# Inflatable Origami: Multimodal Deformation via Multistability 

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#### Abstract

Inflatable structures have become essential components in the design of soft robots and deployable systems as they enable dramatic shape change from a single pressure inlet. This simplicity, however, often brings a strict limitation: unimodal deformation upon inflation. Here, multistability is embraced to design modular, inflatable structures that can switch between distinct deformation modes as a response to a single input signal. This system comprises bistable origami modules in which pressure is used to trigger a snap-through transition between a state of deformation characterized by simple deployment to a state characterized by bending deformation. By assembling different modules and tuning their geometry to cause snapping at different pressure thresholds, structures capable of complex deformations that can be preprogrammed and activated using only one pressure source are created. This approach puts forward multistability as a paradigm to eliminate a one-to-one relation between input signal and deformation mode in inflatable systems.


## 1. Introduction

When safe human-machine interaction is paramount, the design of smart devices and robotic systems often relies on inflatables and cylindrical structures as they support a variety of possible deformations. ${ }^{[1-7]}$ However, a vast majority of these suffer from an intrinsic one-to-one relationship between input pressure and output deformation. In other words, they exhibit

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increasing unimodal deformation with pressure. ${ }^{[8-10]}$ To compensate for this deficiency, common strategies include sequencing multiple elements ${ }^{[11-17]}$ or pressurizing chambers independently. ${ }^{[18,19]}$ Alternatively, material inextensibility ${ }^{[20]}$ and non-linearities ${ }^{[21,22]}$ have been harnessed to achieve bidirectional bending. Despite all this, targeting arbitrary deformation modes with a single pressure input is beyond the capabilities of current inflatable systems.

In the wider domain of adaptive systems, origami principles have extensively been employed to realize transformable architectures, ${ }^{[23-28]}$ self-foldable machines, ${ }^{[29-31]}$ and waveguides. ${ }^{[32-34]}$ Distributed actuation approaches have been used to directly control the fold angle via pressurized air pockets ${ }^{[35]}$ or stimuliresponsive materials. ${ }^{[24,36-39]}$ However, these strategies require multiple input sources and result in bulky assemblies with excessive tethering and/or slow actuation. To overcome these limitations, recent efforts have achieved shape control of origami structures with embedded ferromagnetic elements via remote magnetic fields. ${ }^{[40-42]}$
Additionally, if the origami crease pattern supports a nonconvex energy landscape, multiple stable states manifest, ${ }^{[41,43-50]}$ which can expand the functionality of the structures. For example, introducing multistability in the classic waterbomb origami pattern resulted in the creation of mechanical bits and logic elements; ${ }^{[44,51,52]}$ multistable origami sheets based on the tiling of the degree-four vertex enabled the design of self-locking grippers ${ }^{[53]}$ and energy-absorbing components for drones; ${ }^{[54]}$ finally, bistable configurations of the Kresling pattern ${ }^{[45,55]}$ have been exploited to: i) generate locomotion via peristaltic motion ${ }^{[56]}$ or differential friction, ${ }^{[57]}$ ii) create flexible joints for robotic manipulation, ${ }^{[58]}$ and iii) store mechanical memory. ${ }^{[41,59]}$

Here, we employ the Kresling pattern as a building block to realize inflatable cylindrical structures capable of supporting multiple deformation modes, while being globally actuated using a single pressure input. We start with a monostable Kresling pattern and modify it by introducing two additional valley creases in one of its panels (see Figure 1). This makes the panel bistable, so that during inflation it unfolds and snaps outward, breaking the rotational symmetry of the module. Importantly, upon vacuum such asymmetry gives rise to bending, which persists until a critical negative pressure is reached at which the panel snaps back. Next, we show that these modules can be geometrically


Figure 1. Bistable origami modules as building blocks for multi-output, single-input inflatable structures. a) Schematics of a monostable module based on the hexagonal-base Kresling origami pattern, along with a 3D-printed prototype. The panels of the monostable modules remain always folded inward. We refer to this state of deformation as state $s^{0}$. b) State diagram of the pressurized origami modules. c) Bistable module with a modified panel (highlighted in orange) made of four triangular facets $\mathrm{A}^{\prime} \mathrm{B}^{\prime}, \mathrm{A} \mathrm{O} \mathrm{O}^{\prime} \mathrm{B}^{\prime}, \mathrm{A} \mathrm{O}^{\prime} \mathrm{B}$, and $A^{\prime} \mathrm{B}^{\prime} \mathrm{O}^{\prime}$ and characterized by a depth $\Delta$ from vertex $O$ to $O^{\prime}$, along with a 3D-printed prototype displayed in its two stable states: state $s^{0}$ for which all panels (including the modified panel) are folded inward; and state $s^{1}$ for which the modified panel is popped outward (while all other panels are still folded inward). d) Norm of the vector connecting the two caps' centroids, $\|\mathrm{d}\|$, and bending angle, $\theta_{x z}$, versus pressure, $p$, for the monostable (solid gray curves) and bistable with $\Delta=3 \mathrm{~mm}$ (dashed orange curves) origami modules during inflation and deflation. e) Experimental positive and negative pressure thresholds, $p_{\Delta}^{+}$and $p_{\Delta}^{-}$, as a function of the modified panel's depth, $\Delta$.
programmed to snap at different pressure thresholds and assembled in various order and orientation to form structures capable of multimodal deformation. Distinct deformation modes can be first activated by snapping a selected set of modules and then triggered by applying vacuum. Such modes can be inversedesigned by optimizing the arrangement and orientation of the building blocks. Importantly, the same structure can shape-shift to multiple target deformation modes using only one pressure input. Our approach paves the way for new opportunities in the design of reconfigurable structures with embedded actuation.

## 2. Our Building Blocks Based on the Kresling Pattern

To realize multimodal origami structures, we use building blocks that consist of one layer of the classic Kresling pattern (also known as nejiri-ori). ${ }^{[55]}$ More specifically, in its initial,
undeformed state, the single module is capped by two hexagonal facets with edges of length $l=30 \mathrm{~mm}$, separated by a distance $h=24 \mathrm{~mm}$, and rotated by an angle $\alpha=30^{\circ}$ with respect to each other (see Figure 1a). The hexagons are connected at each side by a panel comprising a pair of triangular facets coupled by alternating mountain (i.e., edges $A^{\prime} B$ and $A B^{\prime}$ ) and valley (i.e., edge $B B^{\prime}$ ) folds. Since the Kresling pattern is not rigid foldable, ${ }^{[45]}$ any change in its internal volume will lead to an incompatible configuration. To accommodate the resulting geometrical frustration, we 3D-print 1 -mm thick triangular facets out of a compliant material (TPU95A from Ultimaker with Young's modulus $E=26 \mathrm{MPa}$ ) and reduce the thickness locally to 0.4 mm to create the hinges (see prototype in Figure 1a). Further, to facilitate coupling between different modules, we 3D-print the hexagonal caps out of a stiffer material (PLA from Ultimaker with Young's modulus $E=2.3 \mathrm{GPa}$ ). Additionally, we coat the origami unit with a thin layer of polydimethylsiloxane (PDMS) to form an inflatable cavity (see


Figure 2. Multimodal deformation via multistability. We create multi-unit structures by combining $n$ modules. Each $k$ th module is defined by three geometrical parameters: a) the modified panel depth, $\Delta^{k}$, b) the chirality of the Kresling pattern, $c^{k}$, and c) the location of the modified panel, $f^{k}$. Note that, for simplicity, for the modified panel of the bottom unit we choose $f^{1}=1$, since it always faces the negative $x$-axis. d) State diagram for any multi-unit structure with $\Delta \in\{2,4\} \mathrm{mm}$. e) Schematic of a 2-unit structure defined by $\left[\Delta^{1} c^{1} f^{1} ; \Delta^{2} c^{2} f^{2}\right]=[2 \backslash \backslash 1 ; 4 / / 1]$ along with experimental snapshots of its different deformation modes under vacuum. f) Schematic of a 2-unit structure defined by $\left[\Delta^{1} c^{1} f^{1} ; \Delta^{2} c^{2} f^{2}\right]=[2 \backslash \backslash 1 ; 4 \backslash \backslash 4]$ along with experimental snapshots of its different deformation modes under vacuum. g) Polar plots showing the angles in the $x z$-plane, $\theta_{x z}$, and the $x y$-plane, $\theta_{x y}$, associated to each state in the three different complex deformation modes for the two 2 -unit structures. The radial distance of the markers represents the norm of the vector connecting the two caps' centroids, $\|\mathrm{d}\|$. Both experimental measurements (filled markers) and numerical predictions (empty markers) are shown.

Section S1, Supporting Information, for fabrication details). Note that the chosen values of the parameters $(h, l, \alpha)$ yield a monostable origami module (i.e., the Kresling pattern is only stable in its initial, undeformed state).

To investigate the response of a single module, we position it on a flat surface and slowly inflate it with air at a rate of $10 \mathrm{~mL} \mathrm{~min}{ }^{-1}$ using a syringe pump (Pump 33DS, Harvard Apparatus). We monitor the pressure using a sensor (Honeywell ASDXRRX015PDAA5) and capture the module's deformation via two digital cameras (SONY RX100 V) positioned in front and above it (see Section S2, Supporting Information,
for details). As expected, ${ }^{[45]}$ the Kresling unit deploys and folds upon inflation and deflation and returns to its undeformed configuration as soon as the pressure is removed (Figure 1b). This state of deformation, in which all panels are folded inward, is referred to as $s^{0}$. To better characterize the response of the module, we monitor the position of its top cap and record the vector connecting the two caps' centroids, d. In Figure 1d, we report the norm of $\mathbf{d},\|\mathbf{d}\|$, and the angle between the projection of $\mathbf{d}$ on the $x z$-plane and the positive $z$-axis, $\theta_{x z}$, as a function of the internal pressure, $p$. We find that $\|\mathbf{d}\|$ increases from 30 to 36 mm during inflation and then decreases to 4 mm
during deflation. Differently, $\theta_{x z}$ remains close to zero during the entire test (see gray curves in Figure 1d), indicating that the module purely deploys upon inflation and folds upon deflation, deforming exclusively along its central axis.

