DESIGN AUTOMATION FOR MULTI-MATERIAL PRINTING

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Abstract

The advent of multi-material freeform fabrication technologies has exponentially increased the mechanical design space available to engineers. The feature-based paradigm of traditional CAD software is insufficient to take advantage of the freedom of internal material distribution and gradients. Here we present a flexible evolutionary design algorithm for 3D multi-material structures that fully utilizes this expanded design space. The material distribution is optimized subject to high level functional constraints, or simple constraints such as maximizing stiffness per weight. The algorithm is inherently capable of shape optimization, or can simply optimize material distribution within a given geometry. We demonstrate autonomous design of freeform shapes, 3D non-uniform structures, and 3D compliant actuators.

Introduction

Despite the ubiquity of computing power available, the field of mechanical synthesis has so far resisted widespread automation. At the root of this problem is the inability of algorithms to transfer multiple competing goals efficiently into a geometry which can be manufactured practically. To accomplish this, an algorithm must incorporate some knowledge about the manufacturing process to be used, and stay within the constraints of the process. These could include factors such as fixtures for a machining process or draft and parting lines for a molding process. However, the advent of freeform additive manufacturing technology allows any 3D shape and topology to be fabricated without penalty (Beaman et al., 1997), removing many complex constraints from the automated design process.

In addition to the lack of geometrical constraints when designing for additive manufacturing (Hague et al., 2003), with the advent of multi-material 3D printing (Malone et al., 2004, Objet, 2009) the mechanical design space available to engineers is increasing ***exponentially***. Traditional feature-based CAD programs are generally insufficient to create optimal freeform geometries (Mantyla et al., 1996), and are severely limited in their ability to design using multiple materials both at a macroscopic and microscopic level. For this reason, design automation will likely play an increasingly important role in mechanical synthesis, especially for parts created using additive manufacturing processes.

Background

The ideal design process would require only the functional goals of the desired part to be input, and would create the optimal blueprint autonomously. Much work has been done in this field (Díaz and Lipton, 1997, Fernandes et al., 1999) regarding the topology or shape optimization of single material structures, with the goal of maximizing stiffness per weight. The most established method in this field is homogenization, as originally demonstrated by Bendsoe and Kikuchi, 1988. This iterative process varies the effective stiffness of each cell within a 2D or 3D matrix according to its strain energy, and optimizes the structure subject to constraints on total volume and minimizing strain energy. Variations on this method have yielded results that maximize deflection for applications such as a simple gripper structure, or even utilize two materials to emulate an actuated structure (Buehler et al., 2004, Nishiwaki et al., 1998, Sigmund and Torquato, 1999).

However, homogenization results are generally limited to optimizing overall deflection or force. This approach become unwieldy or intractable as complexity is added to the design problem, such as competing objectives involving multiple materials or specifying a desired deformed shape.

Evolutionary algorithms have also been explored for the purposes of topological optimization. This class of algorithms maintains a population of possible solutions, which are continually mutated and recombined (crossover) to improve over time. Evolutionary algorithms have not found widespread use in topological optimization for several reasons. First, they are much less efficient than the homogenization method for the single objective structural optimization problems that are often addressed in literature. Secondly, the success of genetic algorithms depends on how the object is encoded (the genotype) to represent the physical object (phenotype). In early attempts at using genetic algorithms to solve topological optimization problems, every individual pixel or voxel was represented explicitly in the genotype (Jakiela et al., 2000, Kane, 1996). In addition to the challenge of making crossover and mutation non-destructive, this method scales poorly to large structures.

Thus, the success of genetic algorithms in solving topological optimization problems depends on using a representation that efficiently defines sensible objects using a minimum number of parameters (Kane and Schoenauer, 1996). Various graph structures, generative encodings, and constrained bit-wise encodings have been proposed to address these challenges, as summarized in Kicinger et al., 2005. These more efficient representations enable genetic algorithms to overcome the functional complexity limitations of homogenization, although at the expense of increased computational effort.

