Subtract to adapt: Autotomic robots

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2023 IEEE International Conference on Soft Robotics (RoboSoft) | 979-8-3503-3222-3/23/$31.00 ©2023 IEEE | DOI: 10.1109/ROBOSOFT55895.2023.10122102

Abstract— **Robot adaptation is typically limited to adaptive control policies or actuated morphology changes (such as shape change). When part of a robot body is removed it is typically viewed as an injury that must be adapted to; the potential for adaptation through subtraction by removal of body components has not yet been considered. Biological systems, on the other hand, provide many examples of subtractive adaptation, including gene or nucleotide deletion at the evolutionary scale, apoptosis at the cellular scale, and autotomy (the deliberate loss of an appendage) at the organismal scale. In this work, we consider the adaptive potential of evolved autotomy in simulated soft robots. To do so we jointly evolved the body plans, control policies, and/or which body parts to remove for soft robots. Our results show that autotomy, rather than policy adaptation, sometimes evolved to change the robot's heading when commanded. In most trials, policy adaptation was favored by the evolutionary algorithm over autotomy for changing heading. But the fact that autotomy appeared as a viable solution in some evolving populations, both when starting body plans were evolved or set manually, suggests that this form of morphological adaptation may be useful for future soft robots.**

I. INTRODUCTION

Humans tend to overlook subtraction as a means of problem-solving, as demonstrated experimentally in [Adams et al., 2021]. Although [Adams et al., 2021] show that individuals have a tendency to overlook subtractive change, they also demonstrated that specific prompts, or a decrease in cognitive load, help beneficial subtractive adaptation—removal of one or more components from a system to improve its operation—to be discovered more often. Natural selection has no such bias: subtractive adaptation occurs at all biological levels of organization. By incorporating these lessons from biology, we posit that deliberately considering subtractive change for adaptation in engineered systems may improve overall performance and facilitate adaptation by providing an alternative to policy adaptation. It may also serve as an alternative to additive adaptation, in which the robot can add spare parts to itself, assuming that it can carry them, rotate them into an appropriate position, and activate them.

A. Morphological Change and Robotic Adaptation

From a robotics perspective, the loss of an appendage or its function usually presents a challenge to be coped with and is not used as an adaptive mechanism of its own. [Najarro and Risi, 2020] evolved Hebbian learning rules in simulated robots as a means of meta-learning locomotion tasks starting from randomized neural network control policies, including in the context of a non-functional limb. [Horibe et al., 2022] combined differentiable programming and neural cellular automata to 'regrow' damaged body plans in simulated soft robots.

Schemes for robotic adaptation, when faced with damage, are not limited to changes in control policy. [Kriegman et al., 2019] evolved morphological changes in a soft robot to adapt to limb removal in a quadrupedal body plan. The actuators in a physical implementation were not strong enough to achieve the evolved posture, but the change recovered mobility in simulation. [Bongard et al., 2006] approached the problem of control recovery after partial limb removal by instilling self-modeling capabilities in a physical robot.

B. Biological Inspiration for Robotic Autotomy

Biological systems exhibit many examples of subtractive adaptation at multiple temporal and spatial scales. At the cellular scale, apoptosis (programmed cell death) is crucial for shaping the central nervous system [Wong and Marín, 2019] and other tissues [Yan and Shi, 2005] during development. Apoptosis also helps to mitigate substantial costs of damaged cells, and evading apoptosis is one of the classic hallmarks of cancer [Weinberg and Hanahan, 2000], [Hanahan and Weinberg, 2011]. At evolutionary scales, gene deletion plays an important role in evolution [Albalat and Cañestro, 2016], and nucleotide deletion is a substantial driver of antibody diversity during somatic hypermutation in mammalian immune systems [Bowers et al., 2014]. In this project, we are primarily concerned with a robotic version of autotomy, the deliberate removal of one or more appendages by an organism.

In mature organisms, autotomy is usually seen as a means to escape predation, escape encumbrance, or reduce the cost of maintaining a (typically injured) limb [Emberts et al., 2020]. Autotomy is also sometimes used to enhance a positive capability, such as the deliberate removal of the sperm-carrying hectocotylus arm in *Argonauta sp.* octopuses [Battaglia et al., 2021]. Several theories for the evolution of autotomy have been proposed in the literature. Slow autotomy, not very useful as an antipredation mechanism, is seen as an intermediate step for the fast autotomy demonstrated by lizards [Zani, 1996], arthropods [Emberts et al., 2020], [Emberts et al., 2019], and amphibians [Wake and Dresner, 1967] to facilitate quick escapes.

