Multi-segment soft actuator design optimization using sequential lexicographic surrogate-assisted genetic algorithm

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Abstract*—Multi-segmented soft robotic actuators can replicate the dexterity of human and animal appendages, but their design is complicated by the nonlinear behavior of soft materials and the large parameter space involved. We address this challenge through the application of a two-stage lexicographic surrogate-assisted genetic algorithm for the optimization and modelling of soft finger architecture. Our pipeline models the finger as a biologically plausible two-pneumatic actuator, two-bone system, parameterized to mirror the metacarpophalangeal (MCP) and proximal interphalangeal (PIP) joints found in human anatomy. A key innovation is the use of a Ludwick-inspired analytic surrogate [1] (trained via radial basis function regression) to predict pressure-dependent actuator bending angles across a broad design space. Prediction of tip position is done through PCC (Piecewise Constant Curvature) based analytical equations [2]. The first stage applies a strictly prioritized genetic algorithm to identify actuator geometries that achieve sub-degree joint angle matching; a secondary energy minimization is performed only among candidates satisfying this constraint. The second stage optimizes bone lengths for each pose using a tip error and bone energy lexicographic policy, exploiting forward kinematic modelling with the fixed optimal actuators. Thus, we have tried to rigorously enforce anatomical joint angles while systematically minimizing actuation energy and fingertip position error. Results across ten anatomically referenced hand poses demonstrate consistently low total joint angle error (mean: 0.355°) and robust tip trajectory matching (mean position error: 11 mm), comparing well with recent soft finger optimization literature. The proposed framework provides a transparent and scalable path for the computationally guided design of multi-segmented soft actuators for bioinspired and prosthetic applications.

***Index Terms*—Surrogate, genetic algorithm, soft finger, lexicographic**

I. Introduction

Multi-segmented soft robotic actuator designs represent a transformative approach to robotics, leveraging the flexibility and compliance of soft materials and bioinspired design together. The application of these designs is immense, from mimicking human fingers to animal claws. Despite recent advancements in modelling techniques, optimization techniques regarding multi-segmented designs still remain challenging due to numerous parameters, added complexity, along with the nonlinear nature of soft materials.

One of the advancements in this direction is usage of FEA based simulations and experimental results as dataset for training and usage of Machine learning algorithms on them [3]. Although FEA provides high-fidelity insight into nonlinear material behavior, each simulation can be computationally expensive, especially when exploring large, multi-parameter design spaces or running iterative optimization algorithms. Similarly, experimental campaigns on physical prototypes are time-consuming, resource-intensive, and often constrained by fabrication tolerances and repeatability issues. These limitations restrict the number of design variants that can feasibly be evaluated and slow down convergence toward optimal solutions. As a result, there is a growing need for surrogate or reduced-order models that can approximate the behavior of soft actuators with sufficient accuracy while dramatically reducing the evaluation cost, thereby enabling efficient multi-objective optimization of complex, bioinspired architectures.

Thus, we have tried to generate a synthetic dataset using a highly proven equation for nonlinear modelling in the form of Ludwig's Equation [1]. We aim to make the generation of the dataset and model training faster and more efficient.

II. Methodology

In this section, the algorithm architecture is decribed. It is mainly divided in 3 key components - inputs, optimization and outputs. Each component will be explained in detail and the whole flowchart can be seen in Fig. 1, Fig. 2 and Fig. 3. Together, these elements form an integrated pipeline in which parameters, constraints, and intermediate results are transferred seamlessly from one stage to the next. This streamlined organization allows the algorithm to follow a sequential lexicographic approach, where each stage addresses a specific priority before passing optimized information forward, ultimately leading to a coherent and efficient optimization framework for multi-segmented soft actuator design.