Results and Discussion

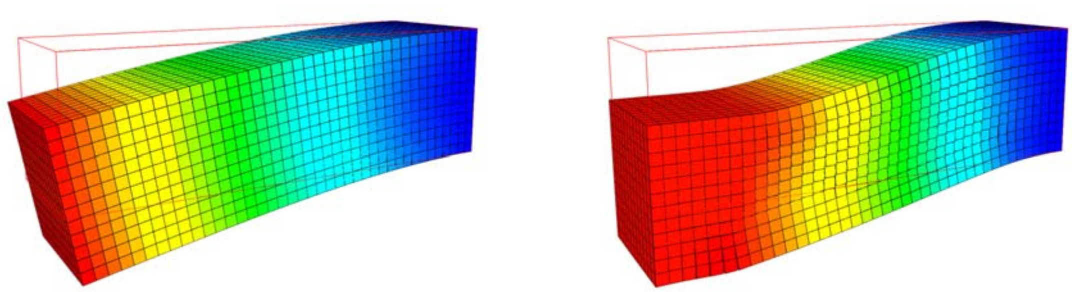
Encoding (how the algorithm thinks about the objects)

Here we propose an encoding which naturally generates smooth, freeform 2D and 3D shapes at an arbitrary level of complexity with a minimal number of parameters for any number of materials. The genotype consists of a series of frequency amplitudes at harmonic multiples, and the phenotype is generated by applying the inverse discrete cosine transform (DCT) to this series. This representation was chosen for its relative simplicity of implementation and evolvability. By representing a three-dimensional object as a 3D matrix of frequency amplitude components, a number of advantages are realized. These include the ability to render the genotype at any resolution, complete dimensional independence, and naturally available symmetry. This comes at the expense of not being able to easily represent sharp corners and flat surfaces in the generated objects. The discrete cosine transform was chosen over other transforms due to its inherent ability to concentrate the most useful information in the lowest order frequency components.

The user-defined complexity metric is worth explaining in greater detail. If desired, the DCT encoding could contain as many frequency components as voxels within the physical object. This would allow any possible configuration of voxels to be generated, but defeats the purpose of having an indirect encoding. As we decrease the number of parameters in the frequency matrix, the ability to create any possible object is lost. However, the encoding was chosen such that sensible, smooth objects suitable for additive manufacturing would be generated with only a few parameters. The complexity metric is defined as the maximum number of frequency components in the longest dimension. If a sample workspace was 40 voxels long, a complexity metric of 10 would result in a minimum feature size of approximately 4 voxels (40/10).

Fitness (How the algorithm evaluates possible solutions)

An integral part of the genetic algorithm is the fitness evaluation. At this step, the algorithm evaluates each design according to user defined criteria. Here, we are concerned with the mechanical reaction of our structures to various conditions, calculated using the linear direct stiffness method as illustrated in Figure 1. For each experiment, certain regions of voxels were defined as fixed to ground or subject to an applied force. Each voxel has an associated stiffness and poisson's ratio, based on the output of the inverse DCT. This defines the global stiffness matrix for a given geometry, which was then solved using the highly optimized PARDISO solver (Schenk and Gärtner, 2006, Schenk and Gärtner, 2004) library to yield the resulting displacements and internal stresses of each voxel of the structure under load.



(a) (b)

Figure 1: The direct stiffness method was used for physical evaluation of multi-material cantilever beams. Shown here are the deformations resulting from a homogenous material (a) and an automatically generated multi-material distribution (b).

Algorithm Details

The genetic algorithm used here is outlined in Figure 2. When two individuals are selected for crossover, each frequency component of the offspring is randomly chosen from either parent. The parent which contributed the greatest number of frequency components is stored as the "most similar" parent for the selection process. To mutate an individual, random variations were introduced into the frequency amplitudes of the genotype. These variations were kept small, such that any value could not change more than 10% for any given mutation. For all experiments presented here, deterministic crowding selection was used with a population of 10-25 individuals and 20% probability of mutation. In this method, each individual was paired with a random mate and crossover was performed. If the child was more fit than its most similar parent, the child replaces the parent in the population. Otherwise, the offspring is disregarded.