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*This work was supported by the National Science Foundation under the Emerging Frontiers in Research and Innovation (EFRI) program (EFMA-1830870)

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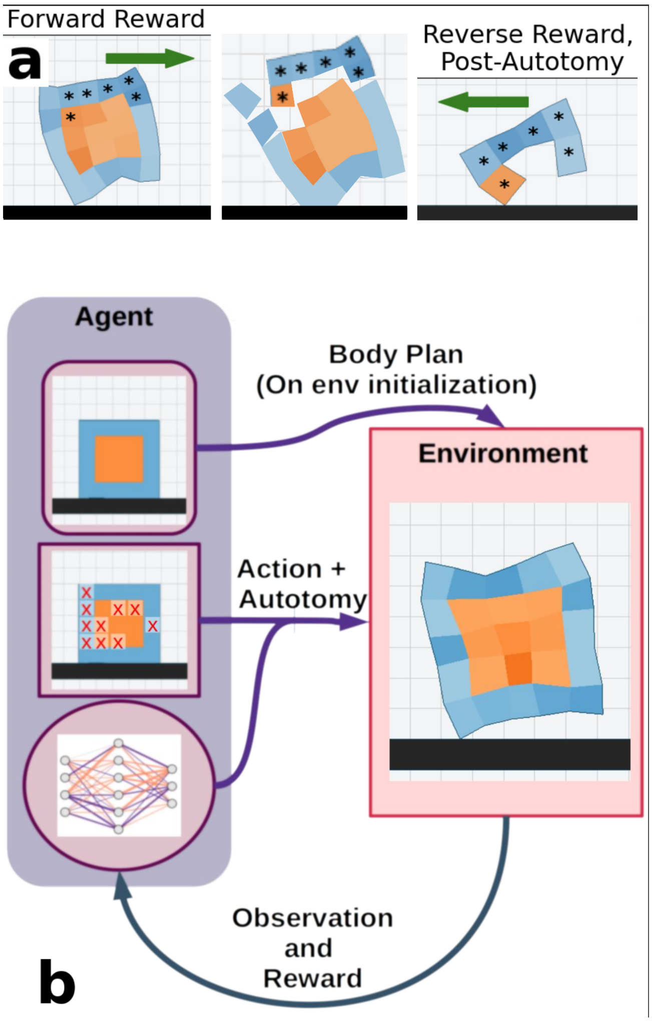

Fig. 1. **Overview**. (a) Each robot is initially rewarded for maximizing rightward movement. If a sufficient distance is achieved, the environment provides a signal to the policy's input that reward is now provided for moving leftward. Additionally, at this moment, the robot may elect to discard one or more modules (squares lacking asterisks denote those that are discarded). (b) Each robot in the evolving robot population has three data structures associated with it: its body (orange denotes squares containing horizontal linear actuators; blue=those with vertical ones); which (if any) body parts to remove (red crosses); and its control policy. In the cases where the body plan is manually set, the first data structure is not evolved. Summary video at `https://youtu.be/rm_N4FvrOwU`.

[Emberts et al., 2020] used a combination of bioinformatic, morphological, and behavioral evidence to support the hypothesis that selection for slow autotomy to reduce the cost of failed molts or injuries paved the way for fast autotomy to evolve in leaf-footed insects in the order Hemiptera.

C. Contributions

In this work, we investigate the artificial evolution of autotomy, not as an escape mechanism but as a means of adapting the morphologies of simulated soft robot bodies to facilitate achieving a changing objective. Our task and environment are simple: to achieve mobility in one direction followed by movement in the opposite direction in the 2D soft robotics simulator, Evogym [Bhatia et al., 2021].

