Automated Synthesis of Bending Pneumatic Soft Actuators

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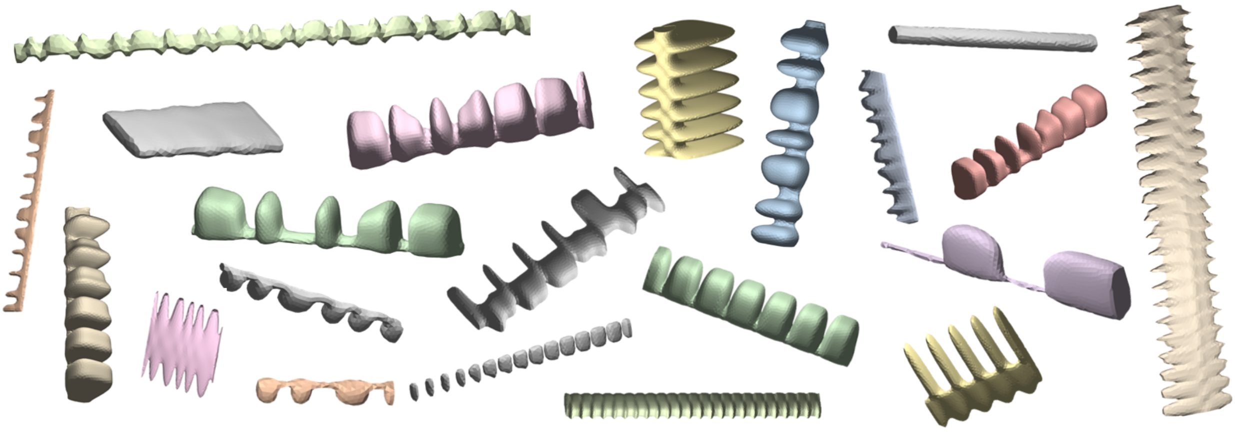

Selection of soft actuators discovered by the automated design approach presented in this paper.

***Abstract*— Soft robotics embraces the design philosophy of function through morphology. Therefore defining the affordances of a soft robotic structure is equivalent to determining the composition and distribution of the materials that make up the robot. This design process has historically been dominated by human intuition and labor-intensive experimentation. However, the design space of multi-material continuum structures is infinite. Automation tools to accelerate soft robot design could enable new designs to be created on-demand, specific to a need, more rapidly and at lower cost than would be possible using human labor alone. In this work we formulate the soft robot design problem as a multi-objective optimization task. We demonstrate a design automation system for bending soft actuators which integrates multi-objective heuristic search with a powerful generative encoding that converts high level design goals, compliance and forcefulness in our case, into mechanical designs automatically. These designs can be directly fabricated using a 3-D printer. We compare numerous simulated results from our optimization and a physical instance fabricated via 3-D printing with a broad survey of contemporary results from the soft robotics literature.**

I. Introduction

Soft robot design is challenging and inherently interdisciplinary, and most soft actuators are designed by teams of human engineers via trial-and-error and fabricated using labor-intensive casting processes. Efforts to standardize the manual design and fabrication of soft robots such as the *Soft Robotics Toolkit* [1] have advanced the field; our recent work proposes an alternative paradigm which facilitates soft actuator synthesis through indirect encodings to create implicit functional representations that can be readily simulated and fabricated [2]. This seamless workflow aims to eliminate the manual processes and bottlenecks between design, evaluation, and fabrication phases that characterize traditional soft actuator design [3]. Implicit geometry functions specify geometry and material distribution, computational networks represent these implicit functions, and the tool automatically generates nonlinear simulations of actuators' response to pneumatic loads and fabrication files compatible with existing multimaterial additive manufacturing technology [2].

To discover novel soft robotic systems that rival the performance of biological and traditional rigid counterparts and avoid stagnation of the field [4], we may offload exploration of this vast and counterintuitive soft robot design space to *automated design* tools. This casts human engineers as "design supervisors," focused on defining high-level design wishes, then deploying automated design tools to carry out the discovery of geometries, material distributions, and control strategies that satisfy them.