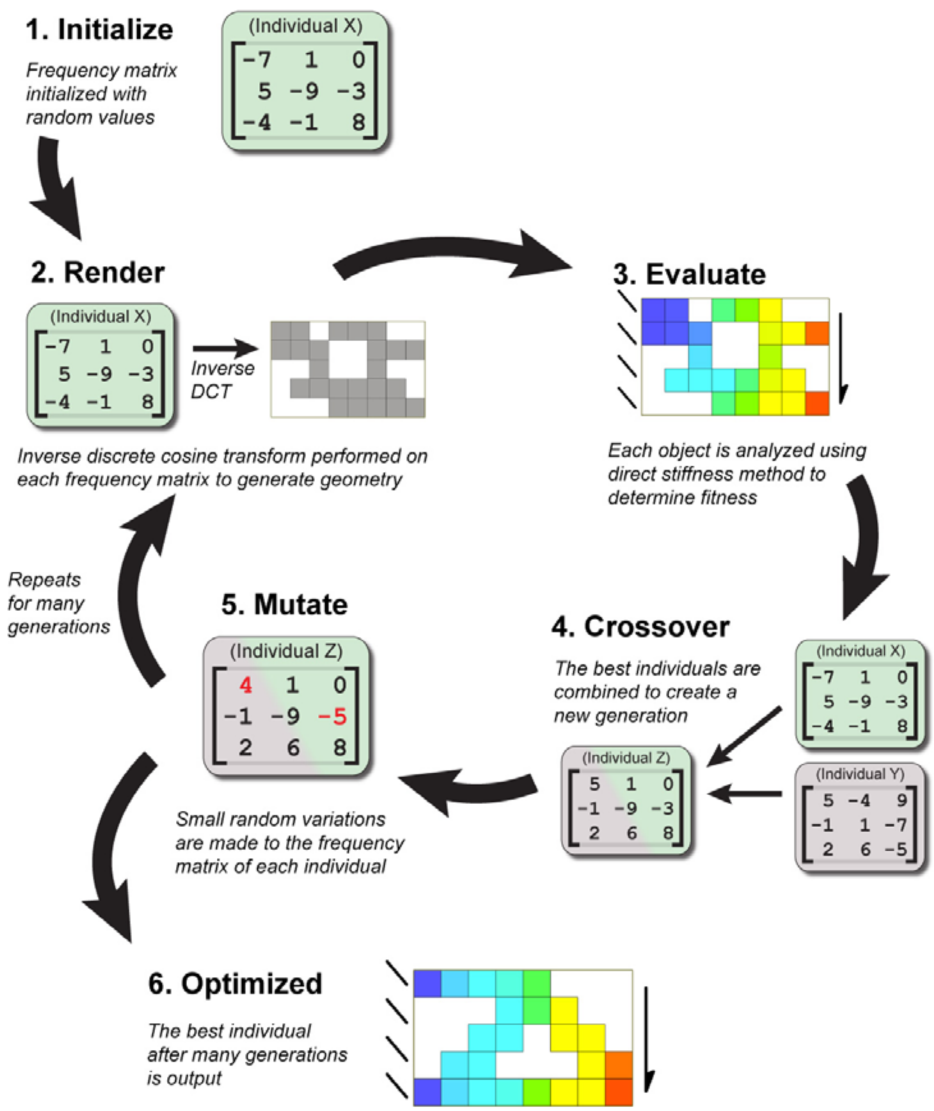
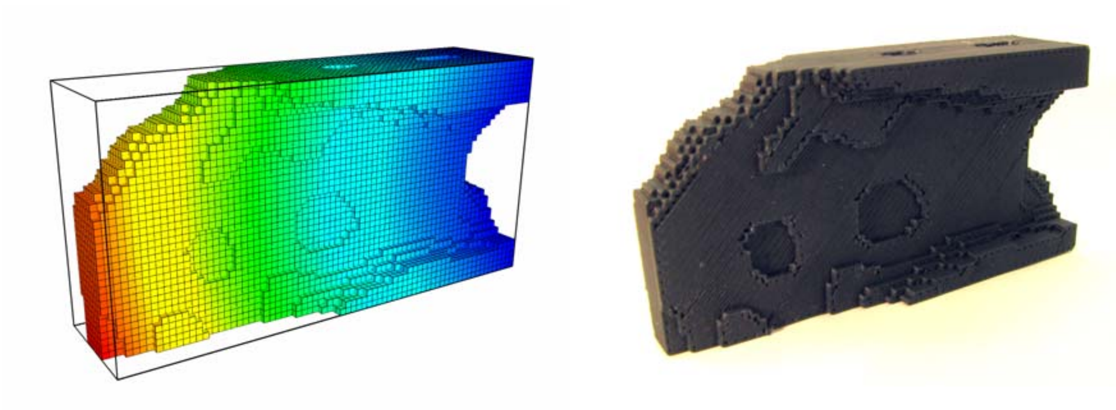


Figure 2: Flowchart of the multi-material genetic algorithm used for design automation. The discrete cosine transform encoding allows freeform objects to be encoded with a minimal number of parameters.