Aiming at unlocking different deformation modes with one single pressure input, we then take inspiration from bistability in degree-four vertices ${ }^{[47,52,60]}$ and modify one of the original Kresling panels by introducing two additional valley creases (i.e., $A O$ and $A^{\prime} O$ with $O$ being the midpoint of crease $B B^{\prime}$, see Figure 1c). While this effectively creates a degree-four vertex, it results in a monostable origami unit, as no snap-through instability is recorded upon inflation (see Section S2, Supporting Information). To increase the geometric incompatibility during deployment and achieve bistability in the unit, we then move the degree-four vertex inward by $\Delta$ (see Figure 1c where $\Delta$ is the norm of vector $\overline{O O^{\prime}}$ perpendicular to vectors $\overline{A A^{\prime}}$ and $\overline{B B^{\prime}}$ ).

Choosing $\Delta=3 \mathrm{~mm}$, for example, we can fabricate an origami unit that can easily transition between two stable states: state $s^{0}$ for which all panels are folded inward, and state $s^{1}$ for which the modified panel is popped outward (while all other panels are still folded inward-Figure 1c). Similar to the unit based on the classic Kresling pattern, upon inflation this modified module deploys with all panels bent inward if $p<26.1 \pm 0.9 \mathrm{kPa}$. However, at $p_{3}^{+}=26.1 \pm 0.9 \mathrm{kPa}$ (where the subscript refers to $\Delta=3 \mathrm{~mm}$ and the superscript refers to positive pressure), the unit snaps from state $s^{0}$ to state $s^{1}$, which is characterized by the modified panel popped outward (Figure 1b)—a transition that results in a sudden small drop of $\|\mathbf{d}\|$ and slight increase of $\theta_{x z}$ (see zoom-in in Figure 1d, left hand side). Finally, a further increase in pressure causes the unit to elongate until the maximum structural limit is reached. Afterward, when the input pressure is removed, the modified panel remains popped outward because of bistability. As such, when we apply negative pressure, the unit not only folds, but also bends (see Figure 1b), exhibiting a behavior that radically differs from that of the monostable Kresling module. In fact, we find that the vector d decreases in length and rotates in space. To characterize such rotation, we position the module with the modified panel facing the negative $x$-direction and monitor the angle $\theta_{x z}$. We find that $\theta_{x z}$ monotonically increases until the two hexagonal caps come into physical contact, effectively clipping the available range of bending deformation to $\theta_{x z}^{\max }=21.7 \pm 0.3^{\circ}$ (see Figure 1d). As previously mentioned, this bending deformation is activated by the snapping of the modified panel, which remains in the popped outward configuration (while the other panels fold under increasing negative pressure) and breaks the radial symmetry. Note that, as the Kresling twists when deflating, $\mathbf{d}$ also rotates in the $x y$-plane. Specifically, at $p_{3}^{-}$the angle between the projection of $\mathbf{d}$ on the $x y$-plane and the positive $x$-axis is $\theta_{x y}=10.6 \pm 0.6^{\circ}$ (see Section S2, Supporting Information, for details). Finally, when the negative pressure passes the threshold $p_{3}^{-}=-21.2 \pm 0.7 \mathrm{kPa}$ (where the superscript refers to negative pressure), the modified panel snaps back to the inward position (see Figure 1b). At this point $\theta_{x z}$ suddenly decreases (see Figure 1d) and the bending deformation mode gets deactivated. If one continues to apply negative pressure to the module, the unit folds (almost) flat with $\|\mathbf{d}\|=3.8 \pm 0.8 \mathrm{~mm}, \theta_{x z}=6.9 \pm 0.9^{\circ}$ and $\theta_{x y}=22 \pm 0.5^{\circ}$ at $p=-30 \mathrm{kPa}$ (see Figure 1d and Section S2, Supporting Information).

Next, we investigate the effect of the depth $\Delta$ of our degreefour vertex panel on the positive and negative pressure thresholds, $p_{\Delta}^{+}$and $p_{\Delta}^{-}$, as well as the deformed configurations reached upon snapping. The experimental results reported in Figure 1e for $\Delta=2,3$, and 4 mm indicate that the absolute value of the pressure thresholds increases with $\Delta$ within the considered range. By contrast, when the units are in state $s^{1}$, we find that for all considered $\Delta$, the angles reach $\theta_{x z}^{\max } \approx 20^{\circ}$ and $\theta_{x \gamma}^{\max } \approx 10^{\circ}$ upon vacuum-a value determined by the contact between the caps and the geometry of the Kresling pattern, respectively (see Section S2, Supporting Information for details). Finally, we note that for $\Delta<2 \mathrm{~mm}$ the modules are found to be monostable. This means that negligible bending is recorded upon application of negative pressure, since the degree-four vertex panel snaps back immediately. Differently, for $\Delta \geq 4 \mathrm{~mm}$, the positive pressure required to snap the modified panel outward is so high that the module fails (see Figure S4, Supporting Information).

## 3. Multimodal Deformation via Multistability

After demonstrating that our bistable module can transition between two stable states (i.e., states $s^{0}$ and $s^{1}$ ) with distinct deformation modes (i.e., deployment/folding and bending), we next combine these units to form multimodal tubular structures whose deformation is controlled by a single pressure input. By connecting $n$ modules, we can construct $(3 \times 2 \times 6+1 \times 2)^{n}=38^{n}$ different structures. This is because for each module $k$ we can select: i) either a regular Kresling pattern or a unit comprising a modified, degree-four vertex panel with depth $\Delta^{k} \in\{2,3,4\} \mathrm{mm}$ (Figure 2a); ii) the chirality of the origami pattern (i.e., the rotation direction of the upper cap with respect to the bottom one), $c^{k} \in\{/ /, \backslash \backslash\}$ (Figure 2b); and iii) the side on which the modified panel is located, $f^{k} \in\{1, \ldots, 6\}$ (note that for the modified panel of the bottom unit we choose $f^{1}=1$, since it always faces the negative $x$-axis-Figure 2c).

For simplicity, we start by considering structures with $\Delta \in\{2,4\} \mathrm{mm}$. In Figure 2d, we show the state diagram of such structures. This is characterized by four pressure thresholds. The positive pressure thresholds $p_{2}^{+}$and $p_{4}^{+}$corresponds to the pressures at which the modified panels of all units with $\Delta=2 \mathrm{~mm}$ and $\Delta=4$ snap outward, respectively. Equally, the negative thresholds $p_{2}^{-}$and $p_{4}^{-}$correspond to the pressures at which the panels snap inward. These thresholds lead to four distinct stable states, $s^{i j}$ with $i, j \in\{0,1\}$, where the subscripts $i$ and $j$ refer to the state of the modified panels with $\Delta=2$ and 4 mm , respectively. The state diagram also establishes the pressure history one has to apply in order to reach each stable state. It shows that the stable states $s^{10}$ and $s^{11}$ can be readily obtained by simply increasing pressure, whereas a more complex pressure path is required to achieve state $s^{01}$, as one has to i) increase pressure above $p_{4}^{+}$and then ii) decrease it below $p_{2}^{-}$.

While the state diagram in Figure 2d applies to all tubular structures assembled using modules with $\Delta=2$ and 4 mm , the deformation modes associated to each stable state upon vacuum depend on the arrangement of the modules. To illustrate this, we consider two structures comprising one module with $\Delta=2 \mathrm{~mm}$ and another one with $\Delta=4 \mathrm{~mm}$ connected via 3D-printed screws
(see Figure S2, Supporting Information, for details). In the first structure, the two modules have opposite chirality and the modified panels facing the negative $x$-axis (i.e., $\left[\Delta^{1} c^{1} f^{1} ; \Delta^{2} c^{2} f^{2}\right]=[2 \backslash \backslash 1$; $4 / / 1]$ - note that we assume the first unit to be the one at the bottom), whereas in the second one the two modules have the same chirality and modified panels located on the opposite sides of the structure (i.e., $\left.\left[\Delta^{1} c^{1} f^{1} ; \Delta^{2} c^{2} f^{2}\right]=[2 \backslash \backslash 1 ; 4 \backslash \backslash 4]\right)$. The experimental snapshots reported in Figure 2e,f (on the right hand side) show that under vacuum both structures simply fold in state $s^{00}$, but support more complex deformations in states $s^{10}$, $s^{11}$, and $s^{01}$. To better characterize these complex deformations, we once again track the vector connecting the bottom and top cap's centroids, $\mathbf{d}$, at the lowest pressure point of bending deformation associated to each state (see inset in Figure 2g). We find that for the first structure the deformations associated to states $s^{10}, s^{11}$, and $s^{01}$ are all bending-dominated and characterized by $\theta_{x z} \approx 20^{\circ}$ and $\theta_{x y} \in\left[-7.34^{\circ}, 20.4^{\circ}\right]$ (filled square markers in Figure 2 g ). Differently, in the second structure, in addition to two off-axis bending modes with $\theta_{x z} \approx 20^{\circ}$ and $\theta_{x y}=-9.40$ and $23.9^{\circ}$, vacuum unlocks a distinct, twisting-dominated deformation mode characterized by $\theta_{x z}=-3.64^{\circ}$ and $\theta_{x y}=108^{\circ}$ (filled triangular markers in Figure 2 g ).

