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Research Paper

Adaptive Nonlinear Model Predictive Control for Soft Robotics Applications

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Abstract. Computer-based adaptive control technology has made significant progress in the real-time management of complex nonlinear system dynamics and the inevitable uncertainties in soft robots. This paper proposes a method for achieving precise and reliable control of soft robotic systems Through the use of adaptive nonlinear model predictive control schemes. Develop a continuous-time dynamic model to identify changes in the core deformation drive state of a multi-link flexible arm; integrate online parameter estimation and model predictive control algorithms to counteract dynamic disturbances caused by environmental or model changes. Adaptive estimation continuously updates its own parameters based on sensor data to achieve an accurate predictive control system under various conditions or uncertainties. The experimental setup uses numerical simulations and a pneumatically driven soft robotic arm to validate the effectiveness of the proposed controller. Compared to traditional MPC and PID control methods, adaptive NMPC can improve trajectory tracking accuracy, anti-interference performance, and execution safety levels. This feature achieves high-reliability real-time computing performance and is suitable for embedded hardware devices. This study proposes a comprehensive approach to ensure the robustness, accuracy, and efficiency of soft robotic systems in resilient control under uncertain environments.

Keywords: *Integrated Manufacturing, Computer Optimization, Adaptive Control, Nonlinear Systems, Soft Robotics*

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Introduction

As a disruptive form of roboticisation, soft robots have rapidly risen in the field of robotics and automation due to their flexibility and compliance that can overcome conventional rigid systems' limitations [1]. Inherent compliance, highly deformable morphologies, and distributed actuators enable soft robots to interact safely and effectively with people and their unknown environment [2]. In terms of the above-mentioned features, some achievements have been made in biomedical Devices [3], Assistive Technologies [4], minimally-invasive Surgery [5], And Handling fragile Or Irregular Objects [6]. In addition, adaptability of soft robots is promoting interests in search and rescue missions [7] and wearable-exoskeletal devices with fine-grained and flexible operation requirements [8]. Due to Continuous Mechanical Variation and Intelligent Materials of soft robots, there are substantial potentials for Adaptation and Force-bearing Ability under Uncontrolled Circumstances.

While progress has been made, achieving precise and stable motion control of soft robots is still fundamental due to the significant non-linearity, unbounded-dimension dynamics system uncertainty issues [9]. Nonlinearity of actuator [10], viscoelastic effects [11], environmental disturbance [12], and time-dependent parameter [13] all significantly affect the problem of system modelling and on-line control. Traditional models-based methods, such as linear or classical-feedback control schemes, have poor robustness to nonlinearities, uncertainties, and dimensions in these high-dimensional systems [14]. Nonlinear model predictive control (NMPC) framework has achieved some progress in managing multiple variables with constraint and nonlinearity; However, it faces problems such as lack of robustness to parametric drift, high computational efficiency and an unreasonably good self-adaptive ability [15]. In addition, most of the existing adaptive control algorithms are not suitable for this type of platform's particular dynamic characteristics and strong coupling phenomenon.

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This paper proposes an improved adaptive nonlinear model predictive control system to address the aforementioned issues. By introducing online parameter adaptation into the NMPC algorithm, its ability to dynamically compensate for modeling errors and unmeasured nonlinear system dynamics can be enhanced. The accuracy of trajectory tracking is improved in uncertain operating environments. Based on the continuous model of soft robot dynamics, real-time development of parameter-adaptive neural network control (NLPC) control strategies, and validation of their effectiveness Through various physical tests and simulation experiments. This part of the paper will be organized sequentially. First, a literature review and background will be provided. Then, the construction of the system model and uncertainty analysis will be introduced. The design of the adaptive NMPC controller will be introduced. Explain the simulation and experimental validation. Finally, summarize and emphasize the research directions for future work.

Related Work

Advances in Soft Robot Control

The advancements in flexible actuators, sensor integration, and computational modeling have driven the development of soft robot control [16]. Soft robots differ from rigid robots in that they require infinite degrees of freedom and nonlinearity in control. Real-time estimation techniques and distributed embedded sensors are being developed to provide reliable and timely closed-loop feedback capabilities. [17] To better describe the complex dynamics and uncertainties in soft robotic systems, data-driven model construction and physics-inspired learning methods have emerged [18]. Closed-loop controllers based on proprioceptive and external sensory feedback enable soft robots to operate in complex surgical and hazardous reconnaissance environments [19]. The gap between the primary motion intentions and the secondary action levels of the morphing system is narrowing.

Nonlinear Model Predictive Control and Adaptive Approaches

Nonlinear model predictive control has been widely used to address issues related to multi-input multi-output nonlinear systems. This is because it excels in predicting the future states of multi-input multi-output nonlinear systems under various constraints [20]. Directly adding system nonlinearity and operational environment constraints to the NMCQ will make it more effective in first-order dynamic systems and multivariable coupling compared to simple linear controllers. Due to the complex computational load and the intricate modeling of soft robots, nonlinear optimization problems cannot be effectively executed in the actual dynamics of systems with complex motion characteristics. N-MPC (Nonlinear Model Predictive Control) employs various adaptive methods to handle model instability and parameters. The adaptive MPC strategy can update the internal model based on real-time estimates of the online model. Therefore, it is capable of occasionally compensating for changes in system dynamics [21]. However, many adaptive NMPC methods designed for rigid robotic systems often overlook the flexible characteristics and time-varying behavior of soft robots. To improve their robustness in unstructured environments that change over time, some scholars have recently combined learning-based adaptive methods with traditional NMPC [22]. In these complex multi-degree-of-freedom systems, there is a strict trade-off between computational efficiency, response time adaptability, and closed-loop performance.

Gaps and Motivation

After a comprehensive review of the current literature on soft robot control, it was found that there are various drawbacks affecting progress and application. Many traditional control methods typically use simple linearized models to describe the dynamics of soft robots. These linearized models or second-order approximations cannot accurately describe the nonlinear and continuous characteristics of soft robot structures. Due to this simplification, the controller may not match the actual soft robot, leading to a decline in system performance and even system failure. Especially, there is the issue of parameter drift. These issues arise because factors such as material fatigue, environmental changes, system wear, and unmodeled interaction forces cannot fully reflect their impact during the robot's operation process [23].