Shape Optimization

Given any set of loading and constraint conditions, the algorithm is successful in creating and optimizing the stiffest shape. Here, the result of the inverse DCT was simply thresholded to determine which voxels were instantiated. The case of a cantilever beam is shown in **Figure 3**. Here, the population size was set at 25 and the domain used while evolving was 24x6x12 voxels. The algorithm was allowed to run for approximately 3500 generations, although the gains past 1200 generations were negligible.



(a) (b)

Figure 3: A cantilever beam was autonomously designed to maximize stiffness and minimize weight (a) using the proposed algorithm. The physical printed beam is shown in (b).

Multi-material gradated material optimization

The optimization of multiple, gradated materials presents a more interesting problem which is not addressed in previous research. In these experiments, a qualitative material model was used to generalize the ability of additive manufacturing processes which simultaneously print high stiffness and low stiffness materials. A two-material system was assumed, where both stiff and flexible materials can be placed and combined in any combination at both the macroscopic and microscopic level. In effect, the material property can vary continuously between the two extremes, as is demonstrated to be reasonable in Hiller and Lipson, 2009. The resulting material property of each location is calculated from the density output by the discrete cosine transform, according to a 4th order exponential weighting.

Two different cases were chosen to illustrate the use of genetic algorithms in designing composite structures with high-level functionality. First, we considered the deflected shape of the top surface of a cantilever beam. Secondly, we considered an actuator that maximizes the two-dimensional deflection of a beam tip subject to applied forces in the mutually orthogonal direction to the desired deflections.

Deflected beam shapes

Given a cantilever beam, a variety of desired deflected profiles were selected, departing to varying degrees from the normal third-order polynomial profile. The resulting geometries are shown in Figure 4, along with plots showing the desired deflected shape overlaid onto the actual, evolved deflected shape.

The algorithm was very successful in meeting these high-level goals. The straight profile (Figure 4 a & d) was considered as a simple geometry which ideally needs only simple regions of stiff and flexible material for the ideal solution. The result shows the expected distribution of flexible material near the grounded edge and stiff material composing the rest of the beam, but does even better by accounting for the zero slope boundary condition imposed by the fixed end of the cantilever beam. A discontinuous slope (sharp bend) was also considered, with similarly successful results (Figure 4b & e). Also, we defined a 4th order polynomial profile involving both positive and negative curvature that matches the fixed zero slope boundary condition of the cantilever beam (Figure 4 c & f). Remarkably, the algorithm found a solution to this problem, which is in a fundamentally different material distribution domain than the other solutions.

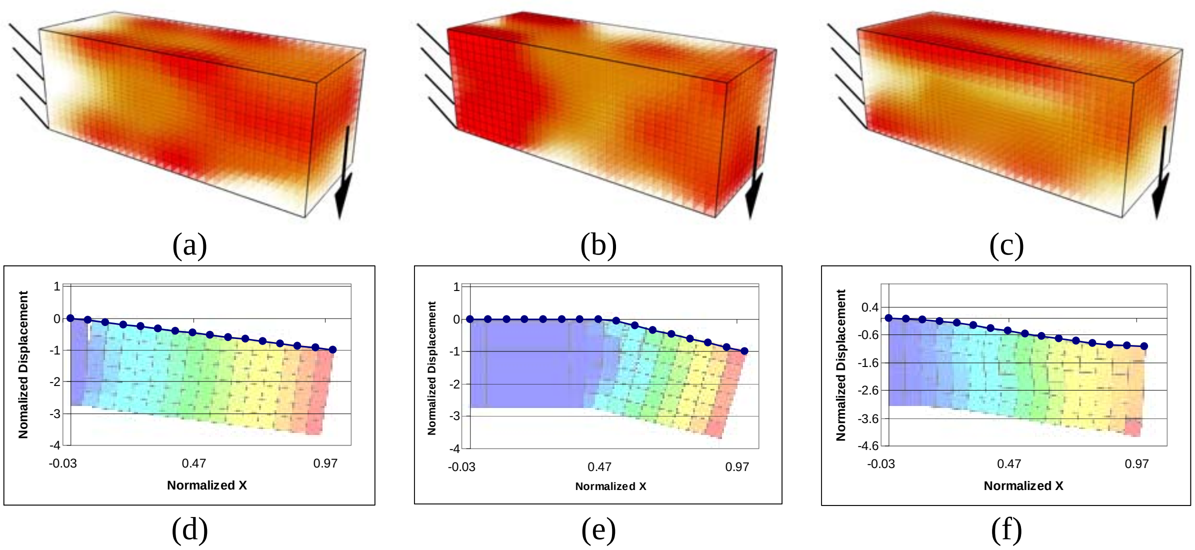


Figure 4: Evolved geometries (a-c) show stiff regions of material as solid red transitioning to transparent yellow for lower stiffness. The results for the deflected shape of each evolved cantilever beam (d-f respectively) demonstrate the ability to control the deflected profile of the cantilever beam to a high degree of accuracy, including slope discontinuities and non-intuitive upward curvatures.