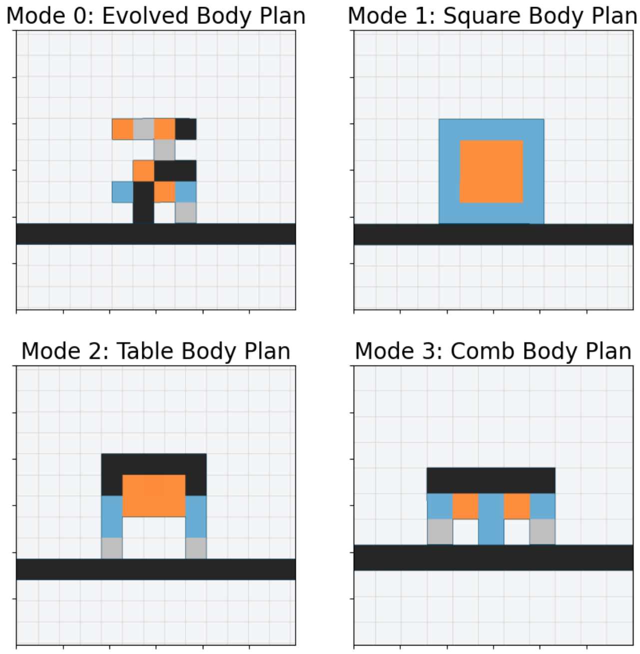

Fig. 2. Body plan modes. Black=rigid and passive units. Gray=soft and passive units. Orange=units containing horizontal linear actuators. Blue=units containing vertical ones.

II. METHODS

To investigate whether and how autotomy might be useful for soft robots, simulated robots were optimized using an evolutionary algorithm to exhibit a particular behavior, but to also be capable of changing behavior when supplied with an external cue[1] (Fig. 1). The evolutionary algorithm was configured such that robots could evolve to switch behavior by jettisoning some of the modules comprising them, or by evolving a policy that altered behavior appropriately if supplied with the external cue. To determine whether the choice of robot structure affects whether or not autotomy is useful, we conducted two experiments: In the first, the evolutionary algorithm could also set the physical structure of the robot. In the second set of experiments, three different manually-designed robots were tested (Fig. 2).

A. The environment.

The robots were evolved in Evolution Gym, a 2D soft physics simulator and a suite of reinforcement learning environments for joint evolution of morphology and control [Bhatia et al., 2021][2]. The task in our environment is to reach a goal location 16 squares to the right of the origin. If a robot manages to reach this threshold, the task reverses and the objective is to make progress to a goal location 16 squares to the left of its current position (this second phase occurs in the same simulation). A robot that moves 16 or more units to the right, and then the 16 or more units to the left is considered to have solved the task. The environment consists of flat terrain and no obstructions. If a robot jettisons

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[1] Code available at `https://github.com/jbongard/autotomy`.

[2] `https://github.com/EvolutionGym/evogym`

body parts, these do not collide and/or otherwise obstruct the robot or impinge on its sensors.

B. The robot.

The simulated robot is comprised of a set of two-dimensional deformable squares, serving as a minimal approximation of 3D voxel-based soft robots (e.g. [Kriegman et al., 2019]). Each robot can contain at most 5×5 squares. If a square is present, it may contain a horizontal actuator that extends or contracts its width or a vertical actuator that alters its height.

C. The policy.

At every time step of the simulation, the relative location and orientation of each square are supplied to a neural network control policy. It is structured as a feed-forward multilayer perceptron with a single, 16-unit hidden layer and rectified linear unit activation. The output layer dictates extension or contraction commands to the actuator inside each active square. The input layer also receives a binary signal indicating whether the robot will receive reward for moving to the right (the first half of the simulation) or left (the second half of the simulation). If a robot elects to discard body parts, the input neurons corresponding to the lost parts are supplied with zero values. The values arriving at the output neurons corresponding to those parts are discarded.

D. Optimization.

Each robot is constructed from a genome $G = \{B, A, \pi\}$. B describes the robot's starting body shape: it is an integer 5×5 matrix: $B_{ij} = 0$ denotes square $[i, j]$ is absent. $B_{ij} = 1$ dictates that that square is rigid and passive. $B_{ij} = 2$ dictates that that square is soft and passive. $B_{ij} = 3$ dictates that that square contains a horizontal actuator. $B_{ij} = 4$ dictates that it contains a vertical actuator. A, the autotomy map, denotes whether and how that robot will exhibit autotomy. It is a binary 5×5 matrix: if the external cue switches, indicating that reward will now be provided for leftward rather than rightward motion, any values in A that equal one causes those squares to be jettisoned. π dictates the robot's control policy: it contains all the synaptic weights within the policy.