Due to significant differences in system dynamics, drive mechanisms, and deformation responses, many studies on adaptive control of traditional rigid-body robots have not been directly applicable to soft robot platforms.

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Compared to rigid manipulators, soft robots possess infinite degrees of freedom, distributed fault characteristics, and dynamic shape changes. In this case, traditional adaptive strategies are usually ineffective. Due to the inability to quickly handle the dynamic changes of multi-dimensional systems, most efforts in the design of customized adaptive technologies for soft robots cannot simultaneously meet robustness and sensitivity.

In addressing this gap, recent progress has been made by combining adaptive algorithms with the Model Predictive Control (MPC) framework. These efforts have mainly been conducted under ideal simulation conditions, lacking empirical validation on physical soft robotic systems. Lack of comprehensive empirical evidence to prove its feasibility, stability, and reliability. Nonlinear Model Predictive Control (MPC) currently requires a significant amount of computational power, and this process necessitates the fast-processing capabilities of embedded devices or limited computational resources.

Three requirements for soft robot control must be met simultaneously: a dynamic model with expressiveness and accuracy that can accurately describe the mechanical behavior of the soft system; the feasibility of high-speed, low-latency computation required by the robot controller; and a robust adaptive parameter identification mechanism that can quickly identify changes in system parameters. To deploy high-precision and safe soft robots, these robots must be able to work accurately and stably in unknown environments, mobile locations, and even hazardous sites.

This study will systematically address these issues by providing an independent adaptive nonlinear model predictive control (NMPC) strategy. An accurate method that simultaneously considers the mechanical and operational characteristics of soft robots, thereby quickly and flexibly obtaining parameters during the model predictive control (MPC) optimization cycle. Using a multi-segment pneumatic-driven soft arm, this paper demonstrates its validation Through both high-fidelity simulations and real-world experiments. Build a complete system using high-end models, adaptive estimation, online adjustment, and hardware-in-the-loop verification applications. By directly addressing the urgent need to develop reliable, accurate, and efficient control strategies, these strategies can ensure the safe and adaptive operational state of next-generation soft robotic systems.

System Modeling and Analysis

Soft Robot Dynamic Modeling

We did not use traditional rigid platforms because they are highly nonlinear and continuously deformable continua, so we did not use them to simulate soft robotic systems. Most soft robots can be described as a series of elastic segments or a continuous backbone, deforming according to the distributed forces and moments. Initially, this segmented-reduced-order model has good bending deformation capabilities and computational simplicity. Therefore, at time t, the configuration of the soft manipulator is described by its state vector $\mathbf{x}(t)$, which contains the position and velocity information of each mode or segment.

In the nonlinear motion equations, the inertial force, damping force, and elastic force are all expressed using compact formulae.

$$\mathbf{M}(\mathbf{x})\ddot{\mathbf{x}} + \mathbf{C}(\mathbf{x},\dot{\mathbf{x}})\dot{\mathbf{x}} + \mathbf{K}(\mathbf{x})\mathbf{x} + \mathbf{f}_{\text{ext}}(\mathbf{x},t) = \mathbf{B}\mathbf{u} \qquad \text{Eq.(1)}$$

where $\mathbf{M}(\mathbf{x})$ is the configuration-dependent mass/inertia matrix, $\mathbf{C}(\mathbf{x},\dot{\mathbf{x}})$ accounts for Coriolis and damping phenomena, $\mathbf{K}(\mathbf{x})$ denotes stiffness contributions, $\mathbf{B}$ is the input distribution matrix, and $\mathbf{f}_{\text{ext}}$ represents external and gravity-related forces [24]. Actuation is typically achieved through applied pressures or tendon forces modeled as a function of internal control signals and manipulator geometry [25].

A typical configuration for a pneumatically actuated soft robot arm includes radially arranged chambers and quasi-continuum deformation, as schematically shown in Figure 1. Each chamber's inflation induces local bending, enabling programmable and highly versatile motion generation.

Sensor arrays embedded along the backbone yield real-time observations that facilitate closed-loop control.

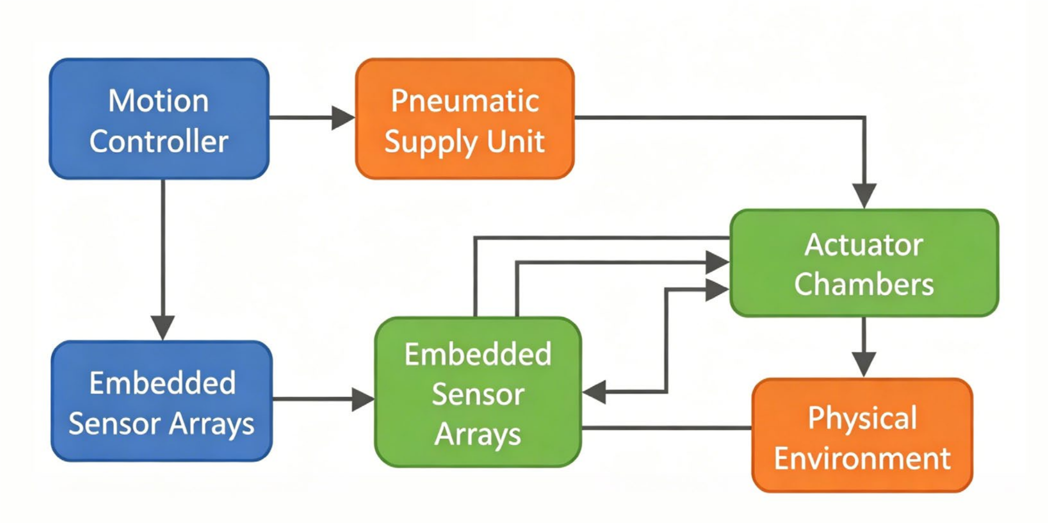

Figure 1. Schematic diagram illustrating a multi-chamber, pneumatically driven soft robotic arm with distributed embedded sensors and actuators

Uncertainty and Parameter Analysis

Soft robots are intrinsically prone to uncertainties, stemming from variable material properties, unmodeled nonlinearities, actuator hysteresis, and unpredictable environmental contacts. In system identification, such uncertainties are often aggregated into a bounded parameter vector $\boldsymbol{\theta}$, governing properties like modulus, viscosity, and input gain for each flexible element. To explicitly represent parameter effects, the dynamic equation's coefficient matrices are parameterized as functions $\mathbf{M}(\mathbf{x},\boldsymbol{\theta})$, $\mathbf{C}(\mathbf{x},\dot{\mathbf{x}},\boldsymbol{\theta})$, and $\mathbf{K}(\mathbf{x},\boldsymbol{\theta})$ [26].