Two-Force actuator

The optimization of a planar actuator was also considered. The loading conditions are shown in Figure 5. Two input forces are applied midway down the beam parallel to the major axis of the beam, and the output was the displacement of the tip of the beam in the two orthogonal directions to the major axis of the beam. Fitness was defined as the reachable area of the center of the tip of the beam.

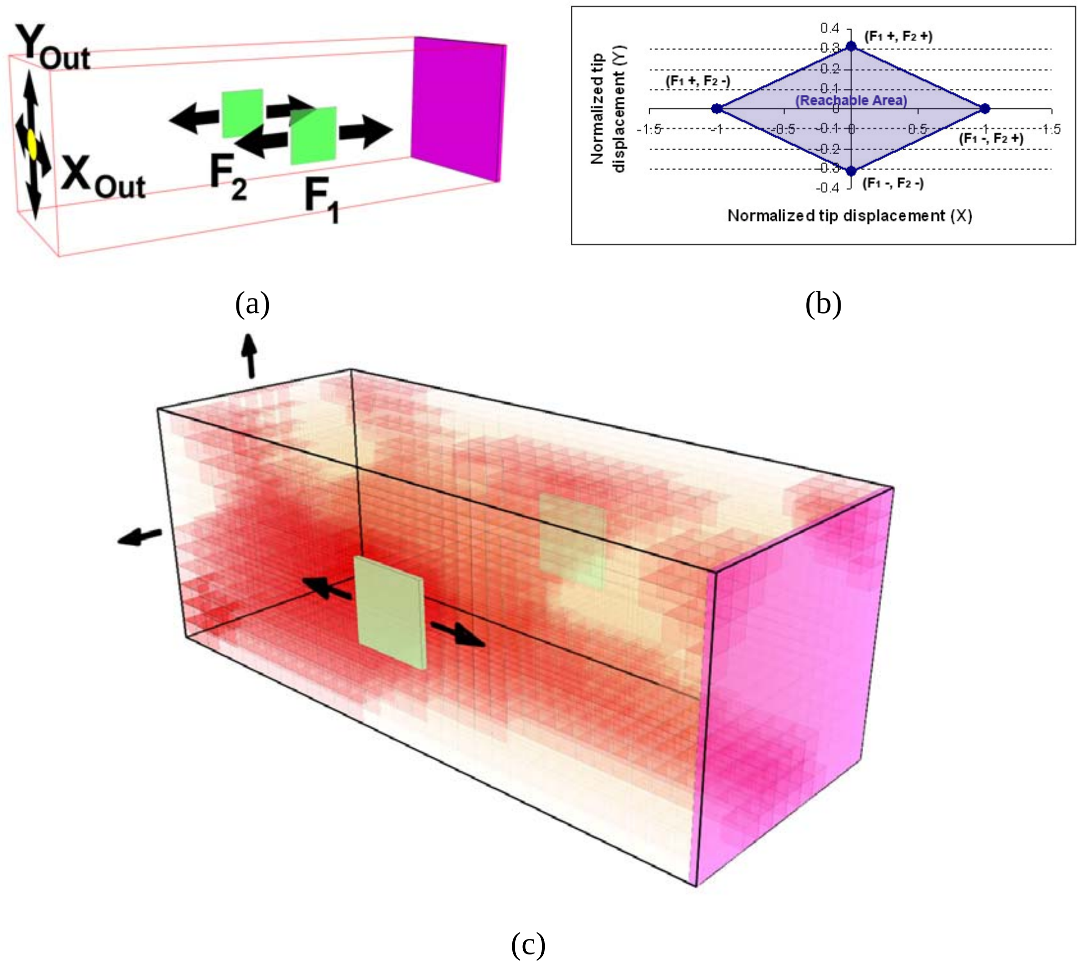
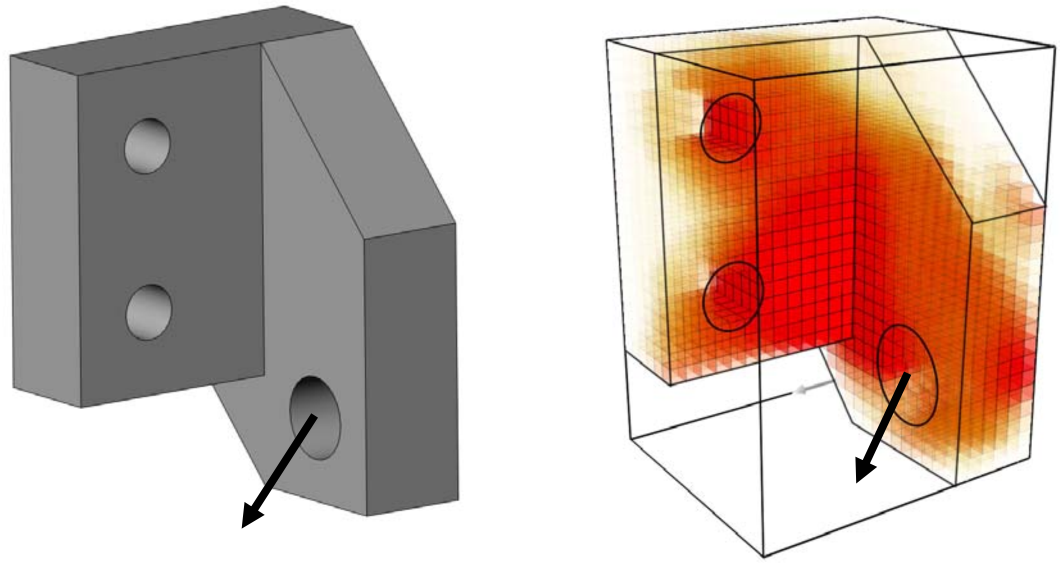


