Supporting Information

Evolutionary Algorithm Guided Voxel-Encoding Printing of Functional Hard-Magnetic Soft Active Materials

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Supplementary Methods

Evolutionary Algorithm (EA) is adopted to design the distribution of magnetization (both magnetization direction and density) for voxel-encoding direct ink writing (DIW) printing of the hard-magnetic soft active materials (hmSAMs). It is based on an open-source framework Distributed Evolutionary Algorithms in Python (DEAP).[1] In this paper, beams with designed magnetization distributions are used to demonstrate the deformation with functional curvature distributions under the applied actuation magnetic field. The beam consists of m voxels along its axial direction and each voxel is composed of n layers of the printed hmSAM. Based on the voxel-encoding DIW printing of hmSAMs, a voxel with n layers can be encoded with $2n + 1$ variations of the magnetization. For example, for a three-layered voxel, the voxel genotypes are labeled as 1, 2, 3, 4, 5, 6, and 7 in the EA to form the magnetization distribution, which is further transferred to a finite element method (FEM) simulation to predict the magnetic actuation.

Three general steps, including selection, crossover, and mutation, are operated in the EA process via DEAP to autonomously update the magnetization distribution until the magnetic actuation with desired curvature distribution is achieved. First, a population with $\mu = 32$ individuals, whose genotypes are randomly created, are translated into magnetization density (M-density) and magnetization direction (M-direction) distributions in the FEM simulations as shown in Figure 3b. A fitness function e is used to evaluate the performance of each individual. Then a portion of top-scoring individuals is selected from the previous generation to form an offspring population with an average size of $\lambda = 38$. Crossover or mutation is then performed to individuals with predefined possibilities $p_c = 0.70$ or $p_m = 0.25$, respectively, to create new individuals for the next generation. Figure S3 shows how individuals' genotypes are operated through crossover and mutation to create new magnetization distributions. Note that the possibility for an individual to be chosen into the next generation without any operation is defined as $p_s = 1 - p_c - p_m = 0.05$. The selection, crossover, and mutation processes iterate until there is one individual whose fitness function e from FEM simulation is smaller than a predefined critical value $e_c = 0.005$ mm, or a predetermined maximum generation number (15 in this paper) is reached. Once one of the criteria is met, the individual's magnetization distribution is exported. With the EA-guided magnetization distribution design, the beam can deform into the target curvature distribution under the external magnetic field, and the corresponding magnetization distribution of the beam will be used in the voxel-encoding DIW printing for experimental testing.

Finite element simulations are used to predict the deformation of a beam under the magnetic actuation. A theoretical framework was recently developed by Zhao et al.,[2] where the magneto-mechanical behavior of a hmSAM is described by incorporating the strain energy of the soft matrix with the magnetic potential of the embedded hard-magnetic particles. The constitutive model was implemented into finite element simulation through a user-defined element subroutine in the commercial software ABAQUS to predict the large deformation of the hard-magnetic soft active materials. The magnetization, shear modulus, and Poisson's ratio are set to be 70 kA m^{-1}, 300 kPa, and 0.495 respectively.

For the experiments in Figure 4 and Figure 5, 50 mm × 4.8 mm × 1.2 mm cantilever beams are meshed into 100 × 1 × 6 elements in FEM simulations. The x and y coordinates of N = 101 nodes along the bottom edge from FEM simulations are used to calculate the fitness function. For the experiments in Figure 6, the 25 mm × 4.8 mm × 1.2 mm beam is meshed into 50 × 1 × 6 elements with symmetry and roller support boundary conditions as shown in Figure 6b. N = 51 nodes along the bottom edge are used to evaluate the fitness function. For Figure7, the 20 mm × 4.8 mm × 0.8 mm cantilever beams to mimic geometries of the in-motion dog legs are meshed into 60 × 1 × 4 elements, giving N = 61 nodes for fitness function calculation.

Fitness function is used to evaluate the performance of FEM predictions with the EA-guided magnetization distribution designs. Fitness function e is calculated as follows:

$$e = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(x_{\mathrm{Target},\,i} - x_{\mathrm{FEM},\,i})^2 + (y_{\mathrm{Target},\,i} - y_{\mathrm{FEM},\,i})^2}\ , \tag{S1}$$

where N is the number of nodes along the beam bottom edge, and $x_{\mathrm{Target},\,i}$, $y_{\mathrm{Target},\,i}$, $x_{\mathrm{FEM},\,i}$, and $y_{\mathrm{FEM},\,i}$ are the i^{th} node's coordinates from the predesigned target shape and the FEM simulation, respectively. The minimum, average, and maximum fitness functions for different target shapes are plotted with respect to the generation number as shown in Figure S4. The results demonstrate the optimization process of EA calculations with different target shapes, illustrating the convergence of EA-guided magnetization distribution designs. The calculated magnetization distributions for different target shapes are plotted in Figure S5.