A generalized uncertain model is thus written as

$$\mathbf{M}(\mathbf{x},\boldsymbol{\theta})\ddot{\mathbf{x}} + \mathbf{C}(\mathbf{x},\dot{\mathbf{x}},\boldsymbol{\theta})\dot{\mathbf{x}} + \mathbf{K}(\mathbf{x},\boldsymbol{\theta})\mathbf{x} = \mathbf{B}(\boldsymbol{\theta})\mathbf{u} + \mathbf{w}(t) \qquad \text{Eq.(2)}$$

where $\mathbf{w}(t)$ aggregates lumped disturbances, unmodeled dynamics, and sensor noise.

To estimate $\boldsymbol{\theta}$ online, a recursive parameter identification scheme is leveraged. For each time instant k, the estimation update is expressed as

$$\boldsymbol{\theta}_{k+1} = \boldsymbol{\theta}_k + \eta \mathbf{J}_k^{\top}(\mathbf{y}_k - \hat{\mathbf{y}}_k) \qquad \text{Eq.(3)}$$

where η is a learning rate, $\mathbf{J}_k$ is the Jacobian of the output with respect to $\boldsymbol{\theta}_k$, and $\mathbf{y}_k, \hat{\mathbf{y}}_k$ are the measured and predicted observations, respectively [27].

Parameter sensitivity, essential for robust controller tuning, is evaluated as

$$S_i = \left|\frac{\partial f(\mathbf{x},\boldsymbol{\theta})}{\partial \theta_i}\right| \qquad \text{Eq.(4)}$$

where $f(\mathbf{x},\boldsymbol{\theta})$ could denote the end-effector position or force output with respect to a particular parameter θ_i [28].

Problem Formulation

The first goal is to realize precise tracking of a given trajectory $\mathbf{x}_d(t)$ for the soft robotic arm; meanwhile, considering system nonlinearity, model uncertainty, etc., as well as physical constraints. The tracking error is defined by:

$$\mathbf{e}(t) = \mathbf{x}(t) - \mathbf{x}_d(t) \qquad \text{Eq.(5)}$$

Set the control target as a function of the penalties for both states' differences and controller input, possibly adding an additional regulariser that learns this parameter automatically:

$$J = \int_{t_0}^{t_f} \left[\mathbf{e}^\top(t)\mathbf{Q}\mathbf{e}(t) + \mathbf{u}^\top(t)\mathbf{R}\mathbf{u}(t) + \beta\|\dot{\boldsymbol{\theta}}(t)\|^2\right]\mathrm{d}t \qquad \text{Eq.(6)}$$

The system dynamics, parameterized by $\boldsymbol{\theta}$, act as equality constraints:

$$\mathbf{M}(\mathbf{x},\boldsymbol{\theta})\ddot{\mathbf{x}} + \mathbf{C}(\mathbf{x},\dot{\mathbf{x}},\boldsymbol{\theta})\dot{\mathbf{x}} + \mathbf{K}(\mathbf{x},\boldsymbol{\theta})\mathbf{x} = \mathbf{B}(\boldsymbol{\theta})\mathbf{u} + \mathbf{w}(t) \qquad \text{Eq.(7)}$$

Furthermore, input, state, and parameter bounds are strictly enforced for physical feasibility:

$$\mathbf{x}_{\min} \le \mathbf{x}(t) \le \mathbf{x}_{\max}, \mathbf{u}_{\min} \le \mathbf{u}(t) \le \mathbf{u}_{\max}, \boldsymbol{\theta}_{\min} \le \boldsymbol{\theta}(t) \le \boldsymbol{\theta}_{\max} \qquad \text{Eq.(8)}$$

Here is a unified expression that serves as the fundamental reference in developing and evaluating adaptive nonlinear predictive control methods used on soft robots.

Adaptive Nonlinear Model Predictive Control Design

Adaptive Parameter Estimation

In soft robotic systems, irregular environments, nonlinear materials, actuator lag, and drift caused by wear are all reasons that lead to system parameters deviating from their original nominal state. Traditional controllers, based on fixed parameter models, cannot guaranty accuracy over long-term operation and lose reliability when external conditions change suddenly. Therefore, to provide fast and accurate control for real-time controllers, a clear and rigorous adaptive parameter estimation system is needed.

The following information can be found from the discrete time step k output of a general nonlinear system:

$$\mathbf{y}_k = f(\mathbf{x}_k, \mathbf{u}_k, \boldsymbol{\theta}_k) + \mathbf{v}_k \qquad \text{Eq.(9)}$$

where $\mathbf{y}_k$ represents the measured output vector, $\mathbf{x}_k$ captures the system states, $\mathbf{u}_k$ is the current control input, $\boldsymbol{\theta}_k$ denotes the vector of model parameters to be identified online, and $\mathbf{v}_k$ is the sensor noise or residual disturbance.

Adaptive estimation is based on recursively updating parameters from the output to predict the output with minimal error. These closed-form updates include previous parameter estimates, an adaptive gain, and the gradient of the model output with respect to its parameters:

$$\boldsymbol{\theta}_{k+1} = \boldsymbol{\theta}_k + \gamma\mathbf{J}_k^\top(\mathbf{y}_k - \hat{\mathbf{y}}_k) \qquad \text{Eq.(10)}$$

Here, γ is a positive adaptation gain (typically determined by convergence-speed and noise sensitivity considerations), $\hat{\mathbf{y}}_k = f(\mathbf{x}_k, \mathbf{u}_k, \boldsymbol{\theta}_k)$ is the predicted model output, and $\mathbf{J}_k = \frac{\partial f}{\partial \boldsymbol{\theta}}\Big|_{\boldsymbol{\theta}_k}$ is the output Jacobian evaluated at the current estimate. This gradient-based method can quickly and data-drivenly optimize the mechanical parameterization of the system to eliminate the dynamic response, drift, or changing environment of uncertain systems.