Figure 5: The design automation algorithm is able to solve a high-level, non-intuitive compliant actuator problem. Given the loading conditions for actuator optimization (a), the solution achieves a large reachable area (b) from the evolved geometry shown in (c). Here, red represents stiff material and transparent yellow is flexible.

In the solution, the algorithm came up a material distribution that make intuitive sense upon examination. A thin row of stiff material connects the grounded face of the beam to the mid-plane of the beam where the forces are applied. Regions of stiff material connect this strand to the two locations of applied force. The outer half of the beam essentially has no forces acting on it, so this region was effectively ignored, leading to a mostly random material distribution within it.

Case Study: Bracket

To further demonstrate the usefulness of this algorithm, we considered a case study where an engineer has already designed the geometry of a bracket, but would like to optimize the internal material distribution to maximize strength vs. weight. Here, we assume that the stiff material is proportionately heavier than the flexible material. The desired geometry and resulting material distribution is shown in Figure 6. The algorithm was successful, and in this case generated a material distribution that makes intuitive sense upon examination.



(a) (b)

Figure 6: The design automation algorithm optimizes the internal material distribution of a pre-designed bracket (a), in order to maximize stiffness and minimize weight. The results are shown in (b), where red represents stiff, dense material transitioning to transparent yellow, which represents flexible, lightweight material.

Conclusions

Genetic algorithms are suitable for designing the complex multi-material objects that have recently become possible to fabricate using additive manufacturing techniques. The lack of existing software design tools to fully take advantage of the capabilities of these fabrication processes enables genetic algorithms to fill a new niche in the mechanical design space. Instead of designing an object using traditional CAD programs, genetic algorithms allow an engineer to simply set high-level goals to be fulfilled and the blueprint is autonomously generated. Likewise, existing geometries can be optimized for multi-material printing.

We have demonstrated this using several examples. The algorithm is successful at optimizing the geometry of a single material cantilever beam. Additionally, by specifying the desired deflected shape of a multi-material beam, or defining vague goals of maximizing deflection area of a compliant actuator, we solve a problem that cannot be easily addressed using current state-of-the-art topological optimization tools. Additionally, by introducing multiple objectives such as minimizing weight in addition meeting the previous criteria, we demonstrated the flexibility of genetic algorithms to easily adapt to competing objectives of very different problems. These results open the door to robust, high-level design tools for complex design problems that can fully utilize the capabilities of multi-material additive fabrication techniques.

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