The results of Figure 2 show that the arrangement of the modules within the tubular structure has a profound effect on the deformation modes associated with each stable state. To systematically explore such effect, we develop a simple algorithm that predicts the geometry of deformation under each mode. First, we extract key geometric features from the experiments conducted on single units, that is, $\|\mathbf{d}\|, \theta_{x z}$ and $\theta_{x y}$ each deformation modes (see Figures S4 and S5, Supporting Information). When assuming pressure continuity, these data allow the prediction of the geometry of deformation of any n-unit structure (see Section S3, Supporting Information, for details on the algorithm). Note that we also assume perfect coupling between units, so that the pressure thresholds, $p_{\Delta}^{+-}$, found in the experimental characterization of Figure 1e, remain unchanged and identical for units with the same geometrical parameters. In Figure 2g, we compare the results from our simple geometrical model (empty markers) with our experimental results (filled markers). Although experiments and model results are qualitatively similar, the error becomes large when the number of units in the structure increases. This error comes from the assumptions in the model, which does not take into account gravity, manufacturing imperfections as well as non-rigid coupling between the units (see Table S1, Supporting Information and Section 6 for the full quantification of the error between numerical predictions and experimental results).

Next, we use our numerical model to systematically investigate the deformation states that can be activated upon application of vacuum in our tubular structures. In Figure 3a, we use black dots to show the location of the top cap's centroid at the lowest pressure for all complex deformation states (i.e., $s^{i j}$ with $i+j>0$ ) of any structure with $n=2$ modules. For reference, we also depict the structure's bottom and top hexagonal plates under atmospheric pressure. When setting $f^{1}=1$, we find that most datapoints are clustered in a very narrow region that is contained within the top unit of the structure (see zoom-in in Figure 3a). To further characterize the supported deformation
states, we plot the angles $\theta_{x z}$ (Figure 3b) and $\theta_{x y}$ (Figure 3c) as a function of $\|\mathbf{d}\| / h$ for all datapoints. We find that the deformation modes for structures built out of only two modules are limited to the narrow range of $\theta_{x z} \in\left[-17.6^{\circ}, 38.8^{\circ}\right]$, whereas $\theta_{x y}$ spans the entire $360^{\circ}$ range. Additionally, since our goal is to realize structures capable of switching between distinct deformation modes harnessing a single pressure source, we select the structure that maximizes
$\Phi=\sum_{\alpha, \beta=1}^{n_{\text {mades }}} \frac{1}{2} \cdot\left\|\mathbf{d}_{\alpha}-\mathbf{d}_{\beta}\right\|^{2}$
where $n_{\text {modes }}=2^{n_{\Delta}}-1$ is the number of supported complex deformation modes ( $n_{\Delta}$ denoting the number of different $\Delta$ used in the structure). We find that for $n=2$ the most distinct deformation modes are achieved in a structure comprising two modules with the same chirality and modified panels located on opposite sides, that is, $\left[\Delta^{1} c^{1} f^{1} ; \Delta^{2} c^{2} f^{2}\right]=[3 \backslash \backslash 1 ; 4 \backslash \backslash 5]$. For this structure, states $s^{10}, s^{01}$, and $s^{11}$ are characterized by $\theta_{x z}=25.9^{\circ}$, $-17.2^{\circ}$, and $13.1^{\circ}$ and $\theta_{x y}=-8.51^{\circ}, 172^{\circ}$, and $-21.5^{\circ}$, respectively (see colored markers in Figure 3a-c). As shown by the front and top views reported in Figure 3d, the structure is able to bend in three different directions.

The complexity and number of deformation modes supported by the structures can be expanded by increasing the number of modules. In Figures $3 \mathrm{e}-\mathrm{h}$ and 3i-1, we report results for structures comprising $n=4$ and $n=12$ modules, respectively. Note that, since $38^{n}$ possible designs exist for a structure with $n$ modules, while we can simulate all possible designs for $n=4$, the number of designs for $n=12$ is too large to perform an exhaustive search. Instead, we select 500000 random structure geometries. As expected, by increasing the number of modules in the structure, we extend the space attainable by the top cap's centroid (see Figure 3e,i for $n=4$ and 12, respectively). Specifically, in addition to $\theta_{x y}$ spanning the entire $360^{\circ}$ range, we find that $\|\mathbf{d}\| / h \in[2.10,3.40]$ and $[3.46,10.1]$ and $\theta_{x z} \in\left[-44.5^{\circ}, 63.3^{\circ}\right]$ and full $360^{\circ}$ range, respectively for $n=4$ and 12 (see Figure 3f,g,j,k) Finally, the numerical snapshots of the 4 and 12 -unit structures that maximize $\Phi$ reported in Figure $3 \mathrm{~h}, 1$ show that by controlling the input pressure these structures can be made to bend in a variety of directions as well as simply contract and twist under vacuum.

## 4. Inverse Design to Reach Multiple Targets

Building on the established platform, we now aim at demonstrating how one can design structures that can reach multiple targets in space, despite being actuated through a single pressure source. However, since the use of $n$ modules leads to $38^{n}$ possible structure designs, it is crucial to use a robust algorithm to efficiently identify configurations leading to the targets. To this end, given the discrete nature of our design variables, we use a greedy algorithm based on the best-first search method ${ }^{[61,62]}$ —a progressive local search algorithm that, at each iteration, minimizes the cost function by looking at a set of available solutions. Although there exists many algorithms to solve this type of discrete optimization problems, ${ }^{[63,64]}$ we find that the greedy algorithm provides the best trade-off between


Figure 3. Exploration of the design space. We use our numerical model to characterize the deformation modes of structures made of $n=2$, 4 , and 12 units. Location of the top cap's centroid (black dots) associated to each complex deformation modes of any structure made of $n=2$ (a) and $n=4$ (e) units as well as 500000 random structures with $n=12$ (i) units. Note that we show $1.296,1.78 \times 10^{6}$, and $4 \times 10^{6}$ different top cap's locations (black dots) for $n=2,4$, and 12 , respectively. Polar plots showing the angles in the $x z$-plane, $\theta_{x z}$, and the $x y$-plane, $\theta_{x y}$, associated to each state in the complex deformation modes for any structure made of $2(\mathrm{~b}, \mathrm{c}), 4(\mathrm{f}, \mathrm{g})$, and $12(\mathrm{j}, \mathrm{k})$ units. In all plots, the radial distance of the markers represents the norm of the vector connecting the two caps' centroids, $\|\mathbf{d}\|$. Numerical snapshots of the deformation modes of the structures with $n=2(\mathrm{~d}), n=4$ ( $h$ ), and $n=12(\mathrm{l})$ units that maximizes $\Phi$.
accuracy and computational cost (see Section S4, Supporting Information, for details and comparison of the different algorithms). Specifically, our greedy algorithm identifies tubular structures built out of $n_{s}$ super-cells each with $n_{u}$ modules (so that $n=n_{u} \cdot n_{s}$ ), whose tip can reach a desired set of targets arbitrarily positioned in the surrounding space. Note that the maximum number of targets a structure can reach is $n_{\text {targets }}=2^{n_{\Delta}}$. At the first iteration, the algorithm starts by selecting the structure super-cell design that minimizes
$\psi=\frac{1}{n_{\text {targets }} \cdot h} \sum_{m=1}^{n_{\text {argets }}} \min \left\|\mathbf{d}-\mathbf{T}_{m}\right\|$
where $\mathbf{T}_{m}$ is the vector connecting the $m$ th target with the origin. Once the first super-cell is chosen, the algorithm stores it in memory and starts a second iteration. This comes to an end when the algorithm identifies a second super-cell that, connected to the first one, minimizes Equation (2). The first two super-cells are then stored in memory and the algorithm


Figure 4. Inverse design to reach multiple targets. We employ a greedy algorithm to inverse design structures able to reach a set of targets with a single pressure source. a) Selected set of three targets (red dots), top and 3D view. b) Targets error, $\Psi$, as a function of total number of units. c) The three deformation modes that most closely match the three targets for the structures that minimize the target error $\Psi$. d) The optimal structure produced by the algorithm along with the respective parameters for each module. e) State diagram for the 12-unit, optimal structure (*) with targets $T$, 72 , and $T 3$ highlighted. f) Top and 3D view of the model and the experimental prototype for the 12-unit optimal structure.
advances to the next one. Note that in this study, to balance the number of available designs and computational cost, we set the greedy algorithm to consider super-cells made out of three units (i.e., $n_{u}=3$, see Figures S9 and S12, Supporting Information, for a comparison across super-cells made with different $n_{u}$ ). Additionally, in order to avoid fabricating excessively long structures whose response could be affected by gravity, we impose that the algorithm should end after stacking five super-cells.

To demonstrate our approach, we select a set of targets within the reachable space (see red circular markers in Figure 4a; Figures S14 and S15, Supporting Information, for additional targets). In Figure 4 b we show the minimum value of the objective function $\Psi$ identified by our algorithm at each iteration for the selected set of targets. Further, in Figure 4c we report the deformed modes that most closely approach the three targets for the corresponding structures. We find that for this set of targets the minimum error is reached for a structure with $n_{s}=4$ (note that the convex shape
of $\Psi$ in Figure 4 b is due to a correlation between the optimal number of units and the average distance of the targets from the origin-see Figure S15, Supporting Information). This design comprises the classic Kresling module as well as bistable units with $\Delta=2,3$, and 4 mm (see Figure 4d). As such, the optimal structure has eight stable states, 14 snapping transitions, and a more complex state diagram in which not all targets are reached consecutively by continuously decreasing pressure (Figure 4e). More specifically, to move from $T 1$ to $T 2$, this structure has to be reset by decreasing the pressure below $p_{3}^{-}$before increasing above $p_{4}^{+}$and then lowering it to $p_{3}^{-}$. As such, in this case the centroid of the top plate of the structure passes through the straight configuration $O$ when moving from $T 1$ to $T 2$ and its trajectory comprises two disconnected loops, $O-T 1$ and $O-T 2-T 3$ (Figure 4 f ). Note that we can add additional constraints to our greedy algorithm to make sure the targets fall within the same closed loop on the state diagram. This leads to a different design and may increase the targets error, $\Psi$
(see Figure S13, Supporting Information, for details). However, the ability to follow sequentially a discretized trajectory along a closed pressure loop makes the platform compelling for robotic applications (see Section S5, Supporting Information, for an example of a single-input robot capable of locomotion through multimodal deformation).