To ensure physical feasibility and system safety, parameters are continuously updated within the feasible range each time:

$$\boldsymbol{\theta}_{k+1} = \mathrm{Proj}(\boldsymbol{\theta}_{k+1}, [\boldsymbol{\theta}_{\min}, \boldsymbol{\theta}_{\max}]) \qquad \text{Eq.(11)}$$

where $[\boldsymbol{\theta}_{\min}, \boldsymbol{\theta}_{\max}]$ are the predefined physically admissible bounds for each parameter based on material properties or hardware limitations. To ensure that the models' adaptation results are always physically and safely sound in predictions to enhance the credibility of online learning.

Nonlinear Predictive Model Formulation

Based on the real-time parameter adjustment, construct a forward-looking model in the controller and periodically update it based on the most recent estimation of the physical state parameters of the soft robot. The development process of the state vector in discrete-time is as follows.

$$\mathbf{x}_{k+i+1} = f_d(\mathbf{x}_{k+i}, \mathbf{u}_{k+i}, \boldsymbol{\theta}_{k+i}), i = 0{:}\, N_p - 1 \qquad \text{Eq.(12)}$$

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where the function $f_d(\cdot)$ represents a reliable discretization of the system's underlying nonlinear continuous dynamics, now parameterized by the adaptively updated estimate $\boldsymbol{\theta}_{k+i}$. Ensure that each predictive roll considers the latest information on actuator performance, structural compliance, and environmental impact to enhance the model's effectiveness in predicting robot paths. This is particularly important because when robot drift occurs, the robot's path may change due to incomplete modeling that does not take into account friction or load variations.

Set the performance objectives of the predictive controller as short-term costs, while imposing penalties on input magnitude and state tracking errors.

$$J = \sum_{i=0}^{N_p-1} \left[\|\mathbf{x}_{k+i} - \mathbf{x}_{\mathrm{ref}}\|_{\mathbf{Q}}^2 + \|\mathbf{u}_{k+i}\|_{\mathbf{R}}^2 \right] \quad \text{Eq.(13)}$$

Where $\mathbf{Q}$ and $\mathbf{R}$ are user-designed positive definite matrices, usually assigned high priority, and $\mathbf{x}_{\mathrm{ref}}$ is a possible non-stationary time-varying reference (e.g., the end posture or end effector position defined by the task), while $\mathbf{Q}$ and $\mathbf{R}$ are user-designed non-stationary time-varying references. This type of quarter is sufficient for the purpose of safe and efficient soft robot localization, as it strikes a reasonable balance between aggressive tracking and obstacle avoidance.

The cost structure of many tasks can be extended to support the objectives. These can include directly considering obstacle avoidance and workspace safety costs, or penalizing parameter changes by limiting the maximum curvature of the trunk to achieve smooth adaptation. However, under the uncertainty and variability of soft robotic systems, optimization relying on temporal evolution and memory of the environment forms the core of necessary predictive forms. This optimization is fundamentally more effective than static or gain scheduling methods.

Control Law Synthesis

At each control iteration, the NMPC algorithm is used to solve a constrained nonlinear optimisation problem to generate an optimal trajectory composed of continuous-time controls that minimise the predicted-cost subject to updated dynamic models and parameters:

$$\left\{\mathbf{u}_k^*, \dots, \mathbf{u}_{k+N_p-1}^*\right\} = \arg \min_{\{\mathbf{u}_k, \dots, \mathbf{u}_k, N_p-1\}} J \quad \text{Eq.(14)}$$

This optimisation considers the current measurement state, the latest adaptive estimated parameters, and includes an entire non-linear model of the soft robot to integrate operational limitations such as actuator boundaries, maximum input rate, workspace safety area constraints, physical restrictions related to a soft continuous mechanism, etc.

After each iteration, only the first computed control input $\mathbf{u}_k^*$ is added to the system, and then the new state is re-obtained. Reviewing the classic fallback horizon method, it adjusts during operation based on external disturbances or parameter changes. Use current data to solve optimization problems.

As shown in Figure 2, the closed-loop system includes online parameter estimation, nonlinear predictive optimization, adaptive model updating, and degraded feedforward constraint control. The diagram shows the real-time transmission paths of sensors, estimation, model adaptation, predictive planning constraints, and high-level actuator processing on soft robots.

Through very tight coupling, the controller can achieve stability in trajectory tracking performance and constraint compliance for systems with uncertain dynamic characteristics in various working environments. This means that the controller can operate normally in various environments. It can also be extended to more complex scenario application environments, such as fault diagnosis, soft constraints, and multi-objective planning.

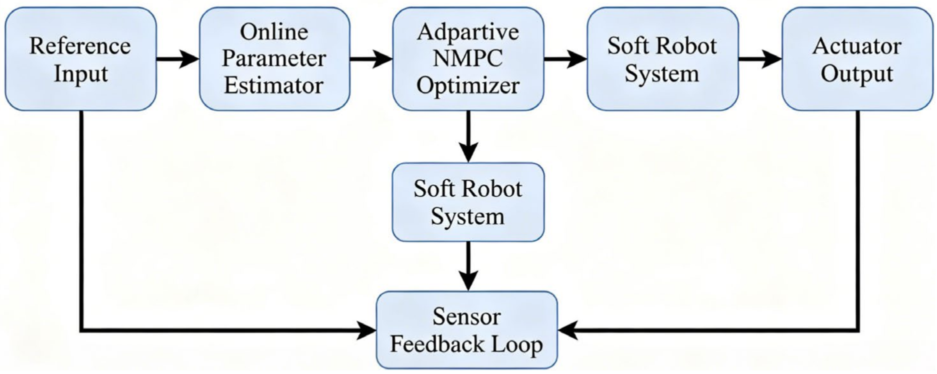

Figure 2. Block diagram of the adaptive NMPC algorithm framework for soft robotic motion control

Simulation and Experimental Results

Simulation Setup & Scenarios

Through a systematic and modular simulation platform, rigorously evaluate the performance of the designed adaptive nonlinear model predictive control (NMPC) scheme in soft robotic systems. Construct an extremely realistic digital twin environment, where all simulation parameter values are as close as possible to the actual system's parameter values, aiming to capture the main deformations associated with the pneumatic drive system. This selection consists of five flexible components, each approximately 40 millimeters long. At this stage, the material's Young's modulus should be approximately 850 kPa to exhibit its superelastic behavior, similar to the performance of the structure under changes in stress or pressure. The parameters of the pneumatic actuator are close to the calibration pressure range for its effective operation. Furthermore, due to their interconnection, a high-frequency range can be maintained in the hardware device for comparison, with the closed-loop frequency set at 100.

