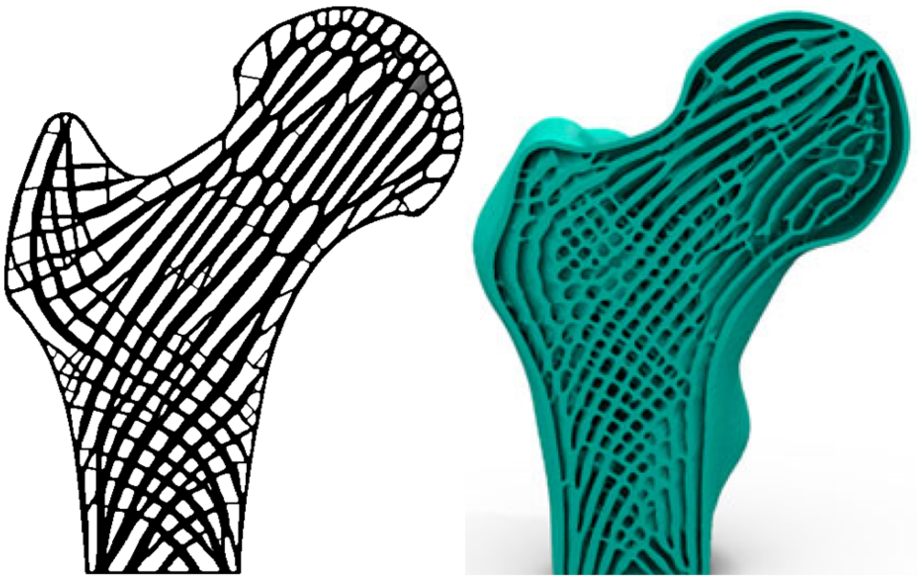

Figure 1: Results of porous infill optimization. Left: 2D result reproduced from [4]. Right: 3D result reproduced from [5].

Abstract

This is a thesis topic provided for master's students.

1 Introduction

Achieving the highest stiffness while using the least amount of material is a fundamental task in mechanical design. This is often formulated as an optimization problem, e.g., topology optimization, in which the material distribution is optimized. The porous infill optimization proposed in [5] has become a popular branch in density-based topology optimization [7]. Unlike the classic topology optimization which only takes the total material consumption as the constraint, also known as the global volume constraint [1, 6], in the contrast, the porous infill optimization employs a local volume

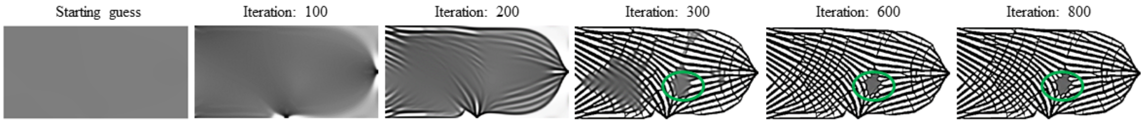

Figure 2: Demonstration of the history of porous infill optimization when the convergence issue is existing.

constraint, i.e., imposing an upper bound of the material consumption for each simulation element and its vicinity locally. In this way, the porous infill optimization produces a lightweight and domain-filling design that is composed of sub-structures spanning different length scales, which exhibits the bone-mimic infill pattern, see Fig. 1.

The density-based topology optimization usually starts from a homogeneous density field (i.e., starting guess) and proceeds by iteratively adjusting the density value of each simulation element till a binary material layout is obtained. At the end of optimization, each simulation element shall only be solid (1) or empty (0) in the final result, thereby in principle, the optimized result can be built directly. In some settings of porous infill optimization in 2D, however, we find that such a binary design cannot be obtained even after hundreds or even thousands of iterations, see Fig. 2.

We've studied the convergence issue of the 2D porous-infill optimization in [3]. We make use of the stress topology analysis to predict the potential low-convergence regions and solve this convergence issue effectively by employing a stress topological skeleton-guided initialization strategy. Specifically, we find that the low convergence region appears around the so-called *trisector degenerate point* of the corresponding stress field. We analyze this is due to the high isotropy of the stress tensor close to a trisector degenerate point, thus, a locally consistent binary material layout cannot be efficiently decided by the optimizer. Comparing Fig. 3a-c and Fig. 3d-f, sequentially. Based on this discovery, and considering the topology optimization is a non-convex problem, i.e., depending on the initialization a different local optimum can be reached, we propose an automatic initialization strategy to guide the material deposition around the trisector degenerate point. This initialization strategy is based on the computation of the *topological skeleton* of trisector degenerate point and achieved by giving the simulation elements visited by the topological skeleton a higher density value than others in the starting guess. In this way, the convergence issue is solved efficiently (Fig. 3g-i). Figure 4 shows the optimization history corresponding to Fig. 2 but with the proposed initialization strategy for starting guess.

Our previous work restricts the discussion only to 2D, now we aim for extending it to 3D.

2 Methodology & Techniques

To proceed with this study, we need a visualizer to help spot the low-convergence regions in the density field during the course of topology optimization, which, in principle, can be arranged into a direct volume rendering problem. In addition, we also need a robust solution to obtain the topological features like degeneracy and topological skeleton of the stress field in 3D [2, 8]. Built upon this, we can study the potential correlation between the convergence issue and the stress topology.