## 5. Conclusion

To summarize, in this work we have presented a platform to design tubular structures that can switch between distinct deformation modes using only one pressure input. The key component of our platform is an origami building block with a degree-four vertex panel, which can be geometrically programmed to snap at a certain input threshold, unlocking complex deformation modes upon vacuum. This, together with the position of the modified panel in the origami module and their direction of rotation, constitute the parameters of a rich design space that we can efficiently scan with a custom greedy algorithm. While in this study we have used a simple geometric model to identify optimal designs, a fully mechanical model ${ }^{[65,66]}$ that accounts for the effect of gravity, the pressure drop during the snap-through transition as well as the non-rigid coupling between the units would reduce the error between numerical predictions and experimental results. In addition, the current design space could be further expanded through investigating the effect of other geometrical parameters (e.g., $l, h$, and $\alpha$ ) on the resulting deformation of the modules, as well as expanding the range of the considered values of $\Delta$. While this could lead to more complex deformation modes and enhanced functionality, a drawback is a more complex state diagram. This means that a given structure might have to go through a longer loading history to reach some prescribed targets, increasing the operational time-span. A potential solution to this is to measure the volume at which the module snaps inward and outward, assume constant flow rate, and derive the time associated to each snapping transition. This time span could then be included as variable in the optimization algorithm, in order to find a design that reaches the target in the shortest possible time. Further, although in this study we have used a specific platform based on 3D-printed origami modules to realize multimodal deformation, the findings are not restricted to these specific structures and could be used in the design of other functional systems. However, we hereby only claim the successful implementation of our method by fabricating the modules with specific equipment, materials, and geometrical parameters. If other equipment/materials/systems are employed, the reader should take care to verify that our findings are still valid. This is due to the fact that a chosen manufacturing technique might not be accurate enough to yield distinct input thresholds (i.e., internal pressures in our case) and to give rise to the distinct stable states. To conclude, given the recent advancement in origami fabrication across scales, ${ }^{[25,35,67,68]}$ we envisage that our concept hereby presented could be employed in future applications where space is limited and simplified controls are required, such as space exploration, surgical devices, and rescue missions.

## 6. Experimental Section

Details of the design, materials, and fabrication methods are summarized in Section S1, Supporting Information. The experimental procedure to measure the pressure-volume curve is described in Section S2, Supporting Information, along with additional experimental data. Details on the numerical model are provided in Section S3, Supporting Information. The optimization algorithms used in this study are described in detail in Section S4, Supporting Information. An example of a single-input robot capable of locomotion through multimodal deformation is reported in Section S5, Supporting Information. Finally, additional results are described in Section S6, Supporting Information.

## Supporting Information

Supporting Information is available from the Wiley Online Library or from the author.

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## Conflict of Interest

The authors declare no conflict of interest.

## Author Contributions

D.M. and A.E.F. contributed equally to this work. A.E.F., D.M., B.G., and K.B. proposed and developed the research idea. A.E.F designed and fabricated the samples. A.E.F., D.M., B.G., and L.K. performed the experiments. A.E.F. and D.M. designed the optimization. D.M. conducted the numerical calculations. A.E.F., D.M., and K.B. wrote the paper. K.B. supervised the research.

## Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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[^1][5] E. W. Hawkes, L. H. Blumenschein, J. D. Greer, A. M. Okamura, Sci. Rob. 2017, 2, 8.
[6] M. Runciman, A. Darzi, G. P. Mylonas, Soft Rob. 2019, 6, 423.
[7] P. Polygerinos, Z. Wang, K. C. Galloway, R. J. Wood, C. J. Walsh, Rob. Auton. Syst. 2015, 73, 135.
[8] B. Mosadegh, P. Polygerinos, C. Keplinger, S. Wennstedt, R. F. Shepherd, U. Gupta, J. Shim, K. Bertoldi, C. J. Walsh, G. M. Whitesides, Adv. Funct. Mater. 2014, 24, 2163.
[9] F. Connolly, C. J. Walsh, K. Bertoldi, Proc. Natl. Acad. Sci. USA 2017, 114, 51.
[10] R. V. Martinez, J. L. Branch, C. R. Fish, L. Jin, R. F. Shepherd, R. M. D. Nunes, Z. Suo, G. M. Whitesides, Adv. Mater. 2013, 25, 205.
[11] R. F. Shepherd, F. Ilievski, W. Choi, S. A. Morin, A. A. Stokes, A. D. Mazzeo, X. Chen, M. Wang, G. M. Whitesides, Proc. Natl. Acad. Sci. USA 2011, 108, 20400.
[12] B. Gorissen, E. Milana, A. Baeyens, E. Broeders, J. Christiaens, K. Collin, D. Reynaerts, M. De Volder, Adv. Mater. 2019, 31, 1804598.
[13] N. Vasios, A. J. Gross, S. Soifer, J. T. Overvelde, K. Bertoldi, Soft Rob. 2019, 7, 1.
[14] M. A. Robertson, J. Paik, Sci. Rob. 2017, 2, 9.
[15] J. W. Booth, D. Shah, J. C. Case, E. L. White, M. C. Yuen, O. Cyr-Choiniere, R. Kramer-Bottiglio, Sci. Rob. 2018, 3, 22.
[16] L. Hines, K. Petersen, M. Sitti, Adv. Mater. 2016, 28, 3690.
[17] E. Ben-Haim, L. Salem, Y. Or, A. D. Gat, Soft Rob. 2020, 7, 259.
[18] L. Paez, G. Agarwal, J. Paik, Soft Rob. 2016, 3, 109.
[19] A. D. Marchese, C. D. Onal, D. Rus, Soft Rob. 2014, 1, 75.
[20] D. R. Ellis, M. P. Venter, G. Venter, Soft Rob. 2021, 8, 478.
[21] S. Wakimoto, K. Suzumori, K. Ogura, Adv. Rob. 2011, 25, 1311.
[22] L. Zentner, V. Böhm, V. Minchenya, Mech. Mach. Theory 2009, 44, 51009.
[23] J. T. B. Overvelde, J. C. Weaver, C. Hoberman, K. Bertoldi, Nature 2017, 541, 347.
[24] E. Hawkes, B. An, N. M. Benbernou, H. Tanaka, S. Kim, E. D. Demaine, D. Rus, R. J. Wood, Proc. Natl. Acad. Sci. USA 2010, 107, 12441.
[25] D. Melancon, B. Gorissen, C. J. García-Mora, C. Hoberman, K. Bertoldi, Nature 2021, 592, 545.
[26] L. H. Dudte, E. Vouga, T. Tachi, L. Mahadevan, Nat. Mater. 2016, 15, 583.
[27] E. D. Demaine, T. Tachi, in Proc. of the 33rd International Symp. on Computational Geometry (SoCG 2017), (Eds: B. Aronov, M. J. Katz), Dagstuhl Publishing, Saarbrücken/Wadern 2017, pp. 34:1-34:15.
[28] Z. Zhao, X. Kuang, J. Wu, Q. Zhang, G. H. Paulino, H. J. Qi, D. Fang, Soft Matter 2018, 14, 8051.
[29] S. Felton, M. Tolley, E. Demaine, D. Rus, R. Wood, Science 2014, 345, 644.
[30] D. Rus, M. T. Tolley, Nat. Rev. Mater. 2018, 3, 101.
[31] C. D. Santangelo, Annu. Rev. Condens. Matter Phys. 2017, 8, 165.
[32] H. Yasuda, Y. Miyazawa, E. G. Charalampidis, C. Chong, P. G. Kevrekidis, J. Yang, Sci. Adv. 2019, 5, 5.
[33] H. Yasuda, C. Chong, E. G. Charalampidis, P. G. Kevrekidis, J. Yang, Phys. Rev. E 2016, 93, 4.
[34] M. Thota, K. W. Wang, J. Appl. Phys. 2017, 122, 15.
[35] J. T. Overvelde, T. A. de Jong, Y. Shevchenko, S. A. Becerra, G. M. Whitesides, J. C. Weaver, C. Hoberman, K. Bertoldi, Nat. Commun. 2016, 7, 10929.
[36] A. Kotikian, C. McMahan, E. C. Davidson, J. M. Muhammad, R. D. Weeks, C. Daraio, J. A. Lewis, Sci. Rob. 2019, 4, eaax7044.
[37] T. G. Leong, C. L. Randall, B. R. Benson, N. Bassik, G. M. Stern, D. H. Gracias, Proc. Natl. Acad. Sci. USA 2009, 106, 703.
[38] Y. Liu, J. K. Boyles, J. Genzer, M. D. Dickey, Soft Matter 2012, 8, 1764.
[39] Q. Liu, W. Wang, M. F. Reynolds, M. C. Cao, M. Z. Miskin, T. A. Arias, D. A. Muller, P. L. McEuen, I. Cohen, Sci. Rob. 2021, 6, eabe6663.
[40] Y. Kim, H. Yuk, R. Zhao, S. A. Chester, X. Zhao, Nature 2018, 558, 274.
[41] L. S. Novelino, Q. Ze, S. Wu, G. H. Paulino, R. Zhao, Proc. Natl. Acad. Sci. USA 2020, 117, 24096.
[42] S. Wu, Q. Ze, J. Dai, N. Udipi, G. H. Paulino, R. Zhao, Proc. Natl. Acad. Sci. USA 2021, 118, 36.
[43] S. Kamrava, D. Mousanezhad, H. Ebrahimi, R. Ghosh, A. Vaziri, Sci. Rep. 2017, 7, 46046.
[44] B. Hanna, J. Lund, R. Lang, S. Magleby, L. Howell, Smart Mater. Struct. 2014, 23, 094009.
[45] C. Jianguo, D. Xiaowei, Z. Ya, F. Jian, T. Yongming, J. Mech. Des. 2015, 137, 061406.
[46] J. L. Silverberg, J.-H. Na, A. A. Evans, B. Liu, T. C. Hull, C. Santangelo, R. J. Lang, R. C. Hayward, I. Cohen, Nat. Mater. 2015, 14, 389.
[47] S. Waitukaitis, R. Menaut, B. G.-g. Chen, M. van Hecke, Phys. Rev. Lett. 2015, 114, 5.
[48] H. Yasuda, J. Yang, Phys. Rev. Lett. 2015, 114, 185502.
[49] A. Reid, F. Lechenault, S. Rica, M. Adda-Bedia, Phys. Rev. E 2017, 95, 013002.
[50] K. Liu, T. Tachi, G. Paulino, Nat. Commun. 2019, 10, 4238.
[51] B. Treml, A. Gillman, P. Buskohl, R. Vaia, Proc. Natl. Acad. Sci. USA 2018, 115, 6916.
[52] S. Sadeghi, S. Li, arXiv:2006.05968, 2020.
[53] J. A. Faber, A. F. Arrieta, A. R. Studart, Science 2018, 359, 1386.
[54] S. Mintchev, J. Shintake, D. Floreano, Sci. Rob. 2018, 3, 20.
[55] B. Kresling, ORIGAMI3, 3rd International Meeting of Origami Science, Mathematics, and Education, (Ed: T. Hull), CRC Press, Boca Raton, FL 2002, pp. 197-207.
[56] P. Bhovad, J. Kaufmann, S. Li, Extreme Mech. Lett. 2019, 32, 100552.
[57] A. Pagano, T. Yan, B. Chien, A. Wissa, S. Tawfick, Smart Mater. Struct. 2017, 26, 094007.
[58] J. Kaufmann, P. Bhovad, S. Li, Soft Rob. 2022, 9, 212.
[59] H. Yasuda, T. Tachi, M. Lee, J. Yang, Nat. Commun. 2017, 8.
[60] H. Fang, S. Li, H. Ji, K. W. Wang, Phys. Rev. E 2016, 94, 043002.
[61] S. Curtis, Sci. Comput. Program. 2003, 49, 125.
[62] V. Vidal, in ICAPS-04 Proc., AAAI Press, Palo Alto, CA 2004, pp. 150-160.
[63] K. Deep, K. Singh, M. Kansal, C. Mohan, Appl. Math. Comput. 2009, 212, 505.
[64] J. Müller, C. A. Shoemaker, R. Piché, J. Global Optim. 2014, 59, 865.
[65] K. Liu, G. H. Paulino, Proc. R. Soc. London, Ser. A 2017, 473, 20170348.
[66] M. Moshtaghzadeh, E. Izadpanahi, P. Mardanpour, Eng . Struct. 2022, 251, 113399.
[67] B. Bircan, M. Z. Miskin, R. J. Lang, M. C. Cao, K. J. Dorsey, M. G. Salim, W. Wang, P. L. Muller, David A. McEuen, I. Cohen, Nano Lett. 2020, 20, 4850.
[68] Q. Ze, S. Wu, J. Nishikawa, J. Dai, Y. Sun, S. Leanza, C. Zemelka, L. S. Novelino, G. H. Paulino, R. R. Zhao, Sci. Adv. 2022, 8, eabm7834.