We used a genetic algorithm derived from the open-source bevodevo library[3] to evolve these parameters. An initial population of 64 randomly-generated genomes was generated. Each B was then used to initialize an EvoGym simulation. Reward is computing while that robot moves in the simulation. If it reaches the goal of moving 16 squares in distance to the right, the external cue is switched, and the robot begins to collect reward if it moves to the left. Note that a robot that never moves 16 units to the right, or that moves that distance and then continues moving to the right when it should not be doing so, may accrue less than 16 units of reward.

Once all G's in the population have been evaluated in this manner and reward assigned to each, those with lower reward are deleted. For each gap in the population, a surviving G is chosen at random, and one or more of the parameters in its B, A, or π are randomly modified. These mutation operators are constrained in several ways. B is constrained so that it produces just one robot: there is only one connected component in B. A is constrained so that it also contains one connected component, and that every element in that component has a corresponding non-zero element in B. Mutations to B may change the shape and topology of the robot, as well as the orientation of its actuators. Mutations to A affect how or whether the robot will attempt autotomy when the external cue changes. Mutations to π affect how the robot will move before and after the external cue changes, regardless of whether the robot attempts autotomy (A contains non-zero values) or it does not (A=0).

E. Experimental modes.

To determine whether the robot's structure affects whether or not it evolves to make use of autotomy, four different experimental modes were pursued (Fig. 2). In the first mode, the robots' body plans evolved during optimization (B was altered by the evolutionary algorithm). In the second, third, and fourth modes, three manually-designed robots were employed (B was set by the authors). Seventeen independent evolutionary trials were conducted for each of the four modes, allowing for the determination of whether and how often autotomy evolved as a strategy for altering behavior.

III. RESULTS

Across 17 different trials, at least 3 evolved populations in each of the four modes used autotomy in the population's fittest individual (champion) at the end of the trial.The most prevalent use of autotomy occurred in mode 1 with a square starting body plan. Joint evolution of body plan alongside the control policy and autotomy map (mode 0) produced the fewest examples of autotomy with just 3 champions using autotomy, each pared down to a single actuating square after autotomy.Examples of autotomized champions for each mode are shown in Figure 3.

Champion agents used a variety of strategies to solve the task. Examples of solutions with and without autotomy are shown in Figure 4. Some agents used autotomy to modify their body plans to solve the locomotion task in the second direction, but others changed their orientation to accomplish the same (as in Figure 4) and others changed direction solely through their control policy.

Not all populations produced champion individuals that solved the task after 85 generations, and solve rates ranged from slightly above half (52.9% in mode 2) to a clear majority (88.2% solve rate in mode 1). Individual fitness curves, and autotomy usage, for all 17 trials in each mode are visualized in Figure 5.

The average fitness for each mode was above the solution threshold of 32.0, a threshold corresponding to the robot reaching both goal locations, but the average fitness of champions that used autotomy was slightly below the solution threshold for mode 2. There is substantial variation in fitness

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[3] Available under the MIT license at `https://github.com/rivesunder/bevodevo`