Three typical testing scenarios in a digital Environment have been set up to assess the reliability, versatility and ability of constraints by the designed controller. In the first scenario, all system parameters were set to their ground-truth physical values in an ideal mode that could be used to evaluate the baseline tracking accuracy, transient responses and steady-state convergence under several aggressive and time-varying reference trajectories, including sudden changes in setpoints and high-frequency sine wave excitation. The second Scenario Systematically studies the effect of parameter drifting, that is, whether there are continuous or sudden changes - a decrease as high as 20% in Young's Modulus at random times over the whole simulation period. This emulates a similar type of global phenomenon such as repeated use, unexpected overheating due to prolonged exposure; The age-related softening or deformation problem affecting mechanical properties over time. The third scenario introduced an external disturbance consisting of both deterministic step force excitation at the end-effector (up to 0.05N), as well as added Gaussian white noise with a standard deviation reaching 0.02N to evaluate the system's performance in resisting disturbances and its robustness under uncertain environment, sensor jitters, etc., un-modeled load impacts.

In order to make the comparisons clear, three different control systems were built and tested at the same time in various Conditions: Firstly, an enhanced adaptive NMPC system with online-parameter updating function; Secondly, A traditional nonlinear MPC without feedback gain tuning mechanism; Thirdly, Multiple Proportional-Integral-Derivatives (PID) Controllers operating together to optimize trajectories when inputs vary greatly. In each controller, there is a problem such as frequency-changing sinusoid up to 1HZ, a random multi-set points sequence with abrupt changes in direction; Focuses on this question's applicability, control law smoothness, constraint achievement degree and calculation speed. Underlying the simulation system built with Python and used CasADi's symbolic optimisation library to support rapid prototyping, high-precision model of system dynamics and seamless integration with subsequent hardware-in-the-loop verification steps directly. An all-in-one simulated system served as both an intense engineering test bed and the backing for transferring experiments.

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Experimental Platform and Implementation

Through experimental validation, the adaptive NMPC control strategy has indeed achieved good practical results to some extent in the physical soft robot system. Therefore, in order to use digital twins for simulation research in experiments, a custom multi-segment pneumatic soft robotic hand was designed. The soft arm is manufactured using platinum-cured silicone rubber Through mold casting to accurately simulate the geometry, compliance, and deformation paths of the five actuator chambers. Based on a digital proportional pneumatic valve with an accuracy of no less than 1 kPa, this valve responds quickly and directly transmits the current output value of the controller.

In order to collect local curvature and deformation data in real-time, a flexible strain sensor array is distributed across each part of the robotic arm. At the same time, the OptiTrack motion capture system precisely locates all components around the world with millimeter-level positioning accuracy. During detection, all sensor output signals are synchronized with a custom timestamp system. This is done to prevent low temporal jitter in data integration during high-speed operation.

The control and estimation routines are implemented in a bilingual system: an efficient estimator that can automatically adjust parameters, a fast prediction optimization algorithm running in C++, and a user interface and log processing module written in Python. The entire control software runs on an edge computing device. The edge computing device is equipped with an Arm-based low-power processor and an integrated FPGA acceleration board to ensure stable closed-loop performance at 100 Hz. The precompiled CasADi optimization routines significantly accelerate the NMPC solution time and real-time parameter updates. The average computation time for offline analysis is 6.2 milliseconds per cycle, with a recorded maximum delay of 10 milliseconds; therefore, it provides sufficient real-time performance margin.

For comparison, the experimental test program is designed to directly replicate the simulation environment. To ensure the reproducibility of the results, the trajectory tracking experiments need to be conducted at least five times under statistical rigor, including randomization of target sequences, smoothing, and mutation setting points. Disturbance suppression can be tested by randomly calibrating a weight of 10 to 20 grams at the end segment of the actuator. Then, combine it with repeated artificial environmental changes under uncontrolled conditions. Due to the presence of local heat sources, artificial parameter drift occurred in certain arm sections, resulting in a reduction of segment stiffness by approximately 20%. This had an impact on parameter estimation for a period during the early training phase. Due to rigorous testing, various parts of the pneumatic system are equipped with safety interlocks and actuator limiters to prevent overpressure incidents and mechanical failures. Detailed logs record real-time data of sensor readings, actuator statuses, and estimated results. Then, Through rigorous analysis, verify whether these results can be consistently replicated based on the following quantitative evidence.

Results and Analysis

Figure 3-7 shows five sets of quantitative validation results, including a performance summary of the adaptive NMPC strategy; each panel also presents a direct simulation-experiment comparison and ablation study with the benchmark model.