The major challenge of such an idea would be the robust identification of degeneracy due to the well-known issue of numerical instability. Given that it's not necessary to compute the precise positions of degeneracy if we just want to compare the spatial distributions of the low-convergence regions and the degeneracy, we plan to circumvent this challenge via a relaxed scheme. Specifically, we'll define a degeneracy metric over each element, which is supposed to quantify the scale of

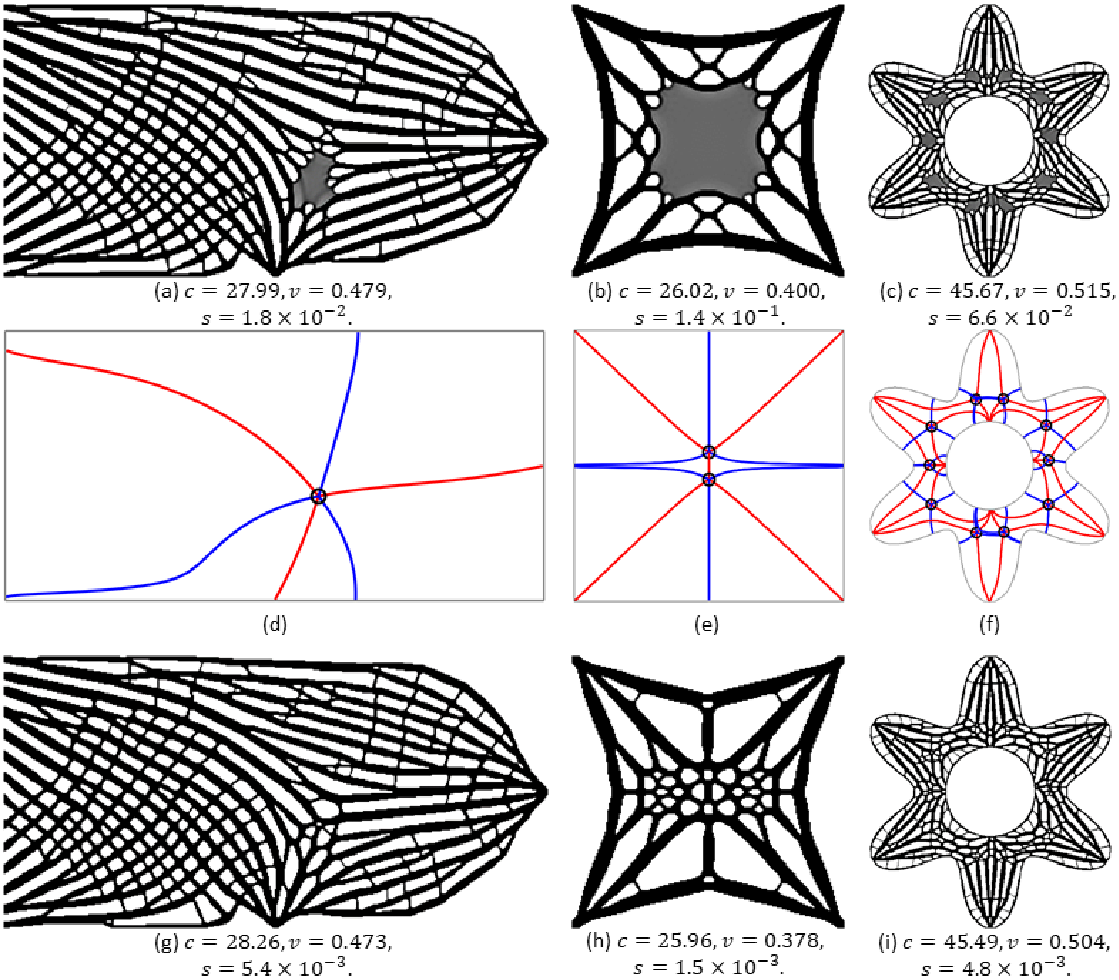

Figure 3: Demonstration of the convergence issue existing in the density-based topology optimization under local volume constraint. (a)-(c) Optimized density layouts of three different examples using the original density-based topology optimization under local volume constraint. (d)-(f) The trisector degenerate points (black circles) and associated topological skeleton corresponding to the stress fields of (a)-(c), the red and blue trajectories distinguish the topological skeleton following the major or minor PSLs, respectively. (g)-(i) Optimized density layouts corresponding to (a)-(c) but with the proposed initialization strategy in [3]. All of the results in (a)-(c) and (g)-(i) experience 800 iterations.

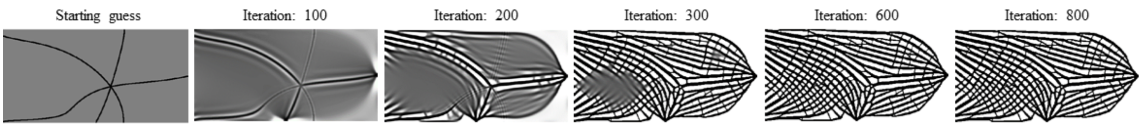

Figure 4: Demonstration of the history of porous infill optimization when the convergence issue is existing, but with the proposed initialization strategy for starting guess.

degeneracy within each element that may contain the degeneracy, then we can convert the rigorous stress topology analysis problem into a rendering problem. In this way, we can expect to obtain an intuitive impression of the possible correlation between the low-convergence regions and the stress topology. If this correlation holds, we'll consider using PSLs around the degeneracy to initialize the starting guess of the porous-infill optimization in 3D.

3 Outlook

In specific, we want to confirm whether such a convergence issue exists in 3D. If it does, we want to further explore the solution for it referring to what we've obtained from [3]. If it does not, we want to give a theoretical or at least heuristic analysis.

4 Prerequisites

The student shall have some fundamental expertise in numerical simulation and computer graphics, e.g., finite element analysis (FEA), numerical optimizer, and volume rendering.

5 Available Resource

The datasets or code (in MatLab) of porous infill optimization will be provided to the student. The 3D stress visualizer is also open to the student, covering the stress trajectories visualization, and identification of the elements that may contain the degeneracy.

References

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