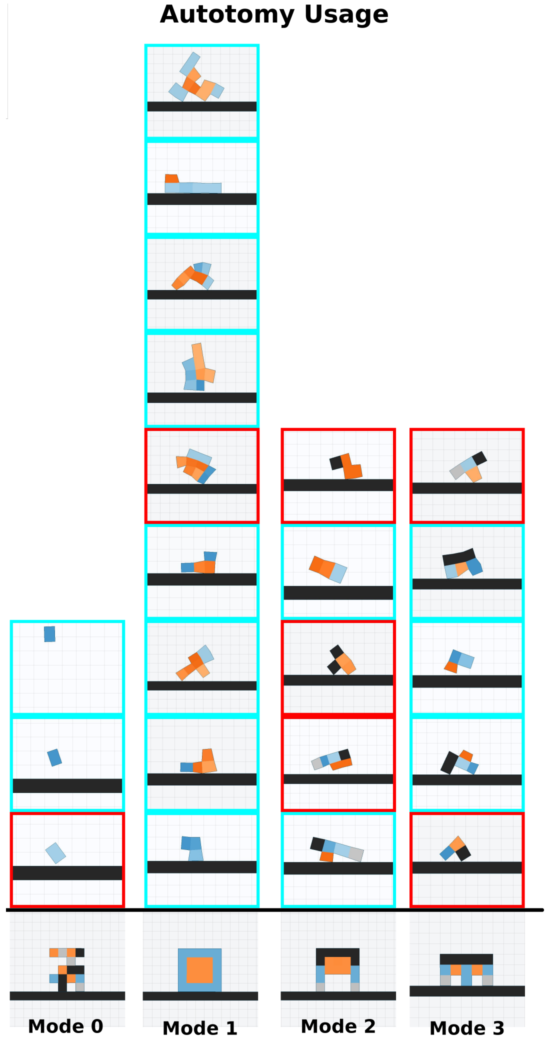

Fig. 3. Out of the 17 evolutionary trials conducted in each of the experimental modes, 3, 9, 5, and 5 of those trials yielded champions that employed autotomy, respectively. Teal borders report champions, post behavior switching, that used autotomy to change direction; red borders indicate champions that employed autotomy as well but did not solve the task. The pre-autotomy body plans for modes 1 through 3 are shown below the black line, and an example evolved body plan for mode 0 is shown below the black line in the first column.

within each mode, so while we can say that each mode *can* be solved by an agent utilizing autotomy, we are not confident to claim a statistical difference for any of the conditions or modes. That being said, the data in Tables I and II and the results in Figure 3 do suggest the hypothesis that autotomy is most useful for the square starting body plan of mode 1, autotomy may be of no consequence for modes 3 and 0 and might even be detrimental in mode 2.

Mode 1 had both the highest solve rate and the highest rate of champions using autotomy. This mode also produced the highest empirical probability of solving the task given that the champion used autotomy (8 out of 9 autotomous champions solved the task).

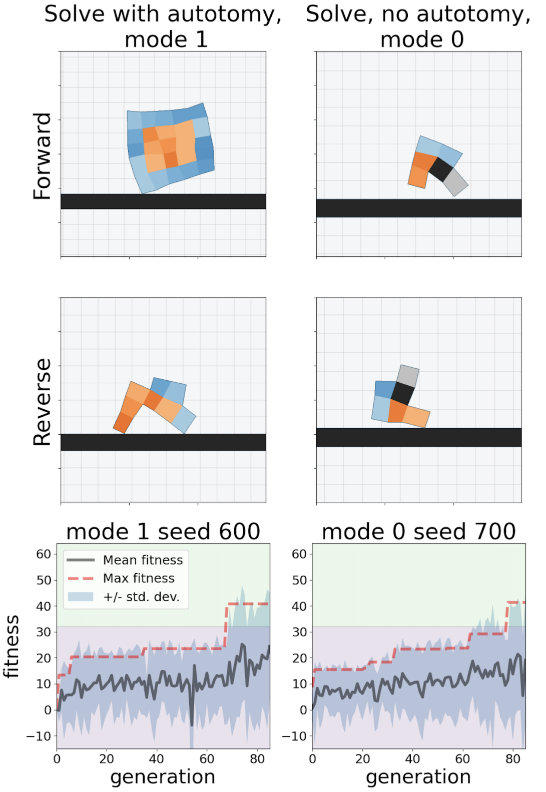

Fig. 4. Examples of body plans used to solve the full forward and reverse displacement task, both with (left column) and without using autotomy (right column). The population fitness curves for each example are shown in the bottom row.

Mode	Fitness ± std. dev.	with autotomy	no autotomy
Mode 0	34.8 ± 8.34	35.2 ± 9.38	34.7 ± 8.1
Mode 1	37.3 ± 7.65	36.7 ± 9.34	38.0 ± 5.02
Mode 2	34.8 ± 8.34	26.9 ± 9.43	36.1 ± 5.92
Mode 3	34.2 ± 7.53	33.9 ± 8.25	34.3 ± 7.2

TABLE I

PERFORMANCE ACROSS N=17 EVOLUTIONARY TRIAL PER MODE.

The average body size for evolved body plans in mode 0 was 4.42 ± 3.11 (standard deviation) before autotomy and 4.12 ± 3.31 after autotomy; every autotomized body plan in mode 0 was a single vertically-actuating square. The evolved body plans from mode 0, 14 of which did not use autotomy and 3 that did, are visualized in Figure 6. Mode 1 starts with 25 squares and the average final body plan size was 15.06 ± 9.53 (6.22 ± 2.39 for morphologies that used autotomy). Starting from a body plan with 19 squares, mode 2 has an average final body plan size was 14.21 ± 6.64 (4.40 ± 1.02 for morphologies that used autotomy). Mode 3, starting with the smallest body plan consisting of 13 squares, had an average final body size of 10.41 ± 4.09 (4.20 ± 1.47 for morphologies that used autotomy).