Trajectory errors are shown in Figure 3. In experiments and simulations, the adaptive NMPC achieved high-order tracking performance under the influence of sudden reference changes or step variations. In this study, this strategy is consistently more effective than traditional NMPC and PID, and the root mean square tracking error is minimized under all conditions. Under conditions where environmental parameters change more frequently or disturbance identification is less regular, detailed charts of tip position and time response tracking errors;

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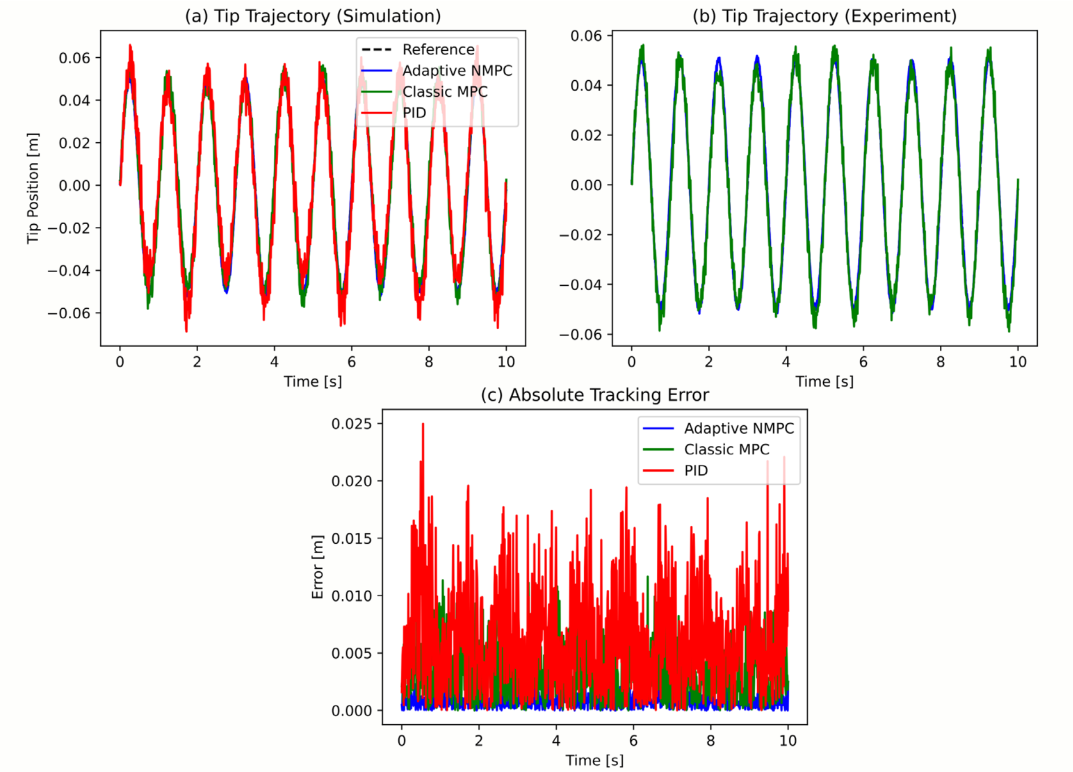

Figure 3. Trajectory tracking performance: (a) Simulation results, tip path against reference; (b) Experimental tracked tip trajectory; (c) Time series of absolute tip error for all control strategies

As shown in Figure 4, these key models underwent sudden changes. By inducing heating or changing parameters, the adaptive NMPC introduces system stiffness and damping characteristics, and then quickly and accurately adjusts the internal estimated state. Due to its rapid modulation effect, no significant errors occurred during this process.

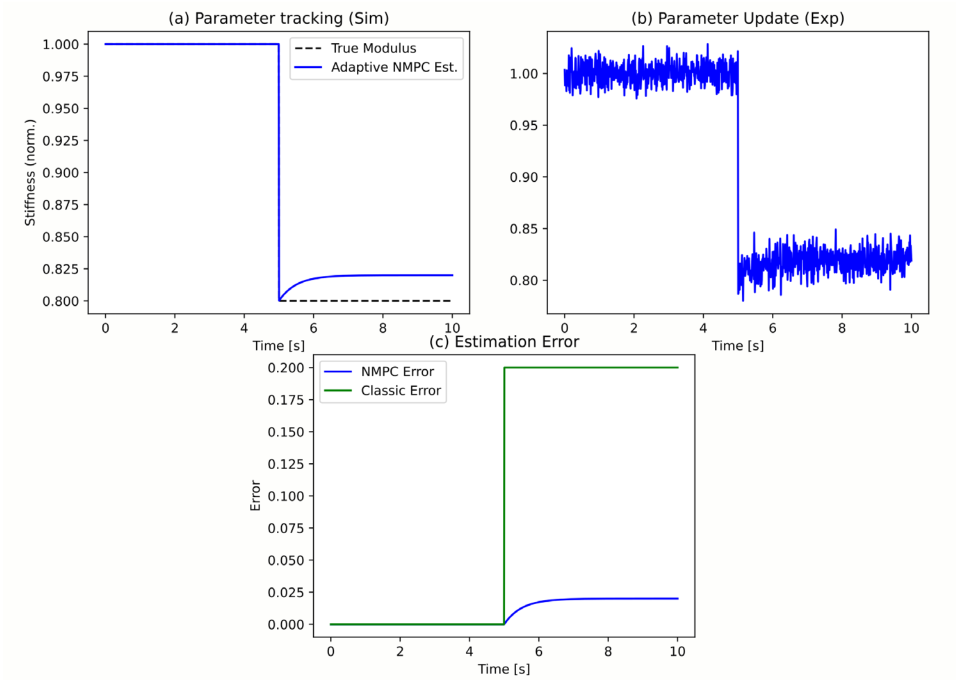

Figure 4. Adaptive parameter identification: (a) Simulation, step change in modulus; (b) Experimental segment-wise parameter adaptation; (c) Error metric between identified and true dynamic parameters

Figure 5 shows the impact of external disturbances. Adaptive NMPC quickly and stably suppresses disturbances in two aspects, while also exhibiting smaller overshoot and rapid setpoint recovery. Compared to traditional MPC or PID, there are significant improvements in step load and continuous random noise. Quantitative indicators show a smaller disturbance range and a higher degree of recovery.