Supplementary Figures and Figure Captions

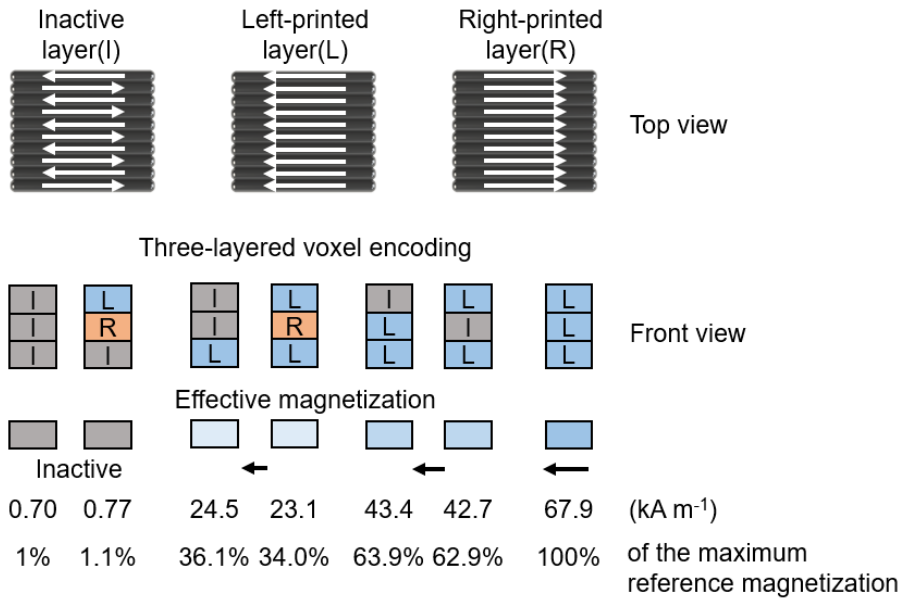

Figure S1. Printing path designs of different types of layers to form a voxel and equivalent effective magnetizations with different M-direction arrangements of the layers in a single voxel. The percentage is calculated over the magnetization of [LLL] printed voxel. Same can be done for the rightward magnetizations.

