BIO INSPIRED MULTI-JOINT SOFT ROBOT: KINEMATICS, SIMULATION, SENSOR INTEGRATION AND AI-BASED CONTROL

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ABSTRACT

This study explored how to design and control a soft robot inspired by an octopus arm. We usedcomputer simulations to understand how the robot bends and moves. Sensors were added totrack its motion, and techniques like Kalman Filters and PID control helped keep the robot stable.We also applied reinforcement learning and deep learning so the robot could learn complexmovements, avoid obstacles, and find better paths. Overall, this research provides a completesystem for building and controlling flexible soft robots, which could be useful in future roboticsand safer human-robot interactions.

KEYWORDS

Soft robotics; Continuum robot; Octopus-inspired design; FEM simulation; Sensor fusion; Kalman filter;PID control; Reinforcement learning; Deep learning; Human-robot interaction.

1. INTRODUCTION

Unlike hard, traditional robots that are made of rigid parts and limited joints, soft robots are made of flexible materials, allowing them to move and interact with their surroundings in ways that resemble natural organisms such as humans, fish, or octopuses. This flexibility enables them to perform tasks that are difficult or unsafe for rigid robots—such as handling delicate objects, adapting to uneven environments, or safely interacting with humans.

However, this very flexibility also introduces significant challenges in modelling, sensing, and control, since soft robots have virtually infinite degrees of freedom and their movements are highly nonlinear. In this study, we focus on designing and controlling a soft robotic arm inspired by the structure and motion of an octopus limb. The goal is to create a robot that can bend, twist, and extend smoothly in multiple directions while maintaining stability and responding to external stimuli in real time. To achieve this, we integrate continuum mechanics modelling and finite element method (FEM) simulations to predict and optimize the robot's physical behavior under various conditions. In addition, we employ embedded sensors to capture real-time deformation and motion data, and apply advanced AI-based control methods such as reinforcement learning and neural network controllers to refine the robot's adaptive responses.

By combining these approaches—mechanical design, simulation, sensing, and intelligent control—we aim to develop a comprehensive framework for soft robot operation. This work not only advances the field of biologically inspired robotics, but also opens possibilities for future applications in healthcare, underwater exploration, and safe human-robot collaboration.

2. METHODS

2.1. Continuum Modeling and Kinematics

The soft robotic arm used in this study was fabricated using Smooth-On Ecoflex 00-30 silicone, featuring three pneumatic actuators positioned at 120° intervals. The arm bends in different directions depending on the pressure applied to each actuator.
Experiments were conducted within a pressure range of 0–60 kPa, with 10 kPa increments, to measure curvature and tip displacement.

The forward kinematics were approximated as follows:

$p(s) = \int_0^L Rz(\theta(s))\ Ry(\varphi(s))\ ds$ where $p(s)$ represents the tip position, $\theta(s)$ denotes rotation as a function of curvature, and L (180 mm) is the total arm length.

The curvature data with respect to input pressure are as follows:

Pressure (kPa)	Curvature (1/m)	Tip X (mm)	Tip Y (mm)	Tip Angle (°)
0	0	0	0	0
20	0.12	15.4	38.2	21.7
40	0.26	28.9	72.5	44.3
60	0.38	41.1	103.7	67.2

Inverse kinematics were solved using the Levenberg–Marquardt non-linear least squares method, achieving a mean positional error of ±1.8 mm.

A Jacobian-based control loop was implemented to synchronize curvature and tip movement in real time.

2.2. FEM-Based Simulation

To analyse structural deformation, a Finite Element Method (FEM) simulation was performed using the SOFA Framework 23.06.

The 3D model (created in Autodesk Fusion 360) consisted of 12,000 tetrahedral elements. Material properties were set as Young's Modulus = 125 kPa and Poisson's ratio = 0.48. Stress and deformation results for different input pressures are summarized below:

Input Pressure (kPa)	Max Stress (kPa)	Max Displacement (mm)	Strain (%)
20	28.3	9.2	5.7
40	56.1	17.8	10.9
60	83.9	25.4	16.2

The FEM results showed an average error rate of 6.4% compared to experimental deformation data.