Despite the promise of automated design tools in the soft actuator design space, limited examples of their use exist - especially when compared to the popularity of topology optimization (TO) in problems such as minimum compliance and heat transfer [5]. This is not for lack of trying - significant obstacles inhibit researchers from developing and wielding automated soft robot design tools. Material, structural, and boundary condition nonlinearities (such as pressure loading and contact) are ubiquitous in

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TABLE I: Survey of Previous Soft Actuator Automated Design / Optimization Efforts

Result	Optimization	Simulation Type	Design Representation	Load Type	Fab.
Bodily 2017	Genetic Algorithm	Kinematic	Parameterized Geometry [A]	Point Loads [DI]	Y
Raeisinezhad 2021	Swarm Algorithm / Deep RL	2D FEA [L]	Parameterized Cavities [A]	Pneumatic [DD]	Y
S. Chen 2021	Gradient-Based Level Set	3D FEA [NL]	Level Set Function [A]	Pneumatic [DI]	Y
Hu 2018	Paramter Sweep	3D FEA [NL]	Parameterized Geometry [A]	Pneumatic [DI]	Y
Guo 2020	NL Program by Quadratic Lagrangian (NLPQL)	2D FEA [NL]	Parameterized Design [A]	Pneumatic [DD]	Y
Spielberg 2021	Gradient Based	3D MPM [NL]	Network [A]	Volumetric [DD]	N
De Souza 2020	SIMP	2D FEA [L]	Density Field [D]	Pneumatic [DD]	N
Y. Chen 2019	Bi-Directional Structural Optimization (BESO)	3D FEA [L]	Density Field [D]	Pneumatic [DD]	Y
Zhang 2017	Solid Isotropic Material with Penalization (SIMP)	3D FEA [NL]	Density Field [D]	Pneumatic [DI]	Y
Ma 2017	Gradient-Based	3D Shape Match [D]	Skeleton Density	Volumetric [DD]	Y
Runge 2018	Genetic Algorithm	3D FEA [NL]	Parameterized Geometry [A]	Pneumatic [DD]	N
Cheney 2013	Neuroevolution of Augmenting Topologies (NEAT)	Beam Model [NL]	Computational Pattern Producing Network (CPPN) [A]	Volumetric [DD]	N
Caasenbrood 2020	Gradient-Based	2D FEA [NL]	Density Field [D]	Volumetric [DD]	N
this work	Genetic Algorithm	3D FEA [NL]	Computational Network [A]	Pneumatic [DD]	Y

NL: Nonlinear analysis; L: Linear analysis; D: Direct geometry encoding; A: Abstract/Indirect geometry encoding; DI: Design Independent pressure loads, less general; DD: Design Dependent pressure loads, most general. Results are listed in increasing order of generality, with no existing results simultaneously exhibiting nonlinear fitness evaluation in 3D, non-parameterized geometry representation, and fabricated results.

soft robotics, increasing the computational cost of evaluating the fitness of candidate designs and challenging the use of *differentiable* [6] simulation. Soft robots are generalists and encounter myriad, unpredictable loading conditions; defining a "minimum spanning set" of scenarios over which to evaluate the fitness of a candidate is not obvious.

Standout exceptions to this rule (Table I) show the power of automated design applied to soft robotics, even as these efforts succeeded largely by restricting the design space to physical parameter tuning, or linearizing/otherwise simplifying fitness evaluation. Caasenbrood et al. [7] demonstrate TO in the context of boundary condition nonlinearity in two dimensions, approximating pneumatic loads by the application of volumetric forces to interior mesh elements. Y. Chen et al. [8] optimize the internal structures of a pneumatic bending actuator using a density-based approach - however they do not consider large deformations or material nonlinearity. Hu et al. [9] and Spielberg et al. [10] use a material point method simulator to discover control strategies for a variety of deformable agents, but their differentiable approach is likely not suited to strongly non-convex problems like soft actuator morphology design.

In this paper we present automated synthesis of bending pneumatic soft actuators.

- In contrast to many related works, we evaluate the fitness of candidate solutions using nonlinear finite elements with material, geometric, and boundary condition nonlinearities undergoing large deformations.
- We present a novel pair of fitness functions developed during experimentation in this nonlinear fitness landscape, which may be applied to other automated design efforts in the soft robotics community.
- We demonstrate the effectiveness of utilizing generative, network representations of implicit geometry functions [2] for automated design, which allows automatic conversion between solution representations used for design, simulation, and fabrication.
- We present a selection of bending soft actuators discovered using a multiobjective genetic algorithm
- Our hybrid simulation approach leverages shell finite elements for speed during early stages of the design process and more traditional volumetric elements for accuracy towards the end of the process
- We demonstrate automated fabrication by additive manufacturing of a Pareto-optimal actuator, and compare it directly to a broad survey of contemporary results, along with simulated fitness metrics of high-performing solutions (Figure 3).