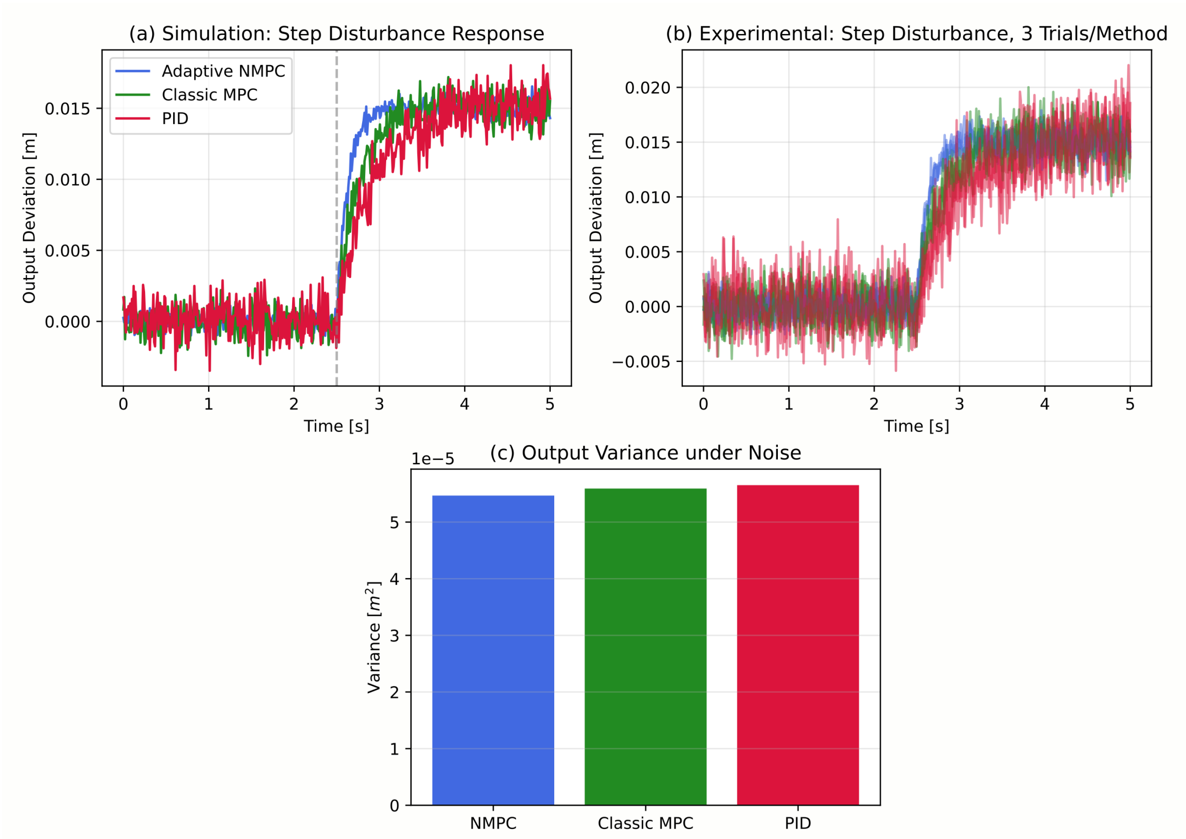

Figure 5. Disturbance robustness: (a) Simulation, step disturbance input; (b) Experimental disturbance and response; (c) Noise robustness, output variance under perturbation

Figure 6 highlights execution smoothness and constraint compliance. Adaptive control can reduce the proportion and duration of constraint saturation, allowing the input signal to be free from the limitations of actuators and safety mechanisms. To avoid mechanical fatigue of soft materials, the transitional dynamic performance is more continuous and gradual. Two sets of simulation and actual results confirm this.

Figure 7 summarizes the real-time feasibility and overhead calculations. All key control optimization functions run seamlessly within 10 milliseconds per cycle; thereafter, they continue to operate at a stable frequency of 100 Hz. The table below shows that the system continuously uses resources in each test; this situation is suitable for the hardware.

The satisfactory match between the measured data and the simulated data indicates that the physical model has sufficient accuracy to demonstrate the effectiveness of the adaptive strategy. Inevitable factors such as sensor quantization and valve delays may cause minor errors, but these errors do not affect the overall stability and accuracy of the system.

According to the data chart in Figure 3-7, adaptive NMPC has a significant advantage over traditional methods in all the aforementioned scenarios. Adaptive control can effectively reduce energy consumption and ensure high-performance stability of system operation. It can quickly track unstable values and maintain them constant over a period of time.

