

# Investigation into Bio-inspired Snake Robot Designs with Co-Adaptation of Morphology and Behaviour

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**Abstract**—Many robots are designed taking inspiration from real world animals or even then human body shape. One type of such robots used in confined spaces or meant for disaster-relieve and search-and-rescue missions are snake robots. However, while many snake robots are inspired by their biological equivalent [1], the design of these robots features primarily equally-sized link-elements or even wheels. In this research and proposed future research we raise the question if the past trend to design snake robots with equally-sized modules is beneficial or if we can uncover better robot designs for optimal control. To this end we make use of recent research in data-efficient co-design of robot morphologies and behaviour with deep reinforcement learning to co-optimize the composition of a snake robot as well as its control policy.

## I. INTRODUCTION

Snakes have served as inspiration for a number of bio-inspired and bio-mimetic robots. However, these robots have been hand-designed by human engineers and feature predominantly equal-sized link-modules connected to motors [2], [3]. However, snakes do not feature these shapes but have connected bone-segments of varying sizes, with short elements towards the ends. We pose the question if using individual-sized modules in snake robots relying on friction to move through the environment is beneficial and allows for energy-efficient and fast locomotion. To this end we present in this paper a first preliminary study of the problem of co-adapting the behaviour and design of snake robots for a real-world snake robot. While our first experiments are limited to simulation, our preliminary results indicate that co-adaptation is indeed beneficial and worthwhile.

## II. EXPERIMENTAL PLATFORM

The snake robot (Fig.1) is composed of 8 segments and 7 connecting motors using Dynamixel XL430-W250-T. The design of the snake’s segments and connectors prioritizes modularity and ease of customization. Each motor connector is carefully crafted to accommodate different lengths, facilitating rapid adjustments to the snake’s morphology via 3D-Printing. This modular design not only streamlines the optimization process but also promotes versatility, allowing

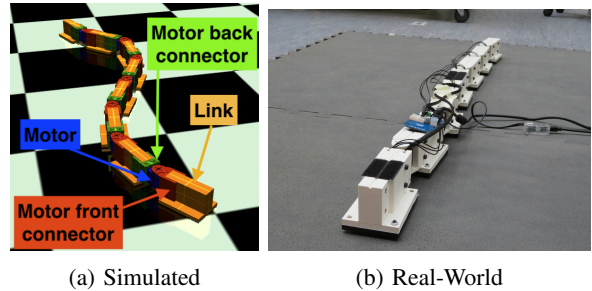


Fig. 1: A newly developed modular snake robot used as experimental platform, which is made of segments which can be adapted in length. Both in the real world and simulation the robot has to move forward via high-contact friction-based locomotion strategies.

researchers to experiment with various configurations to achieve optimal locomotion performance. In our preliminary experiments presented in this paper we used a simulated version (Fig. (1a)) of the constructed real-world robot (Fig. (1b)) to evaluate the feasibility and impact of the proposed methodology before performing experiments in the real world.

## III. METHOD OVERVIEW

In our study we co-optimize the morphology parameters of the presented snake robot, here the link-lengths of the individual modules, as well as a closed-loop neural network controller producing motor commands, utilizing reinforcement learning [4]. This leads to a bi-level optimization problem with  $\max_{\xi} \max_{\pi} \mathbb{E}_{\pi, \xi} [\sum_t \gamma^t R(s_t, a_t)]$  in which we optimize the length parameters  $\xi$  in the outer loop and the policy parameters  $\pi$  in the inner loop. In our experiments we use the recently introduced *Fast Evolution through Actor-Critic Reinforcement Learning (FEAR)* [5] algorithm as co-adaptation algorithm, and Soft Actor-Critic as underlying reinforcement learning algorithm. For specific details about FEAR we refer the interested reader to [5]. Initially, 5 randomly selected robot designs are selected and policies learned, which then serve as the starting point for subsequent training phases. Following this, 55 designs are selected and optimized with FEAR. During this phase, the design selection process alternates between selecting a design proposed by the neural network surrogate and selecting a design randomly from a uniform distribution.

The training is conducted with a simulation of the real snake robot using the Mujoco Physics Engine [6]. The learn-

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ing objective of the robot is to reach a specific goal in  $[x, y]$  from its starting position. The reward function defined for the task with  $R(s, a) = R_g(s, a) * w_g - R_c(s, a) * w_c$ . The reward components are given with  $R_g(s, a) = -w * d(s, s_g)^2 - v * \log(d(s, s_g)^2 + 10^{-\alpha})$  and  $R_c(s, a) = ctrl_{cost} = \frac{\sum_{i=0}^{n-1} |a_i|}{n}$ , where  $d(s, s_g)$  represents the distance to the goal  $s_g$ .  $w$ ,  $v$ , and  $\alpha$  are adaptable parameters. The parameter's values are  $w = v = 1$  and  $\alpha = 3$ . The action  $a_t$  is the torque applied at the  $i^{th}$  servomotor. The weight  $w_g$  and  $w_c$  are respectively 0.8 and 0.2.

