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Path Planning Methods for Bio-Inspired Soft Robots

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Abstract. Due to their flexible morphology and strong adaptability in complex environments, soft robots have shown considerable potential in applications such as healthcare, underwater exploration, and disaster response. Their continuous, highly deformable nature, however, makes path planning especially difficult. This paper provides a systematic review of three main approaches to bio-inspired soft robot path planning: model-based methods, learning-based methods, and hybrid approaches. Model-based methods construct kinematic or mechanical models of robot behavior to support planning, while learning-based methods learn action policies directly from data to establish perception–action mappings. Hybrid approaches combine the prior knowledge embedded in physical models with the adaptability of learning-based methods. In particular, approaches that integrate model-based reinforcement learning (MBRL) with model predictive control (MPC) have achieved a strong balance between planning accuracy and sample efficiency. This review examines the fundamental principles, strengths, and limitations of each approach and identifies several key challenges, including the trade-off between real-time performance and model fidelity, limited contact perception, and the absence of standardized evaluation benchmarks. Finally, the paper discusses future research directions, such as integrating morphological computation into perception–planning frameworks and developing more adaptive and intelligent control systems for soft robots.

Keywords: bio-inspired soft robot, path planning, machine learning, hybrid method

1. Introduction

Traditional rigid robots typically rely on accurate kinematic models and a limited number of degrees of freedom. They work well in structured industrial environments, but their performance declines when tasks involve dynamic changes, complex geometries, or confined spaces. Bio-inspired soft robots, by contrast, show strong potential in medical care, underwater exploration, and disaster rescue because their flexible morphology and adaptability suit unstructured environments. Nevertheless, the infinite-dimensional configuration space and complex contact interactions of soft robots make path planning particularly difficult, and this problem is central to their intelligent decision-making and autonomous control.

To address the challenges posed by high-dimensional, continuously deformable configuration spaces, researchers have developed a range of technical approaches for soft robot path planning.

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Despite considerable progress, balancing computational efficiency, physical modeling accuracy, and generalization across environments remains a fundamental open challenge.

This paper provides a systematic review of recent advances in soft robot path planning for intelligent decision-making. It categorizes existing approaches by their underlying technical principles and compares their advantages, limitations, and applicable scenarios. The review also identifies common challenges and open questions in current research, helping readers choose appropriate planning strategies and informing future work on soft robot intelligence.

2. Differences between traditional robot path planning and soft robot path planning

Path planning for traditional rigid robots has been studied extensively. A rigid robot's configuration space is usually a finite-dimensional manifold with a limited number of degrees of freedom, and its kinematic model can often be described accurately. Planners can therefore search directly for collision-free trajectories in this space. Classical algorithms such as the Probabilistic Roadmap Method (PRM), the Rapidly-exploring Random Tree (RRT), and their variants are well established for rigid systems and often complete planning in milliseconds to seconds. These methods, however, rely on assumptions such as low-dimensional and fixed configuration spaces, accurate kinematic models, and predictable contact interactions, none of which generally hold for soft robots. In particular, the explicit mapping between joint variables and end-effector positions that rigid kinematics provides is replaced by the infinitely many degrees of freedom associated with continuum deformation, so the transformation between configuration space and workspace usually has no analytical closed form.

The fundamental distinction between soft and rigid robots lies in their mechanical structure: soft robots are made of compliant materials and move through continuous deformation rather than discrete joint rotations. This difference creates three major challenges for path planning. First, the configuration space of a soft robot is an infinite-dimensional function space, corresponding to a continuous mapping from material deformation states to three-dimensional spatial configurations, and cannot be searched directly with conventional planning methods. Second, interaction with the environment involves complex contact coupling rather than simple rigid-body collision, so the boundary between obstacles and free space can change dynamically during motion. Third, the viscoelastic properties of soft materials introduce time-dependent deformation behavior, so purely geometric paths cannot fully describe robot motion; time must therefore be included, turning planning into a coupled geometric–mechanical–temporal optimization problem. These differences mean that soft robot path planning cannot simply reuse methods developed for rigid robots; new frameworks must account for the unique material properties and deformation mechanisms of soft systems.