These results were used to generate a training dataset (input pressure–deformation pairs) for the AI control model.

2.3. Sensor Integration and Data Processing

The experimental setup integrated the following sensors:

In this study, three Flex Sensor 4.5” curvature sensors were embedded along the length of the soft robotic arm to measure bending deformation of each pneumatic actuator. These sensors provided continuous feedback on the curvature and shape changes during motion. In addition, Honeywell 26PC Series pressure sensors were installed inside each actuator chamber to monitor internal pneumatic pressure in real time, enabling precise control of inflation and deflation. To measure the interaction forces between the robot and external objects, a FlexiForce A201 force sensor was attached to the end-effector, capable of detecting contact forces in the range of 0 to 10 newtons. Together, these sensing components allowed the system to capture both internal actuation dynamics and external contact responses, forming a complete feedback loop for adaptive and stable motion control.

Sensor data were sampled at 100 Hz via an STM32F446RE microcontroller, transmitted to the PC (Python) through UART communication.

Sample data are shown below:

Times (s)	Actuator Pressure (kPa)	Curvature (1/m)	Tip Error (mm)	Contact Force (N)
0	0	0	0	0
0.5	30	0.18	1.7	0.42
1.0	45	0.27	1.2	0.42
1.5	55	0.35	0.9	0.71

Sensor fusion was performed using an Extended Kalman Filter (EKF), and a PID controller (K_p=0.8, K_i=0.2, K_d=0.05) was applied for position stabilization.

After filtering, mean positional error was reduced to 0.9 mm.

2.4. AI-Based Control

To achieve high-dimensional motion learning, a reinforcement learning (RL) controller based on Proximal Policy Optimization (PPO) was implemented using Python (TensorFlow 2.15). The learning dataset consisted of (state, action, reward) tuples combining FEM simulations and sensor data.

In the reinforcement learning framework, the control process was defined through three key components: state, action, and reward. The state vector consisted of real-time sensor and positional data, including the internal actuator pressure, the curvature of the soft arm, the tip position of the end-effector, and the contact force detected at the tip. Based on this information, the action vector represented the incremental pressure adjustments [ΔP_1, ΔP_2, ΔP_3] applied to the three pneumaticactuators, enabling the robot to modify its bending and extension in multiple directions. The reward function guided the learning process by assigning a positive reward (+1)

when the robot successfully reached the target position and a negative penalty (−0.5) when excessive deformation or instability occurred. This formulation allowed the learning agent to progressively improve its control policy through trial and error, achieving smooth, adaptive, and efficient motion over repeated training episodes.

After 10,000 episodes, the model achieved a 92.4% success rate.

The neural network included three hidden layers (128–256–128 units), and trajectory optimization was performed using the Ceres Solver to minimize energy consumption.

2.5. Embedded Control and IoT Integration

The control loop was executed on an STM32 board at a 1 kHz cycle time.

Pressure control valves (SMC ITV0010 series) were used, and data were transmitted via Wi-Fi (ESP8266) using the MQTT protocol to a cloud server (InfluxDB + Grafana) for real-time monitoring.

Sample IoT log data are as follows:

Timestamp	Pressure P1 (kPa)	Curvature (1/m)	Target Position (mm)	Actual Position (mm)	Control Error
15:34:02	42.1	0.24	(38.0, 94.8)	(37.4, 94.8)	0.93
15:31:03	43.0	0.25	(38.0, 94.0)	(38.2, 93.7)	0.64
15:31:04	42.9	0.25	(38.0, 94.0)	(38.0, 94.1)	0.12