#### IV. EXPERIMENTS

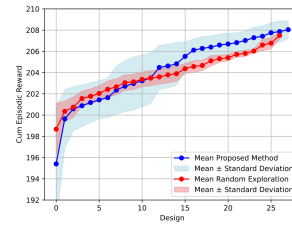
The morphology, here the individual link-lengths, and behaviour of the snake robot are adapted in a first study in the physics simulator Mujoco. Rewards and goal position  $x, y = [2, 2]m$  were chosen to encourage the robot to learn and evolve to traverse the terrain as fast as possible. The design parameters of the robot were adapted every 300 episodes. The design parameters, i.e. link lengths, can vary from a minimum of  $0mm$  and a maximum of  $149mm$ .

Five experiments were conducted, producing 28 optimized designs and 27 randomly selected designs each. To evaluate the performance of a specific snake robot design we measure the maximal episodic return achieved during the training time of the robot (Fig.2a). Figure 2a compares the designs found using an optimization strategy and using random design sampling. We can find that optimization shows increases performance and data-efficiency versus random sampling, however the results also indicate that a larger size of design adaptations may be needed. Overall, the results underscores the advantage of adapting robot designs and the potential of optimizing the shape of snake robots to increase performance and energy-efficiency.

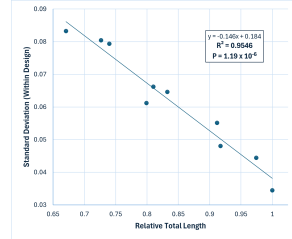
To understand the characteristics of the highest-performing snake designs, we examine the top 10 designs across all experiments. In Fig.(2c), a discernible pattern emerges: the last two segments are consistently close to the longest possible size (red and pink), followed by a shorter third-to-last segment (orange). The fourth segment is medium to long size(yellow), and the fifth segment is short again (green). The first three segments vary across different designs (light blue, blue, and purple). Among top-performers, there is also a strong, significant negative correlation ( $\rho = -0.977, P = 1.19 \times 10^{-6}$ ) between the total length of a given design and the amount of variation in its segment lengths. Longer designs tend to have more evenly-sized segments, mirroring what is observed in the skeletal structure of snakes [7].

#### V. CONCLUSION

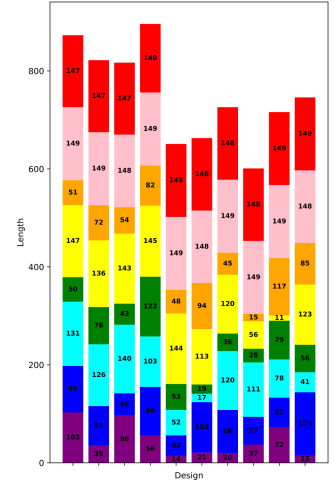
In this first study we investigated the potential and possible impact of performing joint adaptation of robot design and behaviour in snake robots. We were inspired by the fact that most if not all robotic designs in this area are significantly different from their natural counterparts [2], [3], raising the question if biomimetic robot designs and allowing varying link-lengths provide any benefit over the symmetric and equisized modules used in robotics. Our



(a) Performance per design of randomly selected and optimized designs.



(b) Among top performing designs, within-design variation in segment length correlates negatively with total length,



(c) Best 10 design through all experiments - Higher reward design to the left - First segment (head) is purple, last segment is the red. Length values are in mm.

Fig. 2: Experimental results of co-adapting the morphology and behaviour of a snake robot. Link segment lengths are adapted over 55 designs, experiment was repeated five times.

initial experiments demonstrate that we can indeed identify non-equisized robotic snake designs with co-adaptation techniques similar to actual snakes which allow for improved high-contact locomotion. On the other hand, we can replicate the finding that longer designs tend to have more equisized link segments, an observation which can also be made in nature.

The presented results highlight the usefulness of revisiting beliefs about robot design and investigating divergences from natural design, and how co-adapting behaviour and body of robots in the real world can be beneficial. In future work, we are particularly interested in the possibility to investigate open questions in evolutionary biology about mechanism designs found in nature with the help of adaptable robot platforms and co-adaptation methods.

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