3. Model-based path planning methods

3.1. PCC-driven sampling-based planning

The Piecewise Constant Curvature (PCC) assumption is one of the earliest and most widely used modeling strategies in soft robot path planning. Webster and Jones established a kinematic framework based on the PCC model and introduced RRT-Connect and A* search into this setting [1]. The PCC model assumes that each bending segment of a soft robot can be approximated as a circular arc of constant curvature, so continuous deformation can be represented with a limited number of geometric parameters. Although this approximation ignores some local deformation details, it greatly reduces the computational cost of kinematic modeling and planning.

In PCC-based planning, sampling is performed in a low-dimensional parameter space, and the sampled configurations are mapped to three-dimensional space curves via PCC forward kinematics for collision detection. As one of the earliest model-based approaches, PCC-driven methods use analytical kinematic models to turn high-dimensional deformation states into low-order representations and thereby enable efficient planning. More recently, the discrete Cosserat model proposed by Renda et al. incorporated frictional contact into the planning framework in 2022, extending model-based methods to more complex interaction scenarios [2].

In summary, PCC-driven sampling-based planning benefits from the computational efficiency of analytical kinematic models and works best in relatively simple environments with few obstacles. Its performance depends heavily on the accuracy of the underlying assumptions and can degrade under varying external loads or complex contact conditions. These studies illustrate the fundamental trade-off between computational efficiency and physical accuracy in model-based soft robot planning.

3.2. Cosserat-driven DDP for online planning

Combining high-fidelity continuum models with online optimal control is an effective way to improve planning accuracy. Till et al. integrated the Cosserat rod model with Differential Dynamic Programming (DDP), achieving real-time online trajectory optimization on a high-fidelity continuum representation for the first time [3]. Unlike the PCC model, the Cosserat rod model captures bending, torsion, and extension of elastic rods, giving a more accurate description of soft robot mechanics.

Within the DDP optimal control framework, the planner can generate dynamically feasible, smooth trajectories in milliseconds while satisfying system constraints [3]. These results show that model-based approaches can achieve high planning accuracy. More recent discrete Cosserat models have further improved computational efficiency, enabling real-time planning in more complex environments with contact interactions [2].

3.3. Finite element-based contact-aware planning

Finite element-based, contact-aware planning offers a high-fidelity way to model soft robot deformation directly from continuum mechanics, without simplified kinematic assumptions. Duriez developed a full-order finite element model by discretizing both the robot and its environment into finite element meshes; each iteration solves the coupled contact mechanics problem to obtain the distribution and magnitude of contact forces [4].

In 2022, Kim et al. combined visual sensing with finite element models, showing that sensory feedback can markedly improve planning accuracy in soft robotic systems [5]. Full-order finite element methods remain expensive, however, because every optimization iteration requires solving a complex contact mechanics problem over many elements. Real-time replanning is therefore still difficult, especially in fast, dynamic environments.

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4. Learning-based path planning methods

4.1. End-to-end strategies based on deep reinforcement learning

Deep reinforcement learning (DRL) enables end-to-end path planning by learning the mapping from sensory observations to control actions directly. Shih et al. proposed a DRL framework based on electronic skin in 2020, using pressure signals from the skin as state inputs to a Deep Q-Network (DQN). With this approach, a quadruped soft robot learned adaptive locomotion gaits on unknown terrain after roughly 200 training iterations [6].

End-to-end methods represent a direct learning-based approach: they learn perception-to-action mappings from data without an explicit physical model. In 2023, Fang et al. applied deep reinforcement learning to contact-rich path planning for tendon-driven soft robots and reported improved generalization in complex interaction scenarios [7]. Algorithms such as Proximal Policy Optimization (PPO) and Soft Actor-Critic (SAC) have also shown greater stability in continuous action spaces and are now widely used for end-to-end soft robot planning.

End-to-end methods nevertheless have clear limitations: low sample efficiency, limited generalization, and sensitivity to changes in system parameters. Thuruthel et al. reported that a 5% change in soft arm length increased end-point tracking error from about 5 mm to more than 12 mm, illustrating how sensitive purely data-driven approaches can be to morphological variation [8]. End-to-end strategies also lack interpretability, which complicates deployment in safety-critical applications such as medical robotics. To address inefficient exploration and policy overfitting, researchers have turned increasingly to learned dynamics models that support more structured, predictive planning.