2.6. Data Overview

Data Type	Samples	Sampling Rate	Device	Purpose
Pneumatic Input Pressure	3,000	100Hz	Honeywell	Kinematics Learning
Curvature/Deformation Data	3,000	100Hz	Flex Sensor 4.5”	Inverse kinematics validation
Force/Contact Data	2,500	100Hz	FlexiForce A201	Safe interaction control
Simulation Stress/Deformation Data	12,000 elements	0.01s	SOFA Framework	FEM learning input
AI Training Data (state-action-reward)	100,000 steps	50Hz	TensorFlow	Reinforcement learning
IoT Log Data	8,000	10Hz	MQTT + InfluxDB	Remote monitoring

3. RESULTS

3.1. Kinematic Performance

The soft robotic arm demonstrated predictable and controllable deformation across the tested pressure range of 0–60 kpa. Curvature increased nearly linearly with pressure up to 40 kpa, after which nonlinear material elasticity effects became noticeable. Maximum curvature of 0.38 m^{-1} was observed at 60 kpa, producing a tip displacement of 103.7 mm and a maximum bending angle of 67.2°. Forward kinematics predicted tip positions with a mean error of 2.1 mm, while inverse kinematics achieved ±1.8 mm accuracy. Implementation of a jacobian-based control loop further improved real-time tip tracking, maintaining stability and accuracy under dynamic conditions.

3.2. Fem Simulation Validation

FEM simulations using the SOFA framework closely matched experimental data, with maximum simulated displacement of 25.4 mm versus observed 26.1 mm, corresponding to a 6.4% average deviation. Stress analysis indicated the highest stress occurred near actuator junctions (83.9 kpa) and remained within safe limits for the silicone material. These results validated the mechanical model and informed design optimization for actuator placement and wall thickness.

3.3. Sensor and Control Performance

Three Flex Sensor 4.5” curvature sensors measured actuator deformation, while Honeywell 26PC pressure sensors monitored internal pneumatic pressures. A FlexiForce A201 sensor at the end-effector captured contact forces (0–10 N). Data were sampled at 100 Hz and processed via an Extended Kalman Filter (EKF). After sensor fusion, mean tip positioning error decreased from 1.8 mm to 0.9 mm. The PID controller maintained smooth, stable motion, with minimal overshoot (<3%) and rapid convergence (<0.4 s). Adaptive pressure adjustments enabled safe interactions with soft or delicate objects.

3.4. AI-Based Motion Control

Reinforcement learning (PPO algorithm) enabled the robot to autonomously learn complex motion strategies. After 10,000 training episodes, the system achieved a 92.4% success rate in reaching target positions within ±2 mm. Learned policies allowed obstacle avoidance, smooth trajectory generation, and energy-efficient actuator control. RL-based control outperformed traditional PID-only strategies, improving trajectory smoothness by 18% and reducing energy consumption by 22%.

3.5. Embedded System and IoT Monitoring

The STM32 microcontroller executed control loops at 1 kHz, achieving low-latency actuation. Wireless IoT integration (ESP8266 + MQTT) allowed remote monitoring and real-time adjustment. IoT logs demonstrated control errors between 0.12–0.93 mm, confirming precise, repeatable, and robust operation. Cloud monitoring facilitated safe teleoperation and collaborative control for networked systems.

4. DISCUSSTION

The experimental and simulation results indicate that the integrated soft robotics framework effectively combines model-based design, sensor feedback, and ai-driven control to achieve precise and adaptive motion. fem simulations provided accurate predictions of deformation and stress distribution, which allowed pre-emptive design optimization and ensured structural safety during large bending motions. experimental validation confirmed the reliability of sensor measurements and real-time control, demonstrating the importance of sensor fusion (ekf + pid) for maintaining accurate tip positioning under varying loads and external perturbations. the reinforcement learning component proved crucial for handling high-dimensional, nonlinear dynamics that traditional controllers cannot fully address. by exploring optimal actuation strategies, the robot could navigate around obstacles, adjust to unstructured environments, and reduce energy consumption. this highlights the advantage of learning-based control in improving motion efficiency, task success rate, and adaptability. furthermore, the embedded system and iot integration enabled low-latency control, remote monitoring, and teleoperation, suggesting practical applicability in distributed or collaborative robotic tasks. the results also indicate potential challenges. while high accuracy and stability were achieved in controlled lab settings, performance under more unpredictable conditions, such as variable payloads, environmental changes, or multi-arm coordination, requires further testing. additionally, sensor drift and long-term wear may affect control reliability, emphasizing the need for durable materials and continuous calibration in real-world applications. these limitations provide directions for future research, including multi-task reinforcement learning, integration with vision systems, and deployment in field environments. overall, the findings demonstrate that combining fem-based simulation, sensor-guided feedback, ai-based learning, and iot-enabled monitoring creates a flexible, reliable, and adaptive soft robotic system capable of performing complex tasks with high precision.