# FUNCTIONAL 

## Supporting Information

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Inflatable Origami: Multimodal Deformation via Multistability

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## Supplementary Materials

## Inflatable origami: multimodal deformation via multistability

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Other supplementary materials for this manuscript include the following:
Movies S1 to S4

## S1. Fabrication

The structures tested in this study are constructed by connecting 3D-printed origami modules. This section gives details on the design and fabrication of the 3D-printed modules as well as their assembly to create multi-unit structures.

Design of the 3D-printed origami units. Each origami module is 3D-printed using a commercially available multi-material printer (Ultimaker 3). To account for geometric incompatibility during inflation, we print the 1-mm thick triangular facets out of compliant thermoplastic polyurethane (Ultimaker TPU 95A with tensile modulus $E=26 \mathrm{MPa}$ ). The thickness decreases to 0.4 mm at the junction of the triangular facets (hinges), to allow more compliance. This value is the lowest possible thickness our printer is able to print with a 0.4 mm print core. Further, to enable rigid connection of different units and increase bistability, we print the end caps as well as the four triangular facets of the bistable cell out of stiff polyactic acid (Ultimaker PLA with tensile modulus $E=2.3 \mathrm{GPa}$ ). As shown in Fig S1, the single module consists of two hexagonal caps with edges of length $l=30 \mathrm{~mm}$, separated by a distance $h=24 \mathrm{~mm}$, and rotated by an angle $\alpha=30^{\circ}$ with respect to each other. To enable coupling of different units, we print a screw and a threaded hole on the top and bottom surfaces with length $w=6 \mathrm{~mm}$ an thread size $d_{T}=24 \mathrm{~mm}$.


Fig. S1. 3D-printed origami modules. Isometric and projected views of the origami module.

Assembly of an inflatable multi-unit structure. Below are the eight steps needed to fabricate and assemble an inflatable origami structure sample made of multiple modules (see Fig. S2 and Movie S1):

- Step 1: we 3D-print (Ultimaker 3) each origami unit out of polyactic acid (Ultimaker PLA) and thermoplastic polyurethane (Ultimaker TPU 95A), using 0.4 mm print cores with the fine default setting.
- Step 2: we cut the 3D-printed adhesion skirt with scissors.
- Step 3: we remove the 3D-printed support material inside of the origami unit with pliers.
- Step 4: we insert a toric joint on the connection screw to make the unit airtight (see Steps 5-8).
- Step 5: we assemble multiple units together through the connection screws ensuring a tight assembly through the toric joints inserted in Step 4.
- Step 6: we coat the sample with a 0.5 mm layer of polydimethylsiloxane (PDMS) and let it cure for 24 hours.
- Step 7: we fit end caps, making sure to have a tight assembly through the toric joints inserted in Step 4, to create an airtight cavity. Note that one of the end caps has an inlet for actuation.
- Step 8: we test the origami structure by connecting it to a air supply.


Fig. S2. Multi-unit structure fabrication and assembly. Snapshots of the eight steps required to fabricate and assemble inflatable multi-unit origami structures.

## S2. Testing

To characterize the experimental response of the fabricated origami building blocks, we inflate them with air and measure their internal pressure while tracking their height and bending angle. As shown in Fig. S3, we use a syringe pump (Pump 33DS, Harvard Apparatus) to displace air into the origami unit at $10 \mathrm{~mL} / \mathrm{min}$, measure the pressure using a pressure sensor (ASDXRRX015PDAA5 with a measurement range of $\pm 15$ psi by Honeywell), and track the upper cap using two digital cameras (front and top view with two SONY RX100 V).


Fig. S3. Experimental setup for the inflation test. Schematic of the test setup used to characterize the bending angle vs. pressure and height vs. pressure curves of the origami units with (1) syringe pump, (2) pressure sensor, (3) tank, (4) origami unit, and (5) digital cameras.

We summarize all experimental results in Figs. S4-S6 and plot the pressure, $p$, the displacement along the $z$-direction of the top cap's centroid, $u_{z}=\|\mathbf{d}\| \cos \theta_{x z}-h$, and the bending angle, $\theta_{x z}$ of each design tested in this study as a function of normalized time, $T$, for both the inflation and deflation regime. To validate repeatability, we test three specimens for each design and report the mean (solid lines) and standard deviation (shaded region). We find that the classic Kresling module as well as the modified-panel module with $\Delta=0 \mathrm{~mm}$ do not show any snap-through instability. Modules with $\Delta=1 \mathrm{~mm}$ show a snapping transition during inflation, but bend marginally when later deflated. Modules with $\Delta=2,3,4 \mathrm{~mm}$ are bistable as they exhibit discontinuity in their $p-T, u_{z}-T$, and $\theta_{x z}-T$ curves, and show substantial bending when deflated from the snapped configuration. Modules with $\Delta=5 \mathrm{~mm}$ break during the inflation before the panel snaps outward.


Fig. S4. Experimental pressure of our origami modules. Experimentally measured pressure of each design tested in this study as a function of normalized time, $T=t / t_{\text {end }}$ (where $t$ is real time and $t_{\text {end }}$ the duration of the test), for both (a) inflation and (b) deflation. To validate repeatability, we test for each design three specimens and report the mean (solid lines) and standard deviation (shaded region). We find that the classic Kresling module as well as the modified-panel module with $\Delta=0 \mathrm{~mm}$ do not show any snap-through instability. Modules with $\Delta=1 \mathrm{~mm}$ show a snapping transition during inflation, but bend marginally when later deflated. Modules with $\Delta=1,2,3,4 \mathrm{~mm}$ are bistable as they exhibit discontinuity in their $p-T$ curves. Modules with $\Delta=5 \mathrm{~mm}$ break during the inflation before the panel snaps outward.