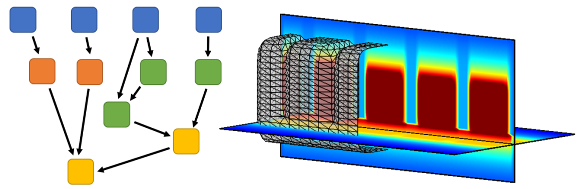

Fig. 1: Computational network representation (left) of soft robot geometry (right), shown in full with geometry inputs in blue (from left: x, y, z, and θ coordinate) and squared (orange), cosine (green), and identity (yellow) activation functions. Geometry is defined by computational network evaluation as per [2].

II. Considerations for Automated Design

The choice of optimization algorithm employed in an automated design effort often receives outsized attention - in fact this is downstream of representation, fitness evaluation, and fitness function selection.

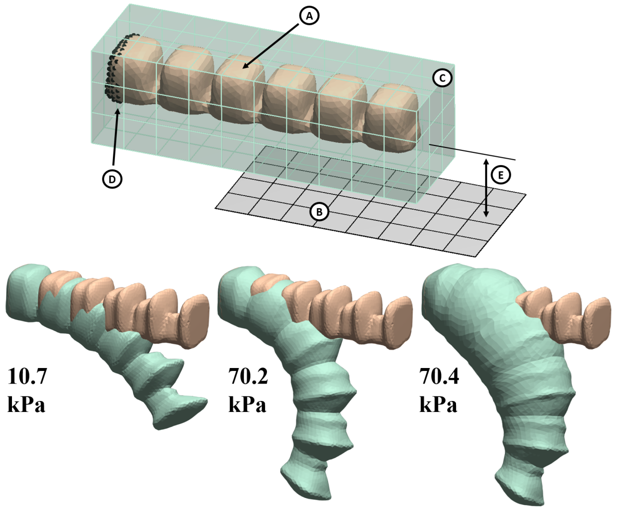

Fig. 2: Top: Candidate solution A specified by a computational network evaluated inside design domain C, Ground plane B with contact interaction offset by distance E, and encastre region D. Bottom: simulation of bending soft actuator using shell finite elements, capturing a global loss of stability at elevated pressure.

A. Representation

Representation refers to the choice of data structure used for storing solutions to an automated design problem [11]. A representation establishes a search space; assigning fitness to points in this space establishes a particular fitness landscape that optimization algorithms attempt to navigate. Ideal representations are problem-specific, and this decision creates trade-offs between the number of decision variables d and the relative "expressiveness" or sensitivity of the solution with respect to each variable. Computational networks are recognized as particularly compact and powerful generative encodings [12][2], and various graph and network structures have been summarized in [13].

In this work we take the computational network shown in Figure 1 as our representation, and operate on this representation by modifying the weights of links and biases on nodes in the network. This presents a compact, expressive representation capable of describing a wide variety of soft actuator geometries. We do not attempt to operate on the topology of the computational network as in [12] and others; we leave this for future work.

B. Fitness Evaluation

Automated design requires many evaluations of candidate solutions before a set of optimal solutions emerges. For this reason many automated design strategies employ linearized or reduced-dimension fitness evaluation. However, this approach partitions off certain potentially interesting regions of the fitness space from an optimization algorithm - several recent soft robot results leverage, rather than avoid, geometric instabilities to enhance performance [14][15]. The most widely used simulation tool for evaluating soft robot designs by far is nonlinear finite element analysis (FEA) [1], which is both general and powerful [16], and well-developed in commercial packages. Shell finite elements offer an attractive balance of computational cost, numerical stability, and accuracy for simulating some pneumatic soft actuators, despite some accuracy limitations [2]. For the purposes of rapid evaluation of candidate designs, and especially during the early phase of an automated design experiment, we propose that the absolute accuracy of a simulation result should be considered *alongside* other factors such as labor cost of simulation setup, stability, and runtime.