IV. DISCUSSION

The fittest agents demonstrated a variety of strategies in solving our locomotion task in two directions, including autotomy, adopting a new orientation, or simply through a flexible control policy. Notably, our control policy is a simple multilayer perceptron with 1 hidden layer and no ability to modify its parameters; different behaviors are mediated through the binary task indication in the observations provided by the environment, and differences in the relative

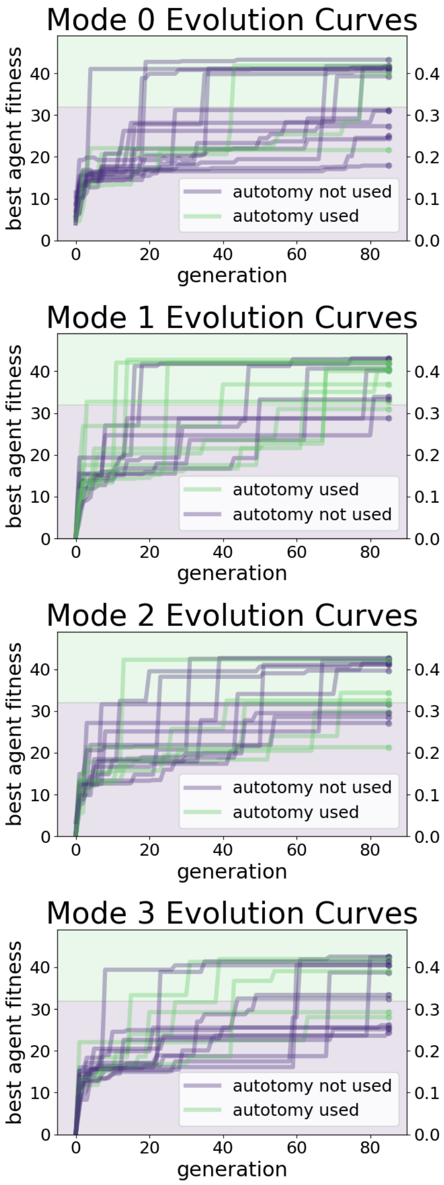

Fig. 5. Evolution progress curves for modes 0 through 3. Lighter green lines indicate generations where the best agent used autotomy and the darker purple lines indicate populations that produced champions without using autotomy. The darker purple background region is below a fitness of 32, the threshold for success.

orientation and velocities of the body components. Although modes 1 through 3 started with body plans made up of 13, 19, or 25 squares, the body plans after autotomy have on average 4.64 squares ± a standard deviation of 2.44, or 5.21 ± 2.12 if we exclude the autotomized morphologies from mode 0, which were all made up of 1 square. Autotomized morphologies are diverse, but in mode 0 (evolved body plans), post-autotomy morphologies are uniformly comprised of a single actuating square.

The convergence on smaller body plans is noteworthy because there is no explicit penalty for energy considerations or larger, more complicated designs. Instead, the fitness of smaller body plans derives from the simulator physics and task specification. Speculatively, more complex terrain that requires robots to cross gaps or climb obstacles, or overhangs that prevent the jumping strategy employed by single-square body plans, might reduce the evolutionary pressure that selects for minimal body plans.

Mode	Solve rate (s)	Autotomy rate (a)	$P(a\|s)$	$P(s\|a)$
Mode 0	0.588	0.176	0.2	0.667
Mode 1	0.882	0.529	0.533	0.889
Mode 2	0.529	0.294	0.222	0.4
Mode 3	0.647	0.294	0.273	0.4

TABLE II

TASK SOLVE AND AUTOTOMY USAGE RATES (N=17 TRIALS / MODE).