Fig. S5. Experimental displacement of our origami modules. Experimentally measured displacement of each design tested in this study as a function of normalized time, $T=t / t_{\text {end }}$ (where $t$ is real time and $t_{\text {end }}$ the duration of the test), for both (a) inflation and (b) deflation. To validate repeatability, we test for each design three specimens and report the mean (solid lines) and standard deviation (shaded region). Modules with $\Delta=5 \mathrm{~mm}$ break during the inflation before the panel snaps outward.


Fig. S6. Experimental bending angle of our origami modules. Experimentally measured bending angle of each design tested in this study as a function of normalized time, $T=t / t_{\text {end }}$ (where $t$ is real time and $t_{\text {end }}$ the duration of the test), for both (a) inflation and (b) deflation. To validate repeatability, we test for each design three specimens and report the mean (solid lines) and standard deviation (shaded region). We find that the classic Kresling module as well as the modified-panel modules with $\Delta=0$ and 1 mm do not exhibit bending when deflated from the snapped configuration. Modules with $\Delta=5 \mathrm{~mm}$ break during the inflation before the panel snaps outward.

From the experimental curves in Fig. S7, we can extract the pressure thresholds at which the modified panel snaps outward during inflation, $p_{\Delta}^{+}$and inward during deflation, $p_{\Delta}^{-}$(see Fig. 1 of the main text). Finally, in Fig. S7, we report the deployment and angles at the lowest pressure point in the snapped (i.e. $\|\mathbf{d}\|^{\text {max }}, \theta_{x z}^{\max }$, and $\theta_{x y}^{\max }$ in state $s^{1}$ ) and unsnapped (i.e. $\|\mathbf{d}\|^{\text {flat }}$, $\theta_{x z}^{f l a t}$, and $\theta_{x y}^{f l a t}$ in state $s^{0}$ ) configurations.


Fig. S7. Deployment and angles at lowest pressure point. Bar chart of the experimentally measured end caps deployment and angles at the lowest pressure point in the snapped (i.e. $\|\mathbf{d}\|^{\max }, \theta_{x z}^{\max }$, and $\theta_{x y}^{\max }$ in state $s^{1}$ ) and unsnapped (i.e. $\|\mathbf{d}\|^{f l a t}, \theta_{x z}^{f l a t}$, and $\theta_{x y}^{f l a t}$ in state $s^{0}$ ) configuration. The values for $\|\mathbf{d}\|^{\text {max }}, \theta_{x z}^{\max },\|\mathbf{d}\|^{f l a t}$, $\theta_{x z}^{f l a t}$ are extracted from Figs. S4-S6. The values for $\theta_{x y}^{\max }$ and $\theta_{x y}^{f l a t}$ were obtained at the lowest pressure point in each stable configuration during the experiments.

## S3. Model

Origami module. We start by using the geometric quantities that we track in our experiments (shown in Fig. S7) to reconstruct the configuration of the origami module at the lowest pressure point in each stable state (i.e. $s^{0}$ and $s^{1}-$ see Fig. S8).


Fig. S8. Modeling the lowest pressure point of our origami modules in each stable state. (a) State diagram for an origami module with a modified panel of depth $\Delta$. The unit can transition between two stable states: state $s^{0}$ when the modified panel is folded inward, and state $s^{1}$ when the panel is popped outward and stays in that position even when the input pressure is removed. Reconstructed geometry of the origami module at the lowest pressure point in state $s^{0}$ (a) and $s^{1}$ (b).

Structure comprising $n$ modules. We can create structure made of $n$ units by simply combining the different stable states and snapping transitions found for the single unit model described in Fig. S8. Note that we impose that any $n$-unit structure forms a closed, inflatable cavity (i.e. they are all subjected to the same internal pressure). By combining $n$ modules, we can construct $(3 \times 2 \times 6+1 \times 2)^{n}$ different structures since for each module $k$ we can select ( $i$ ) either a regular Kresling module or a unit comprising a modified panel with depth $\Delta^{k} \in\{2,3,4\} \mathrm{mm}$; (ii) the upper cap to be rotated clockwise or anticlockwise with respect to the bottom one, $c^{k} \in\{/ /, \backslash \backslash\}$, and (iii) the side on which the modified panel is located, $f^{k} \in\{1, \ldots, 6\}$ (see Fig. 2 of the main text). For a structure made of $n$ units, the number of stable states is equal to $2^{n} \Delta$, where $n_{\Delta}$ is the number of unique modified panel depths $\Delta$. Note that we assume all units with the same $\Delta$ snap synchronously at the pressure thresholds, $p_{\Delta}^{+}$and $p_{\Delta}^{-}$. Since in this study, we consider only the discrete set $\Delta \in\{2,3,4\} \mathrm{mm}$, all our structures have either $n_{\Delta}=0,1,2$, or 3. For each different $n_{\Delta}$, we report the corresponding state diagram in Fig. S9.


Fig. S9. State diagrams. (a) State diagram for any $n$-unit structure made only of Kresling modules. (b-d) State diagram for any $n$-unit structure made with 1,2 , and 3 unique modified panel's depth, i.e. $n_{\Delta}=1,2$, and 3 , respectively.

## S4. Optimization

To identify structures capable of achieving target deformation modes, we solve the following discrete optimization problem

$$
\begin{align*}
\min _{\Delta^{k}, c^{k}, f^{k}} & \Psi\left(\Delta^{k}, c^{k}, f^{k} ; n\right) \\
\text { s.t. } & \Delta^{k} \in\{2,3,4\} \mathrm{mm} \\
& c^{k} \in\{/ /, \backslash \backslash\}  \tag{1}\\
& f^{k} \in\{1,2,3,4,5,6\} \\
& k \in\{1,2, \ldots, n\} \\
& n \in \mathcal{Z}^{+},
\end{align*}
$$

where $\Psi$ is the cost function, $n$ is the number of units making the structure and $\Delta^{k}$, $c^{k}$, and $f^{k}$ are are the modified panel depth, the orientation of the upper cap with respect to the bottom one, and the side on which the modified panel is located for the $k$-unit in the array. Note that all design variables (i.e. $\Delta^{k}, c^{k}$, and $f^{k}$ ) are constrained to be integer value and, for the sake of simplicity, we solve the optimization problem multiple times for fixed number of units $n \in[1,15]$.

In the main text we use the optimization algorithm to identify structures whose tip can approach a desired set of target points and therefore define the cost function as

$$
\begin{equation*}
\Psi=\frac{1}{n_{\text {targets }} \cdot h} \sum_{m=1}^{n_{\text {targets }}} \min \left\|\mathbf{d}-\mathbf{T}_{m}\right\| \tag{2}
\end{equation*}
$$

where $n_{\text {targets }}$ is the number of targets, $\mathbf{T}_{m}$ is the vector connecting the $m$-th target with the origin, and $h$ is the height of the undeformed module.

Optimization algorithms. There are many algorithms able to solve an optimization problem with integer constraints such as the one presented in Eq. [1]. In this study, we used three classic algorithms: (i) the genetic algorithm with integer constraints; (ii) the integer optimization via a surrogate model; and (iii) the greedy algorithm based on best-first search. Note that given the high-dimensionality and complexity of this optimization problem, there is no guarantee that these algorithms will lead to a unique global minimum.

Genetic algorithm with integer constraints. We started by using the genetic algorithm with integer constraints, which attempts to minimize a penalty function that depends on the fitness (value of the cost function $\Psi$ ) and feasibility (design variables are integer) of an individual. For this study, we used the Matlab implementation of the algorithm (Matlab function ga) and imposed the constraint that all design variables, i.e. $\Delta^{k}, c^{k}$, and $f^{k}$ must have integer values with upper and lower bounds reported in Eq. [1]. We ran the function ga multiple times, each time considering a fixed value of $n \in[1,15]$, using a population size of 200 , a max stall generations (i.e. the consecutive number of generations with no change to the cost function value) of 500 and a maximum number of generations of 1000 .

Integer optimization via a surrogate model. Next, we used the surrogate model optimization, which is a derivative-free method that replaces the complex and non-smooth objective function by a surrogate (i.e. an approximation of that function), which is created by sampling the objective function. For this study we used the Matlab implementation of the algorithm (Matlab function surrogateopt) and imposed the constraint that all design variables, i.e. $\Delta^{k}$, $c^{k}$, and $f^{k}$, must have integer values with upper and lower bounds reported in Eq. [1]. We ran the algorithm for fixed values of $n$ with a maximum number of function evaluations of 20,000 .

Greedy algorithm based on best-first search. For the greedy algorithm, we developed and in-house Matlab code based on the best-first search method that creates a structure with $n$ units out of $n_{s}$ super-cells, each super-cell made of $n_{u}$ modules (so that $\left.n=n_{u} \cdot n_{s}\right)$. At the first iteration, the algorithm selects the super-cell design that minimizes $\Psi$ and stores it in memory. Then, in the second iteration, we identify a second super-cell that, when connected to the first one, minimizes $\Psi$. The first two super-cells are then stored in memory and the algorithm advances to the next iteration (see Fig. S10 and Algorithm 1 below).