4.2. Learning-based dynamics modeling

Learning-based dynamics models aim to capture how soft robots move directly from experimental data, using methods such as Gaussian Process Regression (GPR), recurrent neural networks, and Long Short-Term Memory (LSTM) networks. In 2023, Li et al. proposed a dynamics modeling approach based on neural ordinary differential equations (Neural ODEs) and achieved better long-horizon prediction accuracy [9]. Unlike conventional black-box networks, Neural ODEs represent system dynamics as continuous-time parametric models, offering improved extrapolation while retaining the flexibility of data-driven learning.

This line of research is important for learning-based soft robot planning, as advanced neural architectures can improve the predictive ability of learned models. Prediction accuracy, however, typically declines as the horizon grows. Thuruthel et al. found that extending the prediction horizon from 5 to 20 steps increased the average end-point position error by roughly three to five times [8]. The accumulation of prediction errors limits purely learned models in long-horizon planning and motivates model-based reinforcement learning (MBRL) approaches that combine short-term prediction with receding-horizon optimization.

5. Hybrid path planning methods

Hybrid approaches combine the structural priors of physical models with the adaptability of learning-based methods and are now regarded as one of the most promising directions in soft robot path planning. Among existing hybrid strategies, the integration of model-based reinforcement learning (MBRL) and model predictive control (MPC) has attracted the most attention. MBRL

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continually improves a learned dynamics model through interaction with the environment, while MPC treats path planning as a finite-horizon optimal control problem solved by receding-horizon optimization. The two methods are naturally complementary: learning provides adaptability, while model-based control provides predictive capability.

The MBRL-MPC framework is one of the most advanced and widely studied hybrid approaches in soft robot path planning. Zhang et al. proposed an MBRL-MPC framework in which a local Gaussian process dynamics model describes soft arm behavior and an upper-level MPC controller formulates trajectory planning as a finite-horizon optimal control problem [10]. In 2023, Wang et al. introduced online adaptation that continuously updated the learned dynamics model, allowing the framework to compensate for prediction errors caused by environmental changes [11]. In 2024, Zhang et al. combined hybrid MPC with residual dynamics learning, using learned residual models to compensate for unmodeled contact interactions and deformation effects; this method raised the path planning success rate in constrained environments above 95% [12].

Together, these studies show that using model-based prior knowledge to reduce learning complexity and online learning to compensate for model error is an effective strategy for improving both real-time performance and generalization. The main advantage of MBRL-MPC is that physical models shrink the dimensionality and uncertainty of the learning space, while learned residual dynamics absorb modeling error and environmental change. Hybrid approaches therefore currently offer one of the best trade-offs between planning accuracy and sample efficiency.

Real-time computation, however, remains the main bottleneck of MBRL-MPC planning. A single MPC optimization with the Cross-Entropy Method (CEM), for example, can take about 500 ms, which is too slow for online replanning in fast dynamic tasks [10]. Recent work has explored acceleration strategies such as GPU-based parallel computation, approximate dynamic programming, and neural-network-based optimization. These approaches are expected to push MPC computation below 100 ms, making hybrid planning frameworks more practical for real-world soft robots.

6. Challenges and future directions

6.1. Common challenges

Despite significant progress, the three technical approaches still share several common challenges. The most fundamental is the trade-off between computational efficiency and model fidelity. Full-order finite element (FE) methods must solve large, complex contact mechanics problems repeatedly in every control cycle, and the cost grows quickly with model resolution, limiting control frequency. Cosserat-DDP-based online planning can replan at millisecond scale, but its modeling accuracy is lower than that of full-order FE approaches [3]. PCC-based models and lightweight learned models are cheaper and can update more often, yet they often fail to capture complex contact behavior and nonlinear material dynamics. Computational cost therefore constrains control frequency, and control frequency in turn constrains achievable model fidelity.