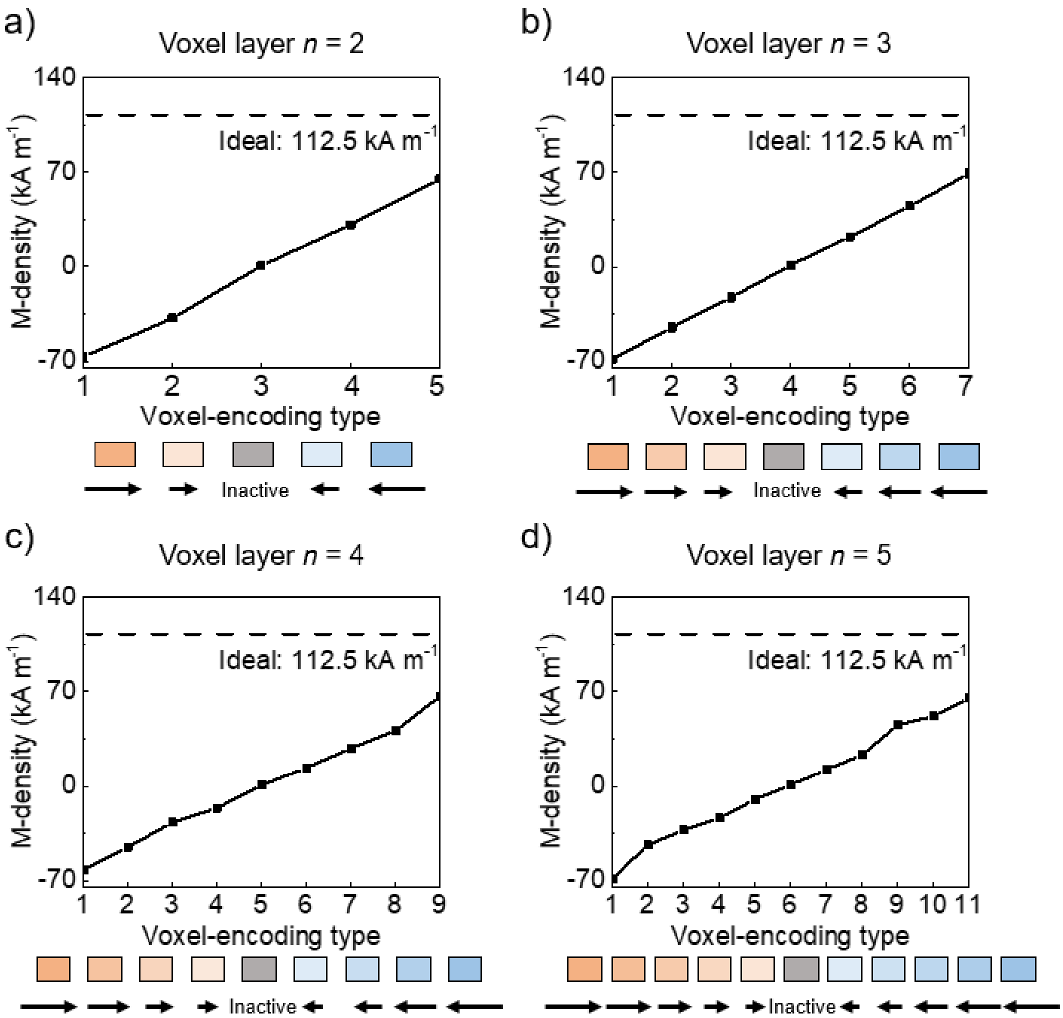

Figure S2. Different directional M-density tunability by changing the printed layer number n in a voxel: a) n = 2, b) n = 3, c) n = 4, and d) n = 5. The ideal M-density is measured from a sample that is magnetized after solidification. Gradient colors represent voxels with different effective M-density.

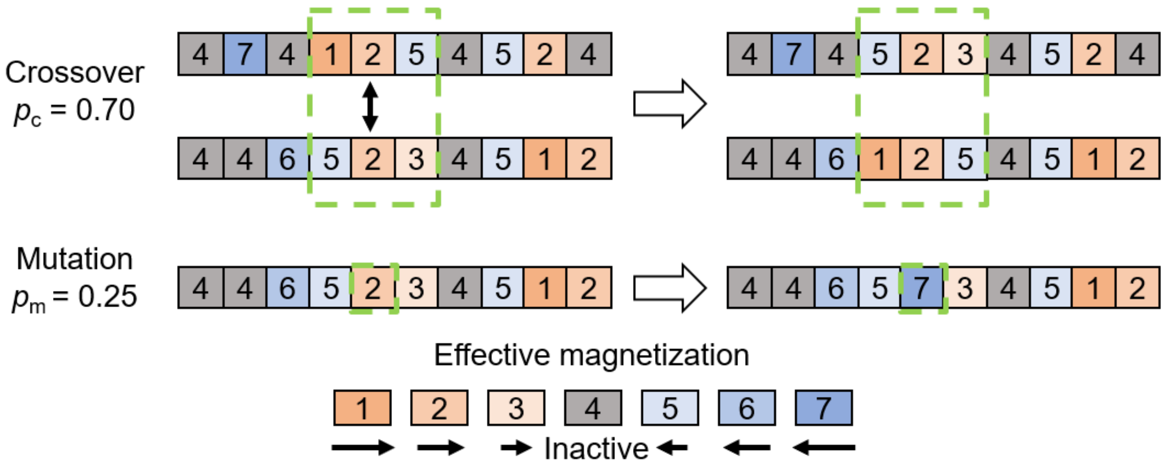

Figure S3. Crossover and mutation operations to individuals' genotypes to generate new genotypes for magnetization distributions. The example shows the voxel case with n = 3, m = 10.