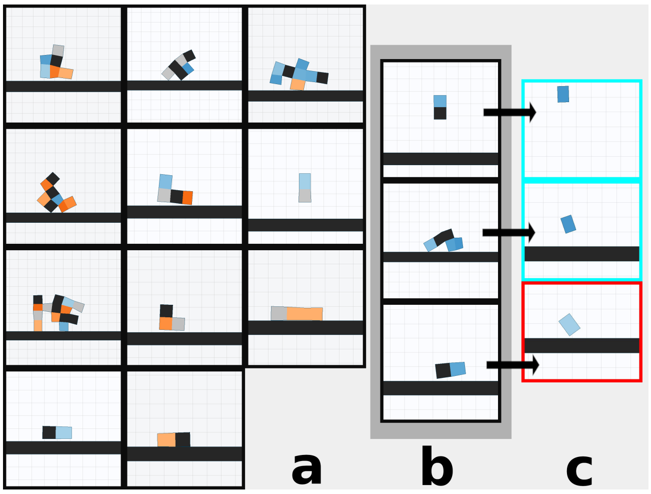

Fig. 6. Body plans evolved in mode 0. **a** shows the 14 body plans that did not use autotomy. **b** shows the initial body plans for the additional three champions that used autotomy and **c** shows the corresponding body plans after autotomy.

Sim2real— Simulation provides a valuable tool for rapidly designing and testing control policies and robot morphologies, but for robots to meet their full potential they must eventually be embodied in the physical world. The reality gap remains a perpetual challenge, as we draw from robotics, machine learning, and simulation to develop robots ready for deployment in real-world environments [Mouret and Chatzilygeroudis, 2017].

The reality gap can be particularly wide in soft robotics. The same positive characteristics that make soft robots desirable (compliance, robustness, flexibility) also make accurate simulation, and consequently transfer to the real world, difficult [Pinskier and Howard, 2022], [Howard et al., 2019]. The many degrees of freedom, complexity, and often large manufacturing tolerances inherent to robot prototypes all contribute to the difficulty of matching simulation in a physical implementation (and vice-versa).

Considering the transfer of the autotomic robots simulated in this work to hardware, we foresee several challenges. While previous elastomeric, pneumatic "voxel-bots" inspired by simulated voxelbots have been realized [Hiller and Lipson, 2011], in some cases, their behavior has contradicted the behavior of the same design in simulation: in [Kriegman et al., 2020] and [Kriegman et al., 2021], some hardware voxelbots traveled in the opposite direction to their simulated counterparts. We attribute such results to unmodeled frictional interactions or forces from the real robot's pneumatic tether. Tethers can have a non-negligible effect on behavior, particularly when a robot is small or weak relative to the tether's mass, as is the case for soft robots constructed of pneumatic silicone voxels.

If the physics surrounding a hardware robot's behavior are understood or discovered by machine learning, they can be embedded in the form of constraints within the simulation and optimization algorithms. Although, we note that simulation software for soft robots is typically fast or accurate, but not both, and the tradeoff must be considered. Nevertheless, connecting data from the real world back to simulation via reality-assisted artificial evolution [Howison et al., 2020] is an increasingly important aspect of building soft robots in general, and autotomic soft robots specifically.

V. CONCLUSIONS

In our experiments, a subset of evolved populations from each mode were capable of solving a locomotion task using autotomy, by adapting their control policy, or both. While we did not discover a clear advantage for simulated soft robots using autotomy, autotomy did not create a clear hindrance either, and in mode 1 more than half of evolved populations produced a champion agent that uses autotomy.

Psychologists describe a systematic tendency for people to overlook subtractive changes, even when they may be the most advantageous solution available [Adams et al., 2021]. This bias appears to apply to robotics researchers as well, as demonstrated by the prevalence of adaptive shape change and relative paucity of subtractive adaptation in the literature.

In situ resource extraction or an inventory of spare materials may enable robotic systems to adapt to new conditions far from home, but subtractive shape change can facilitate adaptation without requiring additional inventory. Although there may be real-world task environments in which autotomy would clearly be useful, such as increasingly narrow apertures, the fact that autotomy was employed for the locomotion over flat ground task above suggests there may be other, more realistic but less obvious task environments where autotomy will eventually prove useful.

By deliberately cuing engineering processes to consider subtractive problem solving, taking advantage of the myriad examples where less is more useful in biology, we can potentially evolve and engineer more robust, life-like systems and avoid overlooking unintuitive optimal solutions.

ACKNOWLEDGMENT

This work was supported by the National Science Foundation under the Emerging Frontiers in Research and Innovation (EFRI) program (EFMA-1830870).

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