Fig. S10. Greedy algorithm. Schematic of the greedy algorithm with $n_{u}=3$. At each iteration, the algorithm selects the structure super-cell design that minimizes $\Psi$.

```
Algorithm 1 Greedy algorithm based on best-first search
Set \(n_{\text {max }}\);
Set \(n_{u}\);
Set \(n_{s}=0\);
While \(n_{s} \cdot n_{u} \leq n_{\text {max }}\)
    \(n_{s}=n_{s}+1\);
    if \(n_{s}=1\) then
        - Calculate \(\Psi\) for each structure design with \(\left(\Delta^{k}, c^{k}, f^{k}\right), k=1: n_{s} \cdot n_{u}\);
        - Find the structure that minimizes \(\Psi\) and set its design variables to ( \(\Delta^{k^{*}}, c^{k^{*}}, f^{k^{*}}\) )
    else
            - Calculate \(\Psi\) for each structure design with \(\left(\Delta^{k}, c^{k}, f^{k}\right)\), where the set of variables from \(k=1:\left(n_{s}-1\right) \cdot n_{u}\) are coming
            from the previous iteration of \(\left(\Delta^{k^{*}}, c^{k^{*}}, f^{k^{*}}\right)\) and \(k=\left(n_{s}-1\right) \cdot n_{u}+1: n_{s} \cdot n_{u}\) are free.
            - Find the structure that minimizes \(\Psi\) and set its design variables to ( \(\Delta^{k^{*}}, c^{k^{*}}, f^{k^{*}}\) )
```

Results. In the following we first compare the performance of the three algorithms and then present additional results obtained using the greedy algorithm.

Comparison between the three algorithms. To test and compare the three algorithms, we considered the set of three targets ( $T_{1}$, $T_{2}, T_{3}$ ) shown in Fig. 3 of the main article and minimized the cost function given in Eq. [2]. In Fig. S11, we report the cost function value with respect to the number of generations/function evaluations as obtained using the three algorithms. We find that for all considered values of $n$ both the genetic algorithm with integer constraints and the surrogate model stall quickly, with a minimum value of the cost function of 1.04 and 1.12 reached for $n=15$, respectively. Further, we find that the greedy algorithm with $n_{u}=3$ outperforms the genetic algorithm and the surrogate model optimization as it identifies a structure design that leads to $\Psi=0.729$ for $n=12$. Note that, for $n_{u}=3$, the greedy algorithm requires about $2.75 \times 10^{5}$ evaluations of $\Psi$ to identify the optimal design, whereas the surrogate model takes about $1 \times 10^{5}$ evaluations of $\Psi$ (the genetic algorithms requires about $8 \times 10^{5}$ evaluations of $\Psi$ with a population size of 200 ). However, the greedy algorithm does not require any other operation apart from a simple computation of $\Psi$ during each iteration. Differently, the surrogate algorithm has to update the underlying model. The simplicity of the greedy algorithm leads to a CPU time of 850 s (parallelized on 24 cores) to solve the algorithm compared to $2,500 \mathrm{~s}$ and $4,000 \mathrm{~s}$ for the genetic algorithm and the surrogate model, respectively. We also investigated the influence of hyper-parameters on the three different optimization algorithms (see Table S2). We find that the greedy algorithm still outperforms the genetic algorithm and surrogate model. We therefore use the greedy algorithm to identify optimal configurations for our structures.


Fig. S11. Comparison between optimization algorithms with integer constraints. Comparison of the (a) generic algorithm, (b) surrogate model, and (c) greedy algorithm based on best-first search to solve the integer optimization problem of minimizing the targets error $\Psi$.

Additional results generated by the greedy algorithm. In Fig. S12, we consider a set of three targets ( $T 1, T 2, T 3$ ) different from that included in the main text and present the results for the optimal design identified by the greedy algorithm. Next, in Fig. S13 we show the inverse design of a structure reaching the same set of three targets considered in Fig. 3 of the manuscript, but with the additional constraint that the targets much be reached successively by decreasing pressure. Finally, in Fig. S14 we show how the minimum value of $\Psi$ found by the greedy algorithm varies with the number of targets, $n_{\text {targets }}$, and the units forming a super-cell, $n_{u}$, and in Fig. S15 how the target radius (i.e. the radius of the sphere fitted with the targets) influences the optimal number of units of the structure.


Fig. S12. A 6-unit structure reaching three targets. For a specific set of three targets, we use the greedy algorithm to find the structure design that minimizes $\Psi$, i.e the error between the targets and the top cap's centroid. Note that we fix $n_{u}=3$ and consider $n_{s} \in\{1,2,3,4,5\}$. (a) Targets error $\Psi$ as a function of total number of units: the optimal structure produced by the greedy algorithm for the three targets is reported as (*), along with the respective parameters for each module. The considered set of targets is shown in the inset. (b) State diagram for the 6 -unit structure (*) with targets $T 1, T 2$, and $T 3$ highlighted. (c) Top and 3D view of the model and the experimental prototype for the 6 -unit structure reaching the targets.


Fig. S13. The 12 -unit structure with additional constraint. We focus on the same set of three targets considered in Fig. 3 of the manuscript and further impose that each targets much be reached successively by decreasing pressure. (a) Targets error $\Psi$ as a function of total number of units: the optimal structure produced by the greedy algorithm for the three targets is reported as (*), along with the respective parameters for each module. (b) State diagram for the optimal 12 -unit structure (*) with targets $T 1, T 2$, and $T 3$ highlighted. (c) Top and 3D view of the model for the 12 -unit structure reaching the targets.


Fig. S14. Random targets error. For a random set of $n_{\text {targets }}$, we use the greedy algorithm to find the structure design that minimizes the target error $\Psi$. Note that each target is bounded by a cubic domain centered with the structure and norm equal to $1 / 2\left(n_{u} \cdot n_{s}\right)$ to ensure that it is within reach. We report the average error based 1000 simulations with $n_{\text {targets }} \in\{1,2,3,4\}$ and $n_{u} \in\{1,2,3\}$. Note that for each set of targets, we fix $n_{u}$ and choose the $n_{s}$ (with the constraint that $n=n_{u} \cdot n_{s} \leq 15$ ) that minimizes the error.


Fig. S15. Optimal number of units as a function of the target radius. For 100 random sets of $n_{\text {targets }}=3$, we measure the target radius, $R_{\text {targets }}$, i.e. the radius of the sphere fitted with the targets, and we use the greedy algorithm to find the number of units that minimizes the error between the target and the top cap's centroid. We report here the target radius normalized by the module height, $R_{\text {targets }} / h$, as a function of the optimal number of units $n$ found by the greedy algorithm. We find that the average target radius increases with the number of units to minimize the error $\Psi$.

## S5. Robotic application

To show the potential of using multimodal origami structures for robotic applications, we first take inspiration from the closed trajectory of a rowing stroke and inverse design a structure able to reach consecutively two targets along a closed triangular loop (Fig. S16). Next, we combine this structure along with its symmetric counterpart to form the arms of a robot connected through a single fluidic line and mounted on a wheeled chassis (see Fig. S17). Further, to harnesses the cyclic motion of the structure and generate positive mechanical work with the ground, we connect two rigid rods to the outer caps that serve as stroke amplifiers and attach silicon patches at their ends to increase friction with the ground.


Fig. S16. Inverse design to reach two targets successively. (a) Top and 3D view of two targets along with the bottom hexagonal cap of the structure. (b)Targets error $\Psi$ as a function of total number of units: the optimal structure produced by the algorithm is reported as (*), along with the respective parameters for each module. (c) State diagram for the 3 -units structure (*) with targets $T 1$ and $T 2$ highlighted. (d) Top and 3D view of the model and the experimental prototype for the 3 -units structure reaching the two targets.


Fig. S17. Single pressure input origami robot. (a) The two identical structures forming the arms of the robot. (b) Schematics of the origami robot. (c) Components of the origami robot. (d) Assembled origami robot.

When increasing the pressure above $p_{4}^{+}$and then lowering it to $p_{3}^{-}$the two structures reach $T 1$. At this point the rigid rods touch the ground. Then, when we further decrease the pressure, the rigid rods move backward to $T 2$ creating a forward thrust and eventually lift off from the ground, completing the stroke. Finally, lowering the pressure below $p_{4}^{-}$resets the locomotion
cycle (see Figs. S18a and b). As shown in the experimental snapshots in Fig. S18c, we can harness this particular trajectory instructed by the model to create locomotion: the robot advances of about 16 cm in 20 cycles. Note that, differently from other robotic platforms with similar performance but requiring one or more structures per leg with dedicated pressure sources $(1,2)$, our robots operate with a single pressure input, which largely simplifies its control.


Fig. S18. Land rowing robot. (a)-(b) Trajectory followed by the robot's arms upon inflation and deflation, as predicted by the model (a) and observed in experiments (b). (c) Experimental snapshots of the robot in the initial configuration and after 10 and 20 cycles.

## S6. Additional results

$\mathrm{n}=14$
a Alternating chirality: $\left[\Delta^{k} c^{k} f^{k} ; \Delta^{k+1} c^{k+1} f^{k+1}\right]=[4 \backslash \backslash 1 ; 4 / / 1]$


$$
n=14
$$

c Random chirality: $\left[\Delta^{\mathrm{k}} \mathrm{c}^{\mathrm{k}} \mathrm{f}^{\mathrm{k}}\right]=[4 \backslash \backslash \vee / / 1]$


Fig. S19. Complex deformation modes. We use our numerical model to investigate the deformation mode upon deflation of structures comprising an array of identical modules (i.e. $n_{\Delta}=1$ ). (a) Initial state $s^{0}$ (blurred) and snapped state $s^{1}$ upon deflation for structures for structures comprising $n=2,4, \ldots, 14$ modules with alternating chirality (i.e. $\left[\Delta^{k} c^{k} f^{k} ; \Delta^{k+1} c^{k+1} f^{k+1}\right]=[4 \backslash \backslash 1 ; 4 / / 1]$, with $k=1, \ldots, n-1$ ). We find that the radius of curvature is small and remains constant at around $2 h$ with $n$, while the bending angle increases. Note that the twisting deformation associated to these deformation modes is negligible. (b) Initial state $s^{0}$ (blurred) and snapped state $s^{1}$ upon deflation for structures made of $n=2,4, \ldots, 14$ units with the same chirality (i.e. $\left[\Delta^{k} c^{k} f^{k}\right]=[4 \backslash \backslash 1]$, with $k=1, \ldots, n$ ). We find that the complex deformation achieved upon deflation is twisting-dominated. (c) Initial state $s^{0}$ (blurred) and snapped state $s^{1}$ upon deflation for structures made of $n=2,4, \ldots, 14$ units with random chirality (i.e. $\left[\Delta^{k} c^{k} f^{k}\right]=[4 \backslash \backslash \vee / / 1]$, with $k=1, \ldots, n$ ). We find that the deformation modes achieved upon deflation are twisting and bending mixed.