In our approach, a candidate actuator is automatically simulated using either triangular or tetrahedral meshes, without any human intervention. We use the meshing capabilities of the Geometry and Image-Based Bioengineering add-On (GIBBON) [17] to extract high-quality triangular meshes suitable for finite elements from scalar field evaluations of computational networks. We derive tetrahedral meshes from the same scalar fields, using constant-distance offset operations and the powerful open source meshing sofware *TetGen* [18]. Leveraging the seamless connectivity between our geometry representation and computational mesh representation, we employ a *hybrid* fitness evaluation approach, whereby shell finite elements are employed early in an automated design effort for their low computational cost, and tetrahedral finite elements are used to accurately evaluate the fitness of mature designs.

In this work we search for actuators which exhibit a bending deformation mode when pressurized, and are able to impart forces on their environment. We evaluate candidate solution fitness in two fitness evaluation scenarios (see Figure 2, top) using large deformation finite element simulations - notably different from previous approaches that assess compliance and force delivery under small displacement assumptions [20]. In the first scenario, the actuator is pressurized while a collection of nodes at the actuator base is fixed. The position of the actuator tip is tracked, and the bend angle θ described by the actuator is computed. In the second scenario, a rigid surface is positioned below the actuator and the normal force from any contact that occurs after pressurization is returned.

C. Fitness Functions

Fitness functions create a map from fitness evaluations to metrics in order to indicate to an optimization algorithm how to better satisfy design objectives. Creating a quantitative mapping that adequately captures the wishes of a design supervisor without rewarding undesirable candidates is nontrivial, especially in the context of soft robotics.

We borrow from research on compliant mechanism synthesis[21][20], and from empirical characterization of soft actuators [22] in formulating our fitness functions. We design these functions to incentivize the discovery of

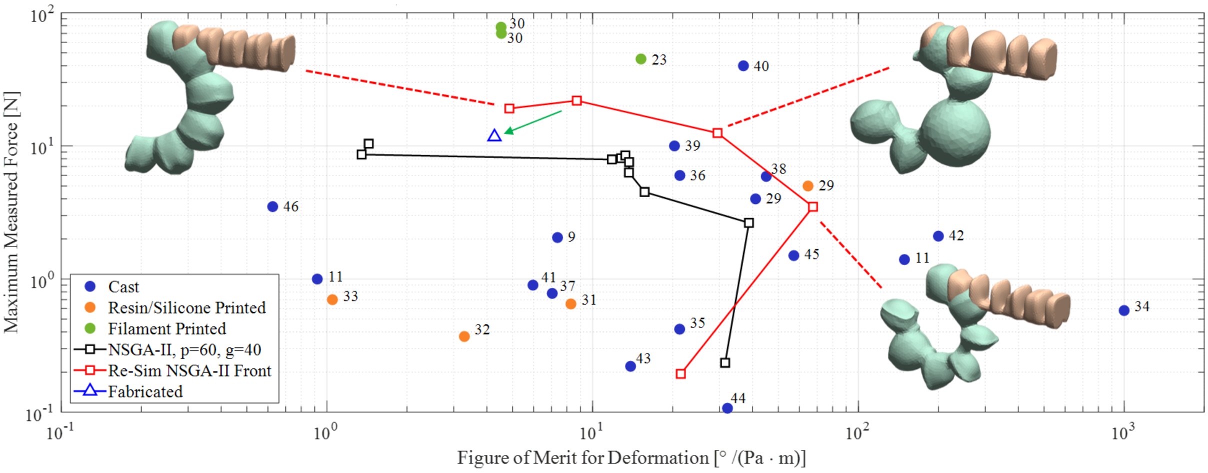

Fig. 3: Pareto plot showing two fitness metrics relevant to bending soft actuators from [19], performance of various human-designed and fabricated actuators, and simulated actuators presented in this work. Pareto front in black is output from an NSGA-II run using shell finite elements to evaluate fitness functions 1 and 2. Red front is re-evaluation and non-dominated sorting of members of the black front using tetrahedral finite elements.

bending actuators that exhibit large deflections at modest internal pressures (compliance) while maintaining the ability for high force output. High compliance has two benefits: first, lower required working pressures enable smaller, lower-cost pressure sources; second, soft actuator designs that respond to lower pressures store less energy in their structures during actuation. Since there is no current method to recover this energy on each cycle, stiffer designs exhaust more energy per cycle - an undesirable quality for energy-constrained systems like mobile robots. Additionally, soft actuators are often characterized by the magnitude of force they can deliver to their environment (called *blocked force*). This design incentive is generally orthogonal to compliance; high performance bending actuators balance these two competing objectives.