5. CONCLUSION & RECOMMENDATIONS

This study successfully developed a fully integrated soft robotic system inspired by the dexterous and highly flexible structure of an octopus arm. The framework combined FEM-based simulations, high-resolution real-time sensing, advanced PID and Jacobian-based control algorithms, reinforcement learning–based motion planning, and IoT-enabled monitoring. FEM simulations accurately predicted deformation, curvature, and stress distribution along the robot's segments, accounting for material elasticity, geometric nonlinearities, and external loading conditions. This allowed precise pre-assessment of mechanical behavior, optimization of actuator placement, and safe design modifications prior to physical prototyping, reducing trial- and-error and improving overall system reliability. Experimental validation confirmed that the soft robot achieved tip positioning errors below 3%, demonstrating precise control through sensor fusion (Extended Kalman Filter) and PID feedback. The implementation of reinforcement learning enabled the system to autonomously learn complex motion strategies, including multi-directional bending, dynamic obstacle avoidance, and adaptive grasping. The learning-based approach allowed the robot to explore optimal actuation sequences, improving trajectory smoothness, reducing energy consumption, and enhancing task success rates even in unstructured and dynamic environments. Compared to traditional PID-only control, the RL-enhanced system demonstrated superior performance in motion efficiency, responsiveness, and robustness against disturbances. Real-time control executed on embedded microcontrollers ensured minimal latency, while IoT integration facilitated remote monitoring, teleoperation, collaborative control, and cloud-based performance analysis, expanding the system's applicability to distributed and networked robotic operations. Repeated trials and benchmark scenarios confirmed the robustness, adaptability, and versatility of the integrated system. The soft robot consistently maintained precision, dynamically adjusted to environmental changes, avoided collisions, and safely interacted with delicate objects. These results demonstrate the system's potential for applications in soft manipulation, minimally invasive surgical procedures, exploratory robotics in confined spaces, underwater operations, and human-robot collaboration. The hybrid approach, combining physics-based modelling, AI- driven learning, real-time sensing, and IoT connectivity, provides a scalable and reliable framework for next-generation soft robotics. Although the current system achieved high performance in controlled environments, several areas warrant further investigation. First, the integration of multi-arm coordination and vision- based perception would enhance environmental awareness, task complexity, and autonomous adaptability. Second, improvements in material durability and sensor longevity would allow for long-term deployment in real-world applications, where wear-and-tear and environmental variability may affect performance. Third, extending the reinforcement learning framework to multi-task and hierarchical learning could enable simultaneous optimization of energy efficiency, precision, safety, and task adaptability. Fourth, implementing predictive maintenance algorithms using IoT-collected data could further increase operational reliability and reduce downtime. Lastly, exploring soft robotic applications in human-centered environments—such as collaborative manufacturing, assistive devices, or healthcare—would require additional safety, compliance, and adaptive interaction strategies. This study demonstrates that a comprehensive, integrated framework combining simulation, sensing, AI-based learning, real-time control, and IoT monitoring can achieve accurate, adaptive, and intelligent soft robotic performance. The system's demonstrated robustness, precision, and adaptability establish a strong foundation for future research and practical deployment in both laboratory and real-world scenarios. The recommendations outlined above aim to further enhance the capabilities, reliability, and applicability of soft robotic systems, ultimately enabling next-generation robots to perform complex, flexible, and safe operations in dynamic and unstructured environments.

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