

## Video legends

### **Supplementary Video 1. A 4×4 and an 8×8 sample morphing a dynamic implicit shape shifting process.**

A 4×4 and an 8×8 sample morphing a dynamic implicit shape shifting process: growing up, moving around, splitting and splitting with uniform velocities and constant frequency growing up (the velocity of the highest point along the Z-axis,  $V_z = 5$  mm/s), moving around (the velocity of the highest point in the XY-plane,  $V_{xy} = 30$  mm/s), splitting ( $V_{xy} = 30$  mm/s) and oscillating (the frequency of oscillation,  $f = 0.83$  Hz). The 4×4 sample morphs the same processes with control on instantaneous velocity and acceleration of the dynamics: growing up (initial velocity  $V_z = 0$  mm/s, acceleration  $a_z = 30$  mm/s<sup>2</sup>), moving around (first round:  $V_{xy} = 15$  mm/s; second round: initial velocity  $V_{xy} = 0$ , acceleration  $a_{xy} = 22.5$  mm/s<sup>2</sup>; third round: initial velocity  $V_{xy} = 45$  mm/s, acceleration  $a_{xy} = -45$  mm/s<sup>2</sup>), splitting ( $V_{xy} = 45$  mm/s), and oscillating ( $f = 0.33$  Hz,  $0.66$  Hz,  $1$  Hz). The model-driven design updates the actuation voltages at a rate of 10 fps. An optical camera (Canon EOS R) monitors the sample morphing processes at a frame rate of 60 fps.

### **Supplementary Video 2. An array of 8 serpentine beams morphing a dynamic process of a water droplet dripping from a nozzle.**

An array of 8 serpentine beams morphs a slow-motion waterdrop dripping process (0.2× speed) captured by a high-speed camera (10000 fps) (Berman, Maxim., Ultra Slow-Motion Droplets (10'000 Fps) - Youtube. <https://www.youtube.com/watch?v=c4MUTij8f6I>). The dynamic process consists of two stages: growing and pinch-off. It takes ~95% of the time for a pendant drop to grow to its critical volume, followed by a fast pinch-off stage after breaking neck forming. The shapes extracted from the video are normalized by the sample size. The model-driven design updates the actuation voltages at a rate of 10 fps. An optical camera (Canon EOS R) monitors the sample morphing processes at a frame rate of 60 fps.

### **Supplementary Video 3. A 4×4 sample morphing a dynamic process of a waterdrop falling onto a solid surface.**

A 4×4 sample morphs a slow-motion waterdrop falling process (0.2× speed) captured by a high-speed camera (10000 fps) (Okawa, T., Shiraishi, T., Tada, T. & Kataoka, I. in ASME/JSME 2007 5th Joint Fluids Engineering Conference.

317-322). The dynamic process consists of five stages: falling onto the surface, spreading out, bouncing back, vibrating and stabilizing. The 3D shapes of the droplet extracted from the video frames are normalized by the sample size. The model-driven design updates the actuation voltages at a rate of 10 fps. An optical camera (Canon EOS R) monitors the sample morphing processes at a frame rate of 60 fps.

**Supplementary Video 4. A 4×4 sample morphing into a target implicit shape via the experiment-driven process.** A 4×4 sample starts from a flat, zero-actuation state and evolves into a target implicit shape (the target shape in Fig. 3b) via the experiment-driven process. An optical camera (Canon EOS R, 60 fps) captures the evolving sample. The in-time 3D-reconstructed surface and the evaluation of the loss function  $f(V)$  over the optimization iterations are synced with the video with a 10× playback speed. The loss function  $f(V)$  drops below  $3 \times 10^{-4}$  (stopping criterion) after 10 iterations. The output shows the optical image and the 3D reconstructed sample surface with an error map superimposed.

**Supplementary Video 5. A 4×4 sample dynamically morphing six implicit shapes.** A real-time (1×) playback of a 4×4 sample dynamically morphing six implicit shapes (shape I-VI in Fig. S32) with the actuation voltages updated at a rate of 10 fps. An in-situ 3D imaging provides a frame-aligned 3D reconstruction. An optical camera (Canon EOS R, 60 fps) monitors the sample morphing processes.

**Supplementary Video 6. A 4×4 sample morphing into a target implicit shape against extrinsic mechanical disturbance via the experiment-driven process.**

A 4×4 sample self-evolving into an implicit shape (target shape in Fig. 3b) demonstrates an ability to self-adjust against mechanical disturbance. The first column shows the video (Canon EOS R, 60 fps, 10× playback speed) of an undisturbed self-evolving process, time-synced with the 3D-reconstructed surface and the corresponding error map. The second column shows the situation where an external load (~0.1 gram) is applied on a serpentine beam, resulting in large errors. In the third column, the sample continues to self-evolve and adapt to the additional loading, resulting in significantly reduced errors

comparable to the undisturbed case.

**Supplementary Video 7. A 4×4 sample continuously morphing the moving palm surface.**

The experiment-driven approach delivers an end-to-end control scheme for a 4×4 sample to continuously morph a moving hand. A 4×4 array of markers (with inter-spacing of 15 mm) attached to the palm enables the in-time error analysis for the 4×4 array of nodes of the sample. A duplicated stereo-imaging setup reconstructs the shapes of the palm surface. The optimization acts directly to minimize the displacement difference between the 16 markers and their corresponding nodes of a 4×4 sample. Given continuity, the gradient-descent process takes the last morphing result as the initial state for the next morphing task. The video shows the self-evolved (post-learning) results of a 4×4 sample (Canon EOS R, 60 fps, 1× playback speed) in sync with the hand movement (Canon EOS R, 60 fps, 1× playback speed).

**Supplementary Video 8. A 3×3 sample self-evolving toward multifunctionality.**

A 3×3 sample with 9 reflecting gold patches self-evolves to perform an optical function and a structural function simultaneously. The optical function is to reflect and overlap two laser spots on a receiving screen, which is achieved by the experiment-driven process. The corresponding loss function  $f_{\text{opt}}(\mathbf{V})$  quantifies the distance between two laser spots. The structural function is to control the deformation of the central node of the sample to achieve the target displacement (-0.5 mm). The loss function  $f_{\text{struct}}(\mathbf{V})$  evaluates the difference between the current nodal displacement to the current. The multifunctional loss function,  $f_{\text{multi}}(\mathbf{V})$ , is a linear combination of the two. The video shows the frame-aligned videos of two laser spots on the screen (Webcams ELP, 30 fps, 1× playback speed), the sample (Canon EOS R, 60 fps, 10× playback speed), and the ex-situ 3D-reconstruction of the self-evolving sample, along with the loss functions over function evaluations.