Fig. S20. Experiments on a Kresling module with six modified panels. Experimentally measured pressure, displacement, and bending angle of a Kresling module with six modified panels of depth $\Delta=3 \mathrm{~mm}$ as a function of normalized time, $T=t / t_{\text {end }}$ (where $t$ is real time and $t_{\text {end }}$ the duration of the test), for both (a) inflation and (b) deflation. Note the six different discontinuities in the graphs representing the snap-trough instability of each of the six degree-four panels.

| Structure | Fig. | $n$-units | Params. | State | $\left.\\|d\\|\right\|^{\text {exp }}$ [mm] | $\\|\left. d\right\|^{\text {num }}$ [mm] | $\epsilon_{\|\|d\|\|}$ [mm] | $\theta_{x y}^{e x p}\left[{ }^{\circ}\right]$ | $\left.\theta_{x y}^{\text {num }}{ }^{\text {c }}{ }^{\circ}\right]$ | $\epsilon_{\theta_{\theta_{x y}}\left[{ }^{\circ}\right]}$ | $\theta_{x z}^{\left.\exp { }^{\text {a }}{ }^{\circ}\right]}$ | $\left.\theta_{x z}^{\text {num }}{ }^{\text {[ }}{ }^{\circ}\right]$ | $\epsilon_{\theta_{\theta_{x z}}\left[{ }^{\circ}\right]}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 2 e | 2 | [2 |  |  |  |  |  |  |  |  |  |  |
| 1;4//1] | $s^{10}$ | 27.75 | 31.09 | -3.34 | -7.38 | -10.63 | 3.24 | 22.47 | 20.86 | 1.60 |  |  |  |
| 1 | 2 e | 2 | [2 |  |  |  |  |  |  |  |  |  |  |
| 1;4//1] | $s^{11}$ | 37.11 | 40.53 | -3.42 | 9.08 | 7.23 | 1.85 | 27.91 | 31.29 | -3.38 |  |  |  |
| 1 | 2 e | 2 | [2\11;4//1] | $s^{01}$ | 36.32 | 30.36 | 5.96 | 20.39 | 23.83 | -3.44 | 17.31 | 15.93 | 1.38 |
| 2 | $2 f$ | 2 | [2 |  |  |  |  |  |  |  |  |  |  |
| 1;4 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 4] | $s^{10}$ | 24.15 | 31.09 | -6.94 | -9.40 | -10.63 | 1.23 | 18.72 | 20.86 | -2.14 |  |  |  |
| 2 | $2 f$ | 2 | [2 |  |  |  |  |  |  |  |  |  |  |
| 1;4 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 4] | $s^{11}$ | 36.74 | 40.53 | -3.79 | 23.88 | 27.02 | -3.14 | 15.30 | 13.61 | 1.69 |  |  |  |
| 2 | $2 f$ | 2 | [2 |  |  |  |  |  |  |  |  |  |  |
| 1;4 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 4] | $s^{01}$ | 24.44 | 30.36 | -5.93 | 108.18 | 112.05 | -3.87 | -3.64 | -6.68 | 3.04 |  |  |  |
| 3 | 4f | 12 | see Fig. 4 f | $s^{110}$ | 238.01 | 152.91 | 85.10 | 40.71 | 60.32 | -19.61 | 54.69 | 69.03 | -14.34 |
| 3 | 4 f | 12 | see Fig. 4 f | $s^{011}$ | 271.21 | 192.24 | 78.97 | -36.69 | -15.31 | -21.38 | 63.14 | 54.41 | 8.73 |
| 3 | 4f | 12 | see Fig. 4 f | $s^{001}$ | 131.38 | 134.64 | -3.25 | -123.37 | -133.30 | 9.93 | 128.72 | 159.21 | -30.49 |
| 4 | S12c | 6 | see Fig. S12c | $s^{110}$ | 100.54 | 97.15 | 3.39 | 73.62 | 96.14 | -22.52 | 6.48 | -5.39 | 11.87 |
| 4 | S12c | 6 | see Fig. S12c | $s^{011}$ | 95.14 | 87.08 | 8.07 | -10.33 | -0.36 | -9.97 | 37.18 | 50.83 | -13.65 |
| 4 | S12c | 6 | see Fig. S12c | $s^{001}$ | 79.52 | 78.63 | 0.89 | -46.80 | -40.90 | -5.90 | 49.24 | 40.38 | 8.86 |
| 5 | S16d | 3 | [4//1;3 |  |  |  |  |  |  |  |  |  |  |
| 5;4//1] | $s^{11}$ | 76.30 | 60.88 | 15.43 | 2.75 | -13.15 | 15.90 | 3.48 | 1.28 | 2.20 |  |  |  |
| 5 | S16d | 3 | [4//1;3 |  |  |  |  |  |  |  |  |  |  |
| 5;4//1] | $s^{01}$ | 54.74 | 50.57 | 4.17 | 12.18 | 10.25 | 1.93 | 13.84 | 17.31 | -3.47 |  |  |  |

Table S1. Experiments vs numerical predictions. Experimental characterization and numerical prediction of the structures' deployment, $\|d\|$, and angles, $\theta_{x y}$, and $\theta_{x z}$ reported in this study.

| Algorithm | Population Size | Min Surrogate Points | Min Sample Distance | $n$-units in supercell | $\Psi[-]$ | CPU Time [s] |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| GA | 100 | - | - | - | 1.81 | 561 |
| GA | 200 | - | - | - | 1.83 | 606 |
| GA | 300 | - | - | - | 1.67 | 1498 |
| Surrogate | - | 40 | $1 \mathrm{e}-3$ | 1.49 | 3195 |  |
| Surrogate | - | 12 | $1 \mathrm{e}-3$ | - | 1.75 | 3334 |
| Surrogate | - | 100 | $1 \mathrm{e}-2$ | - | 1.70 | 3284 |
| Surrogate | - | 72 | $1 \mathrm{e}-4$ | - | 1.92 | 3383 |
| Surrogate | - | - | - | 1 | 1.59 | 3383 |
| Greedy | - | - | - | 2 | 1.82 | 11.4 |
| Greedy | - | - | 3 | 1.79 | 187 |  |
| Greedy | - | - | - | 0.729 | 850 |  |

Table S2. Quantitative comparison between algorithms with different hyper-parameters. Influence of the hyper-parameters on the target error $\Psi$ along with CPU Time (parallelized on 24 cores) for the set of three targets ( $T_{1}, T_{2}, T_{3}$ ) considered in Fig. 3 of the main article. For the genetic algorithm with integer constraints, we vary the population size and fix the number of units to $n=12$. For the integer optimization via a surrogate model, we change the minimum number of points as well as the minimum sampling distance and fix the number of units to $n=12$. For the greedy algorithm, we consider different super-cells and fix the total number of units to $n=12$. We find that the greedy algorithm outperforms the genetic algorithm and surrogate model both in term of minimizing $\Psi$ and computational time.

Movie S1. Fabrication. In order to create multimodal origami structures, we start by 3D-printing modules using a combination of TPU and PLA and connect them via screws. To make an airtight cavity we deposit a layer of PDMS on the structures.

Movie S2. Single-unit structures. We compare the behavior under inflation and deflation of the monostable Kresling and the bistable modules.

Movie S3. Multi-unit structures. We demonstrate the deformation modes of two different 2-unit structures. Both structures comprise modified panels with depth $\Delta$ of 2 and 4 mm , respectively. In the first structure, the modules have opposite chirality and modified panels located at same position. In the second structure, the modules have the same chirality and opposite position of the modified panels.

Movie S4. 12-unit structure reaching three targets with one input signal. We show that a 12 -unit structure, built following the design produced by our model and greedy algorithm, can reach a set of three predefined targets in space using only one input signal.

## References

1. Robert F. Shepherd, Filip Ilievski, Wonjae Choi, Stephen A. Morin, Adam A. Stokes, Aaron D. Mazzeo, Xin Chen, Michael Wang, and George M. Whitesides. Multigait soft robot. Proceedings of the National Academy of Sciences of the United States of America, 108(51):20400-20403, 2011. ISSN 00278424. URL http://www.jstor.org/stable/23077257.
2. Joran W. Booth, Dylan Shah, Jennifer C. Case, Edward L. White, Michelle C. Yuen, Olivier Cyr-Choiniere, and Rebecca Kramer-Bottiglio. Omniskins: Robotic skins that turn inanimate objects into multifunctional robots. Science Robotics, 3 (22), 2018. . URL https://robotics.sciencemag.org/content/3/22/eaat1853.

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    [2] B. Gorissen, D. Reynaerts, S. Konishi, K. Yoshida, J.-W. Kim, M. De Volder, Adv. Mater. 2017, 29, 1604977.
    [3] C. Majidi, Soft Rob. 2014, 1, 5.
    [4] E. T. Roche, R. Wohlfarth, J. T. B. Overvelde, N. V. Vasilyev, F. A. Pigula, D. J. Mooney, K. Bertoldi, C. J. Walsh, Adv. Mater. 2014, 26, 1200.

