IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received November 15, 2020, accepted November 26, 2020, date of publication December 1, 2020, date of current version December 10, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3041616

Nonlinear Model Predictive Growth Control of a Class of Plant-Inspired Soft Growing Robots

HAITHAM EL-HUSSIENY[1,4], IBRAHIM A. HAMEED[2], (Senior Member, IEEE), AND JEE-HWAN RYU[3], (Senior Member, IEEE)

[1]School of Science, Engineering, and Environment, University of Salford, Salford M5 4WT, U.K.
[2]Department of ICT and Natural Sciences, Norwegian University of Science and Technology, 6009 Ålesund, Norway
[3]Department of Civil and Environmental Engineering, Korea Advanced Institute of Science and Technology, Daejeon 34141, South Korea
[4](*On leave*) Department of Electrical Engineering, Faculty of Engineering (Shoubra), Benha University, Cairo 11239, Egypt

Corresponding authors: Haitham El-Hussieny (haitham.elhussieny@feng.bu.edu.eg) and Ibrahim A. Hameed (ibib@ntnu.no)

ABSTRACT Recently, researchers have shown an increased interest in considering plants as a model of inspiration for designing new robot locomotions. Growing robots, that imitate the biological growth presented by plants, have proved irresistible in unpredictable and distal environments due to their morphological adaptation and tip-extension capabilities. However, as a result of the irreversible growing process exhibited by growing robots, classical control schemes could fail in obtaining feasible solutions that respect the permanent growth constraint. Thus, in this article, a Nonlinear Model Predictive Control (NMPC) scheme is proposed to guarantee the robot's performance towards point stabilization while respecting the constraints imposed by the growing process and the control limits. The proposed NMPC-based growth control has applied to the kinematic model of the recently proposed plant-inspired robots in the literature, namely, vine-like growing robots. Numerical simulations have been performed to show the effectiveness of the proposed NMPC-based growth control in terms of point stabilization, disturbance rejection, and obstacle avoidance and encouraging results were obtained. Finally, the robustness of the proposed NMPC-based growth control is analyzed against various input disturbances using Monte-Carlo simulations that could guide the tuning process of the NMPC.

INDEX TERMS Growing robots, obstacle avoidance, model predictive control, soft robots.

I. INTRODUCTION

Motivated by the morphological adaptation capacity shown by snakes, elephant trunks, and octopus tentacles, soft continuum robots have demonstrated the potential to facilitate manoeuvring in tight and restricted environments [27]. As compared to rigid robots, continuum robots have curvilinear structures with regularly bending backbones that make them extremely versatile to the surroundings [22], [29]. However, continuum robots are commonly designed to have small lengths that restrain their applicability in the navigation of distant environments [16].

Investigating the growing process exhibited by plants, new mobility by growth approach has been recently proposed to come up with growing robots. These kinds of robots emulate biological growth by incrementally expanding either their lengths, volumes, or knowledge [5]. Soft growing robots can reach narrow spaces searching for victims or can serve as channels to transfer air or water for them in emergency scenarios [25]. Earlier studies have reported the realization of long flexible robots in congested environments. For instance, Tsukagoshi *et al.* [25] have proposed multiple degrees of freedom growing robot, called "Active Hose," that used for rescue and searching scenarios. This robot has designed to be flexible with the capability of expanding its length by connecting small flexible units of two degrees of freedom in series. A flexible long cable with a ciliary vibration mechanism has developed by Isaki *et al.* [14] to achieve navigation in narrow spaces. Expandable soft robots have also been proposed, such as "Slime Scope" [19] that was a pneumatically driven expendable arm with a camera attached to its tip used for search and rescue people in the rubble environments. Tsukagoshi *et al.* [24] have developed a flexible hose-like robot that was able to steer in narrow environments by manual control.

Lately, vine-like growing robots, which mimic the growing process displayed by plants, have proved magnificent performance towards undertaking investigation and rescue

The associate editor coordinating the review of this manuscript and approving it for publication was Zheng H. Zhu.

missions [21], [28]. Hawkes *et al.* [13] have developed a novel growing robot using the concept of tip eversion mechanism [2]. These vine-like robots made of thin-walled polyethene tubing that can expand up to several tens of meters while navigating challenging environments either through teleoperation [8] or guided by obstacles [9], [10]. A steerable vine robot version is developed by Greer *et al.* [11] by inflating multiple series of pneumatic artificial muscles placed around the robot's spine. The increased length-to-diameter ratios, the lengthening capability, and the flexible structures allow vine-like robots to penetrate cluttered environments as evaluated in [4].

Although the potential of vine growing robots in unstructured and congested environments, there is still a notable paucity towards feedback controlling their growth in spatial environments. This in particular is due to the challenges that exist in vine robots in terms of their coupled dynamics and the lack of practically deploying sensors on their lengthy bodies. In general, controlling soft continuum robots in joint and task spaces has been addressed in the literature. For instance, dynamic control of planar multi-link soft continuum robot is proposed in [6] considering interaction with the environment. The curvature of each segment is selected as the controlling variables for the robot to achieve the target while assuming the robot's length is assumed to be inextensible. Seleem *et al.* [23] have developed a computed torque control based on the derived dynamics for multi-section spatial continuum robot. The physical constraints of sections' lengths have been considered in the control loop as saturation blocks, which potentially could lead to non-linearity and under-utilization of the control scheme.

There have been many attempts towards controlling the growth of vine-robots, either in the joint or in the task space. For instance, in [21] a stimulus oriented control that imitates the plant root behaviour is employed to control the movement of the root-like plant-inspired robots based on the tactile information received from the sensor embedded on the robot's root.Due to the relatively slow-growing process reported in root-like robots, considering irreversible constraints is not crucial in the control process. An optimal control problem is formulated in [20] to control the tip of a plant-inspired root to minimize the energy spent by the root while penetrating the soil environment.The proposed control approach assumed planar robot's dynamics where the robot's length and curvature are the controlling variables. In [7], a Proportional-Derivative (PD) controller with gravity compensation is presented to the derived dynamics model of vine robots to ensure the performance in terms of trajectory following in the robot's joint space. Although the success of these attempts of conventional control schemes, handling the irreversible growing process exhibited by growing vine-robots by such schemes could be challenging since once the robot has grown to a certain length, it can not be retracted back to lower length values.

In this article, inspired by the significant improvement achieved by applying Model Predictive Control (MPC) [3] in controlling of planar redundant manipulators [26], we developed a Nonlinear MPC scheme to control the growth of vine-like growing robots in task-space. Meanwhile, considering the irreversible growing process and the actuator limits in the control loop. MPC is a class of optimal control that has long been used for large multiple-input, multiple-output control problems in the control of the chemical processes. The key idea is that we minimize an objective function over a finite time prediction horizon subject to the dynamics of our robot model represented as an equality constraint [17]. Meanwhile, other constraints such as the irreversible growing process and the limits of the actuator of vine robots could be described as inequality constraints during the prediction horizon as well. Hence, an optimization problem is solved at each time step to find the optimal control sequence suitable for deriving the robot model to the required position in spatial space while considering the system's constraints. Since this optimization problem is solved at each time step before applying any control inputs to the process, MPC-based control schemes has the potential to succeed in controlling growing robots compared to other conventional control approach mentioned in the literature.

The key challenge of applying the MPC control scheme in growing robots is the coupled nonlinear dynamics that complex the prediction model that should be incorporated in the control scheme. The nonlinear MPC control approach has been proposed in hydraulic systems as in [12] with nonlinear dynamics have been incorporated in the prediction model. Although dynamics model implies a better representation of the real system, it requires high computations. Thus, in this article, the contributions consist of the following aspects. (1) Application of NMPC-based growth control in plant-inspired vine growing robots to control its spatial movements in task-space considering the irreversible constraints exhibited by the robot's growing process. (2) Incorporation of the robot's kinematics model as the NMPC prediction model to reduce the required computational cost while achieving significant performance assuming the relatively slow movements of vine-robots while navigating the working environment. (3) Proposing a Monte-Carlo simulation-based approach to guarantee the robustness of the proposed NMPC while guiding the process of parameter tuning.

After introducing the kinematic model of growing robots in Section II, the proposed Nonlinear Model Predictive Control (NMPC) for growth control of vine robots is discussed in Section III: first, the robot model is introduced; then, the objective function and the controller design are summarized. After simulation validations of the proposed NMPC-based growth control in Section IV, a final conclusion is drawn in Section V.

II. KINEMATICS MODEL OF VINE ROBOT

In this research, the "vine robot" developed in [4] is under discussion, where this kind of robots can elongate their tips up to tens of meters via eversion mechanism [11]. Air pressure is applied to its core tube as depicted in Figure 1 to facilitate tip

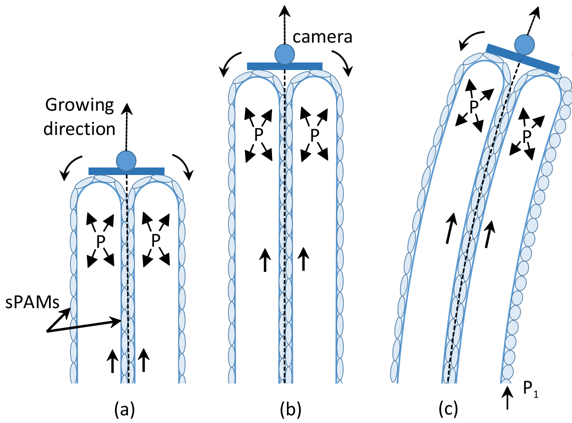

FIGURE 1. Working principal of the growing vine robot.

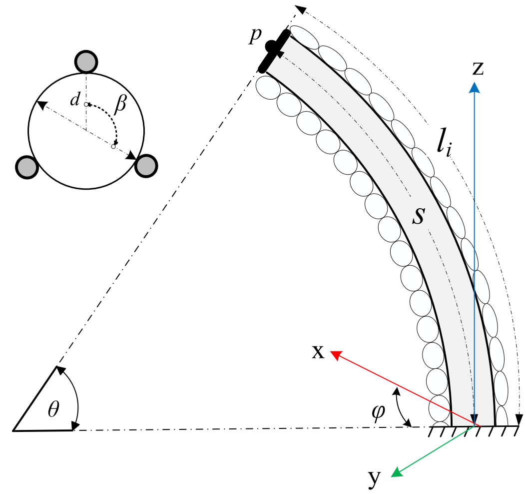

FIGURE 2. Schematic of vine growing robot with its configuration parameters.

extension, while steering is achieved by applying air pressure through one or two of the serial Pneumatic Actuator Muscles (sPAM) that are placed around the robot circumference. A camera or other sensing device could be added to its tip to facilitate the navigation capability of the robot.

A. DIRECT KINEMATICS

The constant-curvature model [15] that is commonly applied in modeling continuum-like robots is assumed here to find the forward kinematics of the vine growing robot. The distal tip pose $\mathbf{T}_r^b$ with respect to its base is derived in terms of the robot configuration parameters $\boldsymbol{q} \in IR^3$ including its length s, the bending angle θ and the plane angle ϕ as shown in Figure 2. Thus, $\mathbf{T}_r^b$ is obtained as

$$\mathbf{T}_r^b = \begin{bmatrix} \cos^2\phi(\cos\theta - 1) + 1 & \sin\phi\cos\phi(\cos\theta - 1) & -\cos\phi\sin\theta & \frac{s\cos\phi(\cos\theta-1)}{\theta} \\ \sin\phi\cos\phi(\cos\theta - 1) & \cos^2\phi(1-\cos\theta) + \cos\theta & -\sin\phi\sin\theta & \frac{s\sin\phi(\cos\theta-1)}{\theta} \\ \cos\phi\sin\theta & \sin\phi\sin\theta & \cos\theta & \frac{s\sin\theta}{\theta} \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{1}$$

The robot tip position $\boldsymbol{p} = [x, y, z]^T \in \mathbb{R}^3$ in Cartesian space could be extracted from Eq. (1) as,

$$\begin{aligned} x &= \frac{s\cos\phi(\cos\theta - 1)}{\theta}, \\ y &= \frac{s\sin\phi(\cos\theta - 1)}{\theta}, \\ z &= \frac{s\sin\theta}{\theta} \end{aligned} \tag{2}$$

Although the actual actuation space of the vine-robot is the sPAMs lengths $\boldsymbol{l} = [s, l_1, l_2, l_3]$, using the shape space generalizes the control problem to suit any kind of continuum-like robots with constant curvature model.

B. DIFFERENTIAL KINEMATICS

The growing robot tip velocity, $\dot{\boldsymbol{p}} \in \mathbf{R}^3$, is related to the time derivatives of the robot configuration parameters $\dot{\boldsymbol{q}}$ as follows,

$$\dot{\boldsymbol{p}} = \boldsymbol{J}(\boldsymbol{q})\,\dot{\boldsymbol{q}} \tag{3}$$

where the Jacobian matrix, $\boldsymbol{J}(\boldsymbol{q}) \in \mathbf{R}^{3\times 3}$, is computed analytically as follows,

$$\boldsymbol{J}_q(\boldsymbol{q}) = \frac{\partial \boldsymbol{p}}{\partial \boldsymbol{q}} = \frac{\partial \boldsymbol{p}}{\partial(s, \kappa, \phi)} \tag{4}$$

where $\boldsymbol{p}$ is the robot tip Cartesian position mentioned in Eq. (2).

III. NONLINEAR MODEL PREDICTIVE GROWTH CONTROL

In this section, we present the NMPC-based growth control scheme proposed to control in closed-loop the growth of the vine robot. The NMPC aims to consider the irreversible growth constraint and the input constraints exhibited by vine robots while achieving the control objectives: point stabilization, obstacle avoidance, and trajectory tracking in task-space that will be discussed.

A. MODEL DESCRIPTION

To involve the irreversible growth constraint exhibited by vine robots, the state $\boldsymbol{x} = [\boldsymbol{p} \quad \boldsymbol{q}]^T \in \mathbb{R}^6$ has been selected to combine both the robot tip position $\boldsymbol{p}$ in Cartesian space and its joint variables $\boldsymbol{q}$. Hence, the non-linear model representing the movement kinematics of vine robots is described as

$$\dot{\boldsymbol{x}} = \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \\ \dot{s} \\ \dot{\theta} \\ \dot{\phi} \end{bmatrix} = f(\boldsymbol{x}, \boldsymbol{u}) = \begin{bmatrix} \boldsymbol{J}(\boldsymbol{q}) \\ \boldsymbol{I}_3 \end{bmatrix} \boldsymbol{u} \tag{5}$$

where $\boldsymbol{J}(\boldsymbol{q}) \in \mathbb{R}^{3\times 3}$ is the robot Jacobian obtained in Eq. (3) while $\boldsymbol{u} = \dot{\boldsymbol{q}} \in \mathbb{R}^3$ is the velocity in the robot's configuration space representing the manipulated variables. The vine robot state $\boldsymbol{x}$ is the controlled variable and is assumed to be fully observable. Although the full observability assumption could be challenging in real applications of vine robots, this step aims to prove the applicability of MPC in controlling the growth of such robots. In future work, state estimation could be incorporated to relax this assumption. The irreversible growing process shown by vine robots is represented as an inequality constraint imposed on its growing velocity and its length, i.e.,

$$\begin{bmatrix} 0 \\ 0 \end{bmatrix} \leq \begin{bmatrix} \dot{s}(t) \\ s(t) \end{bmatrix} \leq \begin{bmatrix} \dot{s}_{max} \\ s_{max} \end{bmatrix}, \quad \forall t \geq 0 \tag{6}$$

B. CONTROL OBJECTIVE

The key aim of the proposed MPC-based growth control is to guarantee the growing robot stabilization performance over a desired reference state $\boldsymbol{x}_r = [x_r, y_r, z_r, s_r, \theta_r, \phi_r]^T$ defined in task and joint space. The controller should also consider the constraint imposed physically by the irreversible robot's growth while searching for optimal control actions. Thus, the cost function J is chosen in such a way to evaluate the tracking performance and the control action over a prediction horizon N as follows

$$J(k) = \sum_{j=1}^{N} \boldsymbol{e}^T_{(k+j)} \boldsymbol{Q} \, \boldsymbol{e}_{(k+j)} + \sum_{j=1}^{N} \Delta \boldsymbol{u}^T_{(k+j-1)} \boldsymbol{R} \, \Delta \boldsymbol{u}_{(k+j-1)} \tag{7}$$

where $\boldsymbol{e} = \boldsymbol{x} - \boldsymbol{x}_r$ denotes the tracking error, while $\Delta \boldsymbol{u}$ indicates the predicted control increment. The matrices $\boldsymbol{Q} \geq 0$ and $\boldsymbol{R} \geq 0$ are the weighting matrices that are assumed to be constant over the prediction horizon N.

C. CONTROLLER DESIGN

The MPC strategy that is proposed to control the growth of vine-robots is shown in Figure 3. The manipulated variables ($\boldsymbol{u} = \dot{\boldsymbol{q}}$) is the velocity in configuration space that used to either elongate or steer the vine robot. The aim is to bring the robot state $\boldsymbol{x}(t)$ to the reference input $\boldsymbol{x}_r$ in the case of point stabilization and the reference trajectory $\boldsymbol{x}_r(t)$ in the case of trajectory tracking for all instance t. Meanwhile, the growth and the control input constraints mentioned earlier have to be considered.

In conventional MPC, a discrete-time linear model of the plant under control is usually employed as the prediction model. However, as depicted from Eq. (5), the kinematic model of vine robots is nonlinear and continuous since it depends on the robot's configuration $\boldsymbol{q}$. Thus, in the proposed NMPC-based growth control, the prediction model is a discrete version of the robot's kinematics model that is obtained using Euler discretization at each sample k along the predication horizon,

$$\boldsymbol{x}(k+1) = \boldsymbol{x}(k) + \Delta T \begin{bmatrix} \boldsymbol{J}(\boldsymbol{q}(k)) \\ \boldsymbol{I}_3 \end{bmatrix} \boldsymbol{u}(k) \tag{8}$$

where ΔT denotes the sampling time. Thus, by using this prediction model, the NMPC predicts the robot's state $\boldsymbol{x}_p$ along the prediction horizon while applying all admissible control inputs $\bar{\boldsymbol{u}}$ as highlighted in Figure 3.

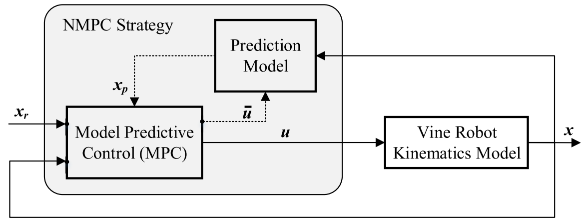

FIGURE 3. Block diagram of the proposed Model-predictive control (MPC) strategy used to control the growth of the vine robot.

IV. RESULTS AND DISCUSSION

In this section, we present simulation experiments conducted to evaluate the proposed NMPC-based growth controller while considering the locomotion and input constraints of vine-like robots. The NMPC-based growth controller is built using CasADi framework [1]. The MATLAB/SIMULINK is used with *ode45* solver to simulate the vine robot model in (1) with the proposed NMPC-based growth control. First, we explain the experiment scenarios that are accompanied by the experimental results that confirm the capabilities of the proposed NMPC scheme.

A. POINT STABILIZATION RESULTS

As mentioned earlier, one of the applications of vine-like robots is to serve as a conduit to deliver essentials to people in disaster scenarios. Thus, in the first simulation experiment, starting from an initial state $\boldsymbol{x}_0 = [0, 0, 0.4, 0.4, 0, 0]^T$, the proposed NMPC-based growth controller is utilized to stabilize the tip of the vine-like robot within a set of predefined goal states in the space, $\boldsymbol{x}_d \in \mathbb{R}^6$. These states could represent potential locations for the robot to visit with the environment. The sampling time has chosen to be $T_s = 0.1\ s$ with a prediction horizon $N = 10$. The state and the input weighting matrices in (7) are chosen to be diagonal, where $\boldsymbol{Q} = \text{diag}(1, 1, 1, 0, 0, 0)$ while $\boldsymbol{R} = \text{diag}(0.5, 0.5, 0.5)$.

The first three elements in the robot's state are constrained between $[-4, 4]$ defining the reachable space in the environment, while the other remaining three-state elements are constrained according to the robot's configuration limits highlighted earlier in the kinematics section.

$$-4 \leq \begin{bmatrix} x(m) \\ y(m) \\ z(m) \end{bmatrix} \leq 4, \quad \begin{bmatrix} 0 \\ -\pi \\ -\pi \end{bmatrix} \leq \begin{bmatrix} s(m) \\ \theta(rad) \\ \phi(rad) \end{bmatrix} \leq \begin{bmatrix} 10 \\ \pi \\ \pi \end{bmatrix} \tag{9}$$

On the other side, the input inequality constraints that respect the irreversible nature of the growing vine-like robot and the actuator limits are chosen as follows

$$\begin{bmatrix} 0 \\ -\frac{\pi}{10} \\ -\frac{\pi}{10} \end{bmatrix} \leq \begin{bmatrix} \dot{s}(m/s) \\ \dot{\theta}(rad/s) \\ \dot{\phi}(rad/s) \end{bmatrix} \leq \begin{bmatrix} 0.1 \\ \frac{\pi}{10} \\ \frac{\pi}{10} \end{bmatrix} \tag{10}$