A second major challenge is reliable contact-state perception. Contact information is essential for distinguishing useful interactions from unwanted collisions during planning, yet accurate real-time measurement of contact forces remains difficult in soft robots because of their deformable structures and complex material behavior. Model-based estimation can help, but it often depends on the planner's own predictions, which can create a circular dependency between state estimation and planning.

The third challenge is the absence of standardized evaluation benchmarks. Soft robots are highly heterogeneous: actuation mechanisms range from pneumatic actuators to shape memory alloys (SMAs) and dielectric elastomer actuators (DEAs). Without unified simulation platforms, benchmark tasks, and evaluation metrics, fair comparison across methods is difficult [13]. Different actuation mechanisms also change the robot's dynamics, so transferring the same algorithm between platforms typically requires additional parameter tuning. Establishing open-source benchmark platforms has therefore become an important goal for the research community [13].

6.2. Future directions

One promising direction is morphological computation, in which the soft robot's physical body contributes to planning through its material properties and structural design. Recent studies have shown that passive deformation can reduce the computation needed for obstacle avoidance, and that intrinsic material damping can partly replace trajectory smoothing [13]. Advances in variable-stiffness mechanisms, origami-inspired structures, and intelligent materials are turning this idea from theory into practice. A variable-stiffness soft arm, for example, can locally stiffen when it meets an obstacle, creating a temporary "virtual joint" that converts continuous deformation into approximately rigid-body motion. Similarly, origami-inspired structures let robots adjust their geometric configuration in response to environmental conditions, improving obstacle avoidance.

Another important direction is joint learning of perception and planning, moving beyond the conventional perception–planning–control pipeline. Integrating deformation-state estimation with motion planning in a single learning framework could give soft robots more adaptive decision-making [5]. Deformable electronic skin arrays and vision-based multi-view deformation reconstruction systems provide essential sensing support. Self-supervised learning can also let robots collect deformation data during task execution and improve their perception models without extensive manual annotation, potentially easing the data-labeling bottleneck in soft robot perception.

Another critical direction is adaptive planning frameworks that can incorporate new observations in real time. Such frameworks would let soft robots adapt quickly to changes caused by material aging, external loads, and environmental disturbances [11]. Incremental Gaussian process models combined with Bayesian optimization, together with online system identification based on parametric models, are promising routes to continuous adaptation. Combining online adaptation with morphological computation could improve performance further, since actively adjusting body properties may reduce the computational burden of replanning. Ultimately, real-time adaptability will be a key criterion for deploying soft robot path planning systems in practice.

Unified cross-platform simulation benchmarks and standardized evaluation protocols are also essential for accelerating progress. Open-source simulation environments, standardized soft robot model libraries, and representative task suites should be developed to reduce differences caused by actuation mechanisms and experimental platforms. These efforts would support fair comparison, reproducibility, and systematic evaluation of soft robot planning algorithms under consistent conditions [13].

7. Conclusion

This paper has reviewed recent advances in bio-inspired soft robot path planning and grouped existing approaches into three main paradigms: model-based, learning-based, and hybrid. Model-based methods use physical models to achieve high planning accuracy and interpretability, but often at the cost of high computation and limited adaptability in complex environments. Learning-based methods are flexible and adaptive, deriving planning strategies directly from data, yet they suffer from low sample efficiency, limited generalization, and weak interpretability. Hybrid approaches combine the strengths of both, offering a more favorable balance among accuracy, adaptability, and computational efficiency.

Based on a comprehensive analysis of the principles and representative studies behind these three approaches, this review shows that soft robot path planning has advanced considerably. Still, balancing real-time performance with physical fidelity remains a fundamental challenge. The lack of reliable contact-state perception and standardized benchmarks also continues to hinder further development and fair comparison.

Overall, model-based methods suit offline planning tasks that demand accuracy and have enough computational resources. Learning-based methods are better suited to rapid adaptation and deployment in dynamic, unknown environments, while hybrid approaches currently perform best in complex, contact-rich tasks. Looking ahead, morphological computation, joint learning of perception and planning, and real-time adaptive frameworks should help address the limitations identified here. The integration of these technologies will also accelerate the transition of soft robots from laboratory research to practical applications.

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