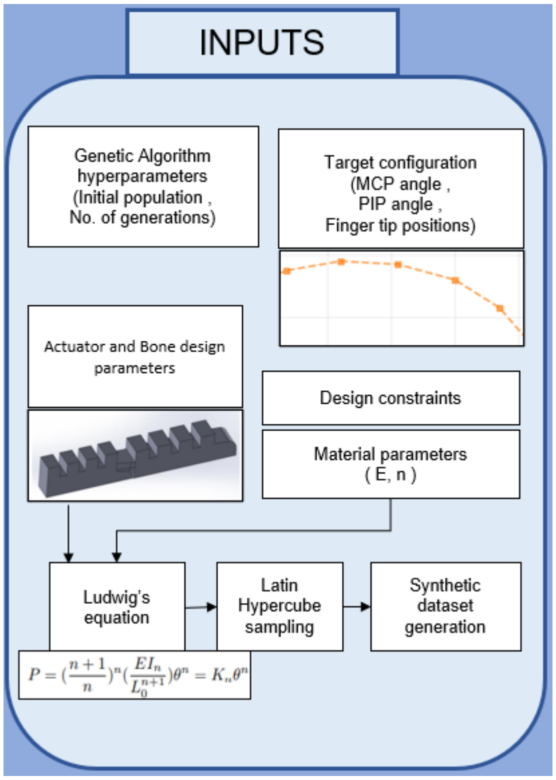

Fig. 1. Input component

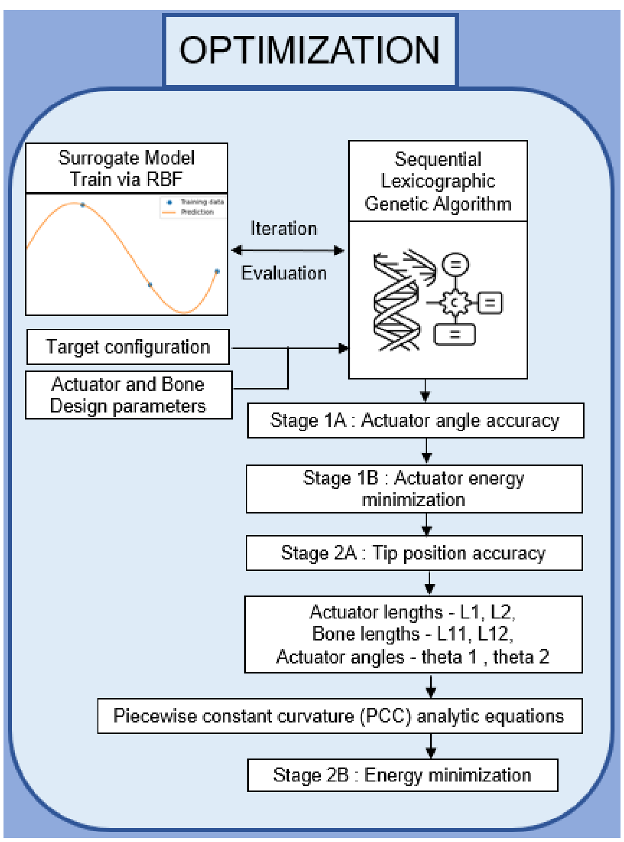

Fig. 2. Optimization component

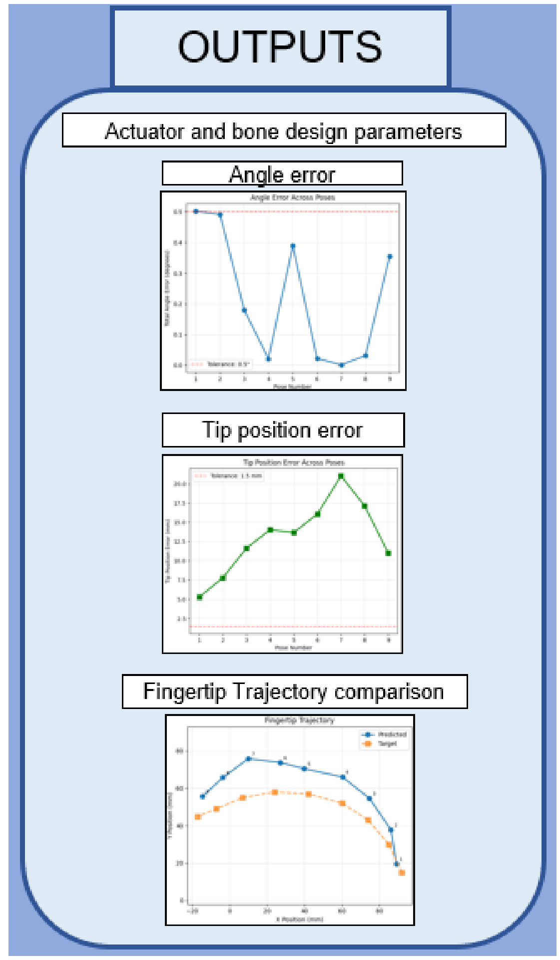

Fig. 3. Output component

A. Inputs

The inputs section include the parameters which can be changed by user according to their specific requirements. The process begins by defining the problem space with a comprehensive set of inputs:

- Genetic Algorithm Hyperparameters: We first set the foundational parameters for the genetic algorithm, including the initial population size and the total number of generations for the evolutionary process.
- Target Configurations: To guide the optimization, we provide a series of desired performance benchmarks. These are based on the motion of a human finger and include specific Metacarpophalangeal (MCP) and Proximal Interphalangeal (PIP) joint angles, along with the corresponding fingertip positions that define the target trajectory.
- Design Parameters & Constraints: The algorithm is given the geometric parameters for both the actuator and the internal bone structure. We also impose design

constraints and define the material properties, such as the Young's Modulus and the Ludwig exponent for the chosen material (Ecoflex).