To reward candidates which exhibit large angular displacements in response to internal pressure, we propose:

$$F_c = max\left(\frac{atan(\frac{u_r}{L-u_z})}{\left[L\int PdV\right]^{1/p}}\right) \tag{1}$$

where F_c is the compliance fitness, u_r is the radial displacement of the actuator tip, u_z is the axial displacement of the actuator tip, L is the actuator length, $\int PdV$ is the pressure work, and p is a penalization factor.

We normalize by length and pressure work to reward actuators that exhibit large displacements while requiring low input energy, since energy used to deform the actuator is not available to do work on the external environment. We penalize this term with a heuristic factor p in order to avoid rewarding actuators that undergo small displacements at near zero input energy.

To reward candidate solutions capable of delivering large forces to their surroundings, we propose:

$$F_{bf} = max\left(\frac{f_{bf}}{P}\right)\Big|_{d_{bf}} \tag{2}$$

where F_bf is the blocked force fitness, f_bf is the blocked force fitness, and d_{bf} is the offset distance from the surface of the actuator and the rigid surface.

Beyond specifying these fitness functions and the spatial extents of the design domains (represented in Figure 2), we place no geometric constraints on allowable actuator designs. This is simply because the optimal geometric configuration, and therefore a useful set of constraints, is unknown; we hope that high-performance designs emerge from the multiobjective optimization process without our intervention.

D. Optimization Algorithm

Optimization algorithms navigate a fitness landscape, searching for candidate solutions that achieve optimal fitness metrics. We employ the well-known elitist multiobjective genetic algorithm Non-dominated Sorting Genetic Aglorithm-II (NSGA-II) to identify a set of soft actuators which occupy Pareto-optimal points in fitness space. We use a population size $p = 60$ and iterate for $g = 40$ generations, leveraging the *Matlab* (©Mathworks) function *gamultiobj()*. We use the native mutation and crossover operators, which act on a vector containing the ordered, normalized link weights and node biases to modify a candidate solution between iterations. We set the hyperparameter controlling relative likelihood of mutation vs. crossover to 0.8 until generation 20, and 0.2 thereafter. This encourages random mutation at the outset of the effort, creating a diverse population in phenotype space, and spends the final generations largely creating offspring of these high-performing individuals and their children.

III. Results: Automated Design Exploration

Our automated design approach identified a set of high-performing actuators, which we compared directly to published results across the two fitness metrics presented

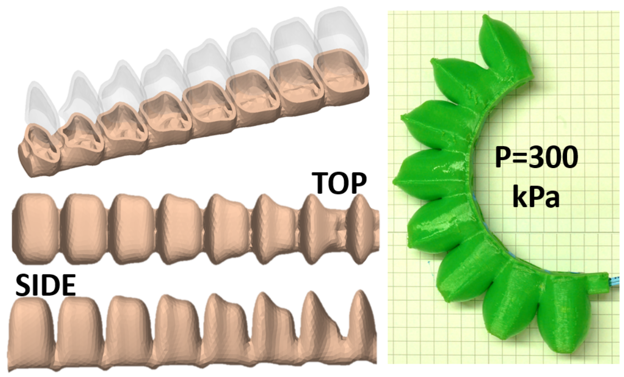

Fig. 4: Pareto-dominant actuator selected for fabrication by additive manufacturing. Internal structure features complex folds and rolled features; these would be near-impossible to fabricate by any other means.

in [19]. None of the automatically discovered solutions were Pareto-dominant; they did not outperform *all* prior manually-designed bending actuators (Figure 3), including those manually designed by our team in previous work [2]. We hypothesize several possible explanations for this outcome. First, this effort involves exploring only a single computational network topology, restricting the searchable design space relative to an optimization approach that operates on network topology [12]. Additionally, the method we use of converting implicit functions to surface triangulations produces strictly manifold geometries of a single material, whereas some high-performance published actuators [22] are both multi-material and non-manifold. Finally, our fitness functions do not consider fabrication constraints of additive manufacturing, allowing the optimization algorithm to include actuators in the population that are not airtight when fabricated. We anticipate that our future research will demonstrate the benefits of resolving these three limitations. However, our current work demonstrates the relatively low computational cost, and far lower manual effort required to automatically discover and fabricate actuators near the Pareto front (our automatically discovered actuators do outperform many contemporary results), compared to the many person-weeks of effort required to do so manually in previous work. The Pareto front identified in Figure 3 required only 304 core-hours of simulation on a fast but affordable desktop PC (AMD Ryzen 3900xCPU, 24 threads, 4.1GHz, 64GB of RAM).