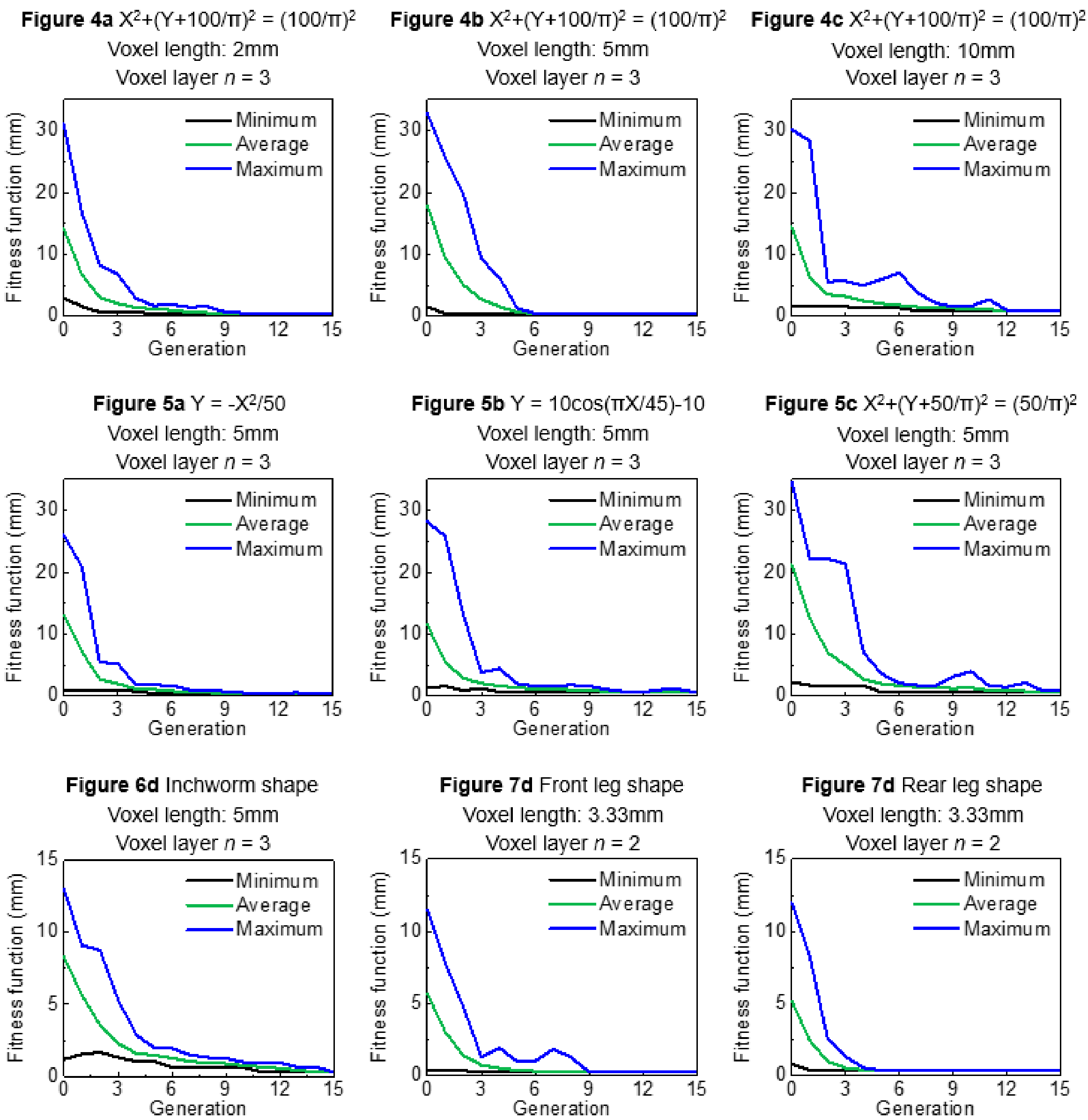

Figure S4. Fitness functions of different target shapes plotted with respect to the generation number.