- Governing Physical Model: The relationship between actuation pressure (P), material properties (K and n), and the resulting actuator bending angle (θ) is modeled using Ludwig's equation [1]. This equation forms the physical basis for our simulations.
- Synthetic Dataset Generation: To avoid computationally expensive simulations, we first generate a synthetic dataset. Using Latin Hypercube Sampling, we create a diverse set of design variations and calculate their corresponding bending angles with Ludwig's equation [1].

B. Optimization

The core of our methodology is a two-stage optimization process driven by a surrogate-assisted genetic algorithm. These are explained as follows:

- Surrogate Model Training: This synthetic dataset is then used to train a surrogate model based on a Radial Basis Function (RBF). This model acts as a rapid evaluator, capable of accurately predicting an actuator's bending angle almost instantly, making it feasible to run the genetic algorithm.
- Sequential Lexicographic Optimization: The optimization is performed sequentially, prioritizing key objectives in a lexicographic manner.
  - Stage 1 (Actuator Optimization): The first stage focuses on the actuator geometry.
    * 1A (Angle Accuracy): The algorithm first searches for designs that minimize the actuator angle error compared to the target poses.
    * 1B (Energy Minimization): From the pool of accurate designs, it then selects the one that requires the minimum energy to actuate, ensuring both accuracy and efficiency.
  - Stage 2 (Bone Optimization): With the optimal actuator design fixed, the second stage optimizes the bone structure.
    * 2A (Tip Position Accuracy): Using Piecewise Constant Curvature (PCC) analytic equations [2], the algorithm finds the bone parameters that minimize the fingertip position error.
    * 2B (Energy Minimization): Finally, it applies an energy minimization function to select the most efficient bone structure from the set of candidates that achieve the desired tip position.

C. Outputs

The result of this pipeline is a fully optimized soft finger design, characterized by a set of clear performance metrics:

- Optimized Design Parameters: The primary output is the final set of actuator and bone design parameters that best meet the target objectives.
- Performance Metrics: We generate comprehensive results to validate the design, including plots showing the angle error and tip position error across all target poses.
- Trajectory Comparison: A final, crucial output is the fingertip trajectory comparison, which visually plots the path of the optimized finger against the target trajectory, demonstrating the high fidelity of the final design.

III. Results and Conclusions

A. Angle error

Results across ten anatomically referenced hand poses demonstrate consistently low total joint angle error (mean: 0.355°). The graph of angle error across multiple poses can be seen in Fig. 4.

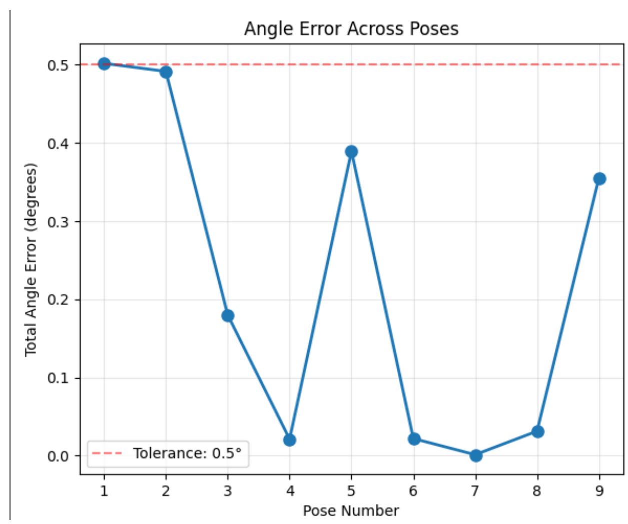

Fig. 4. Angle error

B. Tip position error

Results across ten anatomically referenced hand poses show robust tip trajectory matching (mean position error: 11 mm). The graph of tip position error across multiple poses can be seen in Fig. 5.

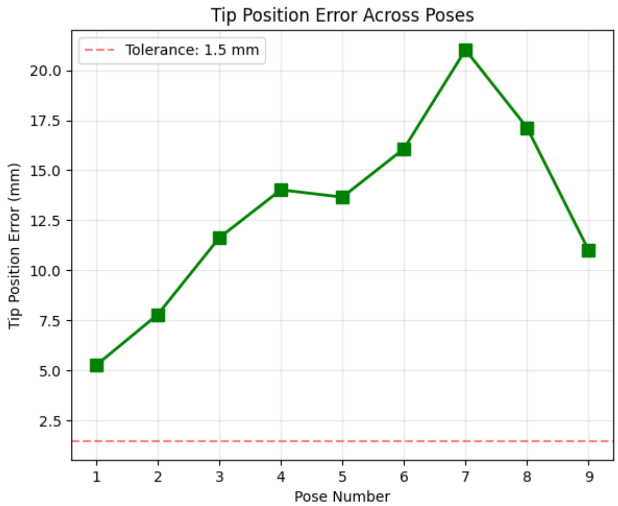

Fig. 5. Tip position error

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