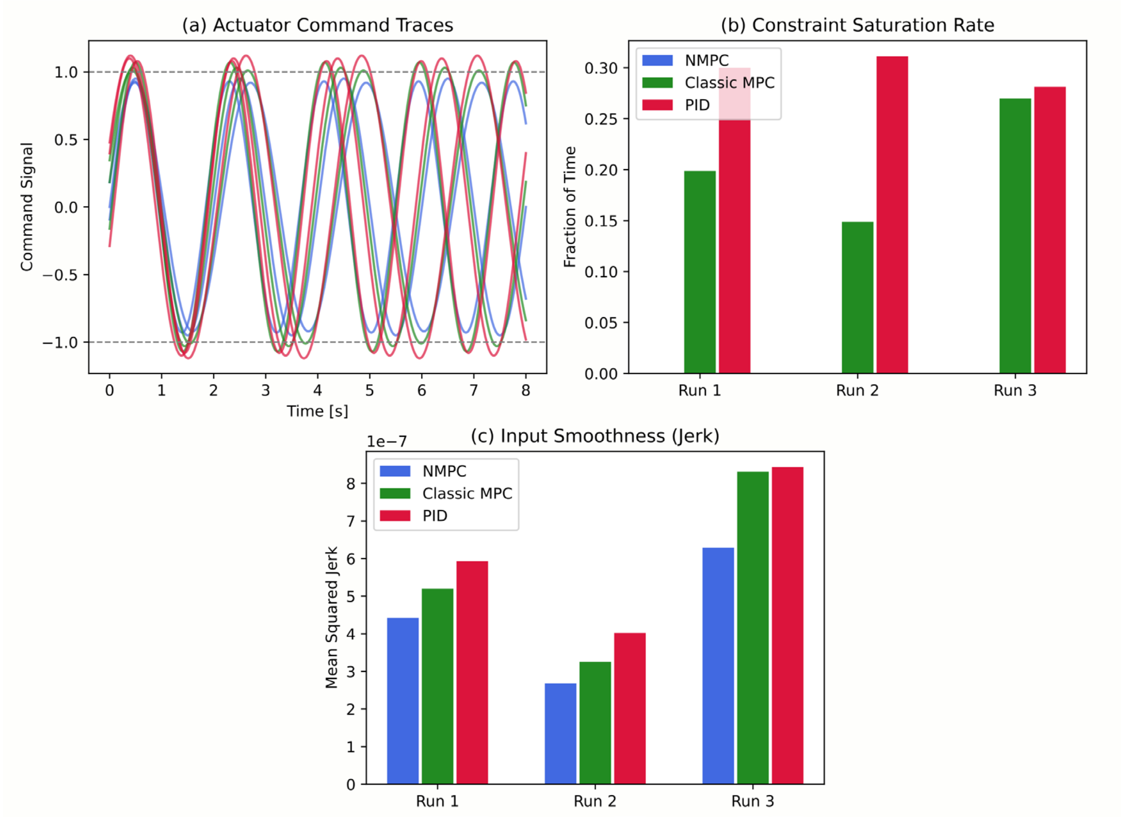

Figure 6. Control and constraint activity: (a) Actuator command trajectories; (b) Constraint activation frequency; (c) Measure of input smoothness

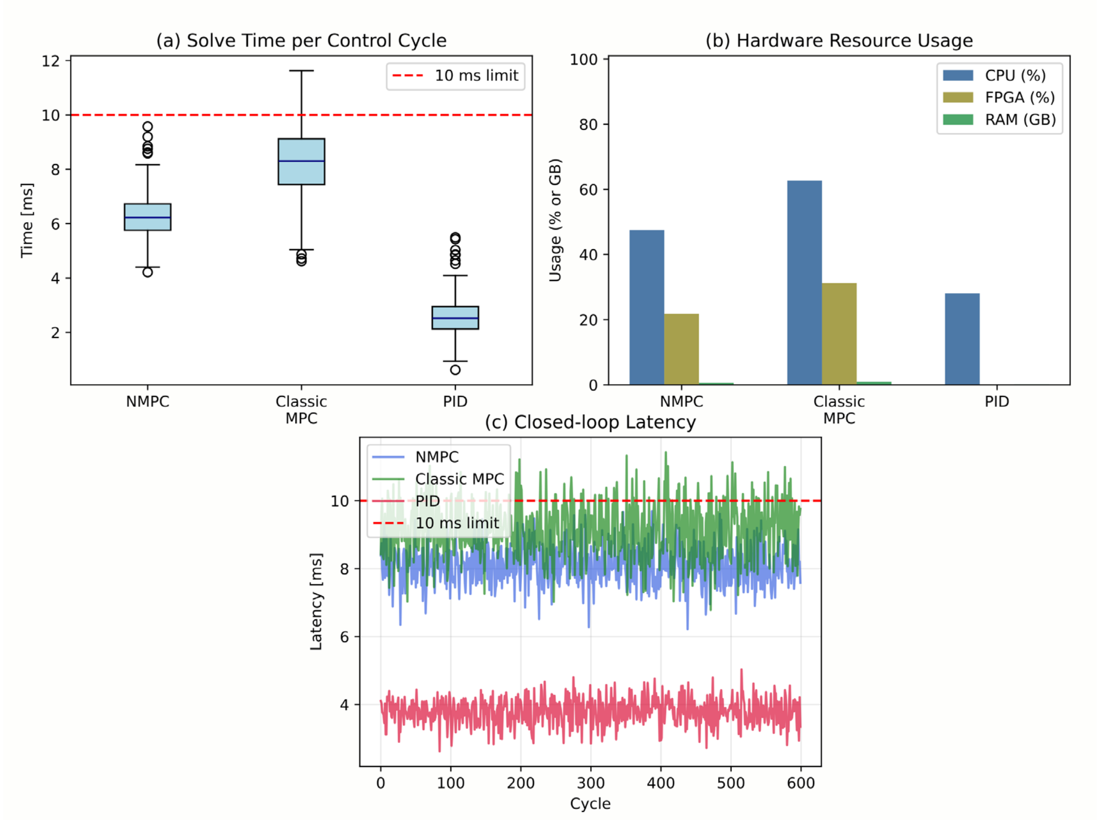

Figure 7. Real-time computation: (a) Average solve time per MPC cycle; (b) Platform resource usage; (c) Closed-loop latency distribution

Conclusion

This paper proposes a comprehensive structure for adaptive nonlinear model predictive control of soft robotic manipulators. Addressing the issue of uncertain systems in soft robot dynamics, real-time response to changes in system conditions is achieved by combining online parameter estimation with an integrated control scheme. Using a close match between digital and physical twins to achieve the physical significance and quantitative effectiveness of multi-segment soft arm systems. A more reasonable approach to improve the regulatory compliance of highly rigid, nonlinear robotic systems; it lays the theoretical foundation for the safe and precise control of soft robots.

The proposed adaptive NMPC achieved consistently good trajectory tracking performance Through rigorous hardware simulations and testing. It performs well under various conditions, such as normal use, gradual parameter drift, and severe external disturbances. Compared to traditional NMPC/PID regulators, this controller excels in online response capability to sudden disturbances in system parameters. At the same time, it still maintains good tracking performance and stability characteristics. In multiple test cycles, stability constraints were identified, with the results showing improved disturbance suppression and smoother control inputs. In addition, it has been demonstrated that the system possesses robust real-time performance in handling computational demands and can process quickly within the constraints of current embedded devices. It can be concluded that this solution is highly feasible, as the simulation results fit almost 1:1 with the experimental data.

This study is expected to generate many future research areas and applications. First, the combination of improved learning-based models with adaptive NMPC may enhance performance and generalization capabilities under non-stationary conditions. Secondly, extending this method to handle more complex branched or high-degree-of-freedom soft morphing systems, such as wearable robots and bionic robots. Finally, it can be concluded that after deploying the aforementioned systems in fields such as medical rescue, industrial production automation, and intelligent services, autonomous or collaborative robotic systems will become more common. These opportunities are considered important enabling technologies for the next generation of intelligent soft robots based on adaptive NMPc.

Author Contributions

Andrzej Zielinski and Dorota Urban contribute to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition. All authors have read and agreed with the manuscript before its submission and publication.

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Institutional Review Board Statement

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