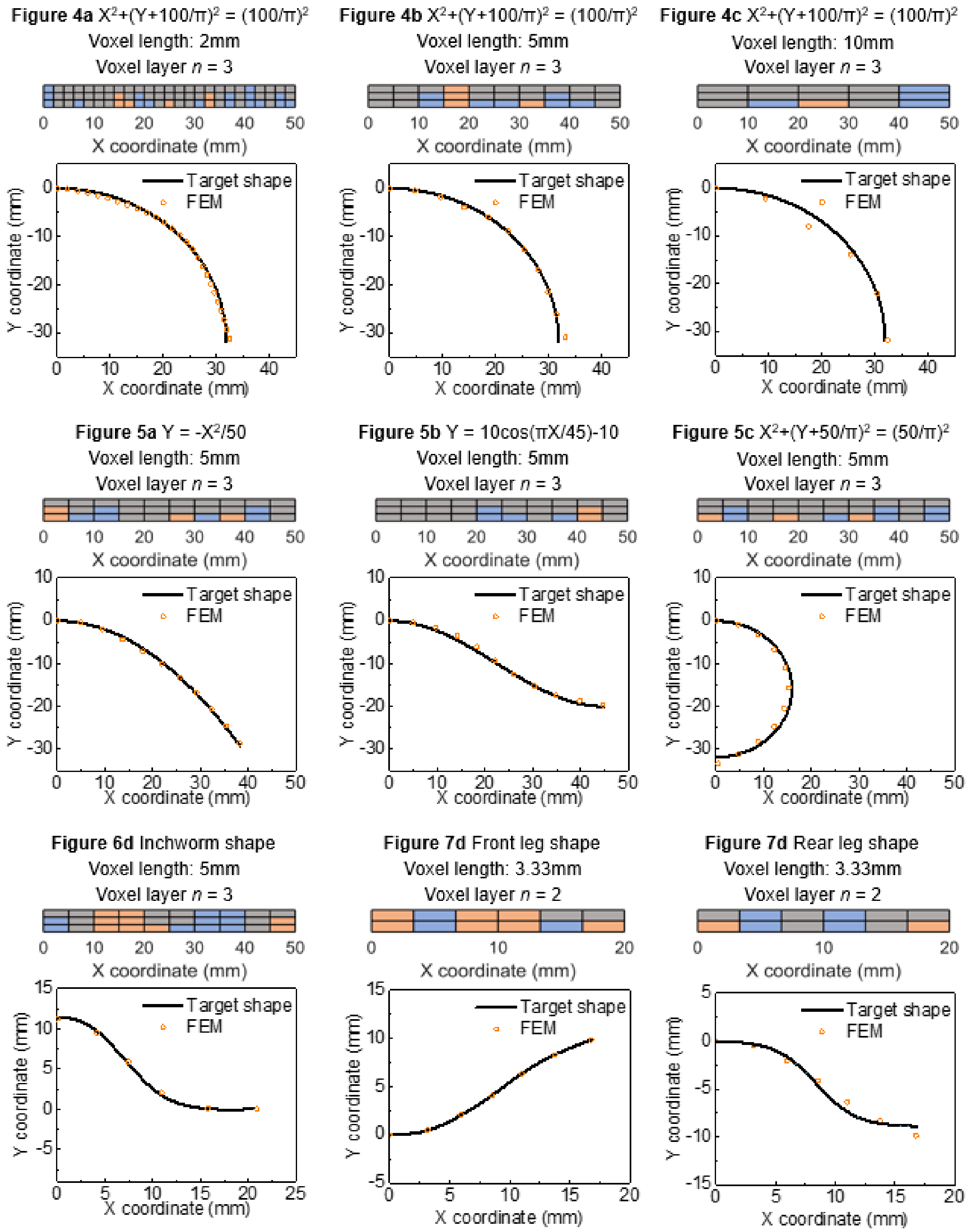

Figure S5. Generated magnetization distributions of the hmSAM layers.

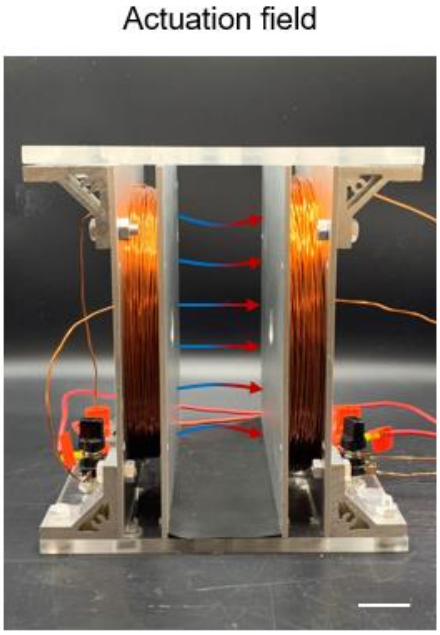

Figure S6. A pair of Helmholtz coils to generate a homogenous magnetic field for the actuation of printed structures. Scale bar: 5 cm.

Supplementary Video Captions

Video S1:

Effect of voxel size on evolutionary algorithm guided design strategy and DIW printings (Figure 4).

Video S2:

Magnetization distribution for different target shapes (Figure 5).

Video S3:

Magnetization distribution design for body curvature distribution of a biomimetic crawling robot (Figure 6).

Video S4:

A walking robot mimicking a dog's trot gait (Figure 7).

References

[1] D. Rainville, F.-A. Fortin, M.-A. Gardner, M. Parizeau, C. Gagné, presented at Proceedings of the 14th annual conference companion on Genetic and evolutionary computation **2012**.

[2] R. Zhao, Y. Kim, S. A. Chester, P. Sharma, X. Zhao, *Journal of the Mechanics and Physics of Solids* **2019**, 124, 244.