We fabricated one of the high-performance actuators identified during automated design and measured its fitness empirically (Figure 4), finding it to underperform its counterpart simulated using tetrahedral elements, but outperform its counterpart simulated by shell elements. We hypothesize that this sim-to-real gap is caused by imperfect prediction of inherent actuator stiffness in simulation, possibly due to anisotropy in the as-fabricated designs inherent in the fused filament fabrication process.

IV. Conclusions and Further Research

In this work we present the application of automated design onto a seamless workflow for synthesis of pneumatic soft actuators. We note several considerations for future automated design efforts:

- leveraging shell element simulations for fitness evaluation significantly extends the reach of automated design algorithms by allowing for faster evaluations early in an experiment, and switching to volumetric elements later in the experiment improves fitness evaluation accuracy
- formulation of fitness functions that reward solutions that satisfy a designer supervisor's intentions is nontrivial. We show two, suitable for designing compliant, forceful bending actuators.
- live visualization and periodic monitoring of in-progress experiments is invaluable for early detection of candidate solutions that exploit fitness evaluations/functions in undesirable ways

We see many opportunities for future research in automated soft actuator synthesis, and we have built our workflow to be agnostic about actuator morphology, and forward-compatible with novel fitness evaluations. In contrast to manual design, which requires new human effort to explore each new desired capability, our automated design approach could rapidly address new performance metrics simply by introducing new fitness functions.

Generative multi-objective search often produces diverse and unexpected behaviors. Our automated search for soft bending actuators produced an interesting appendage-like candidate with internal asymmetry that causes it to first bend towards a contact surface then slide along it in response to applied pneumatic loads, see Figure 5. This

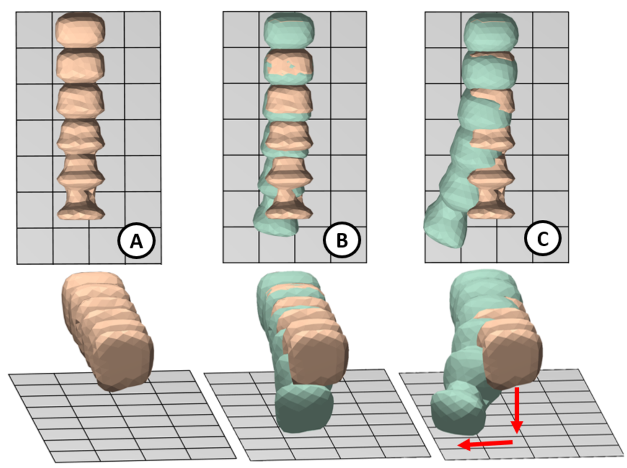

Fig. 5: Gait-like behavior arising from asymmetry of internal actuator geometry. This was not directly rewarded or penalized by our algorithm, suggesting an opportunity for further discovery of novel locomotion strategies. Notably this behavior is impossible to recover using small deformation evaluation of solution fitness, as is common in the literature.

behavior was neither penalized nor rewarded in our experiments, and we envision developing fitness evaluation scenarios and their associated fitness functions to promote this emergent behavior.

We are particularly interested in extending this research to include automated exploration of the computational network topology design space, using algorithms such as NeuroEvolution of Augmenting Topologies (NEAT). Previous work has demonstrated that computational networks are powerful genetic encodings which enable automated design algorithms to access far-reaching corners of a phenotypic space [23] [12].

Finally, fabricating automatically designed actuators remains an open challenge. Although additive manufacturing releases many manufacturing constraints and enables the hands-free fabrication of free-form geometries, some constraints remain. These include guidelines for maximum overhang angles, and maximum bridging distance to guarantee leak-tightness and support-free printing. Future work into automated design checking and conversion into an additional fitness function, or in automated "healing" of problematic actuator regions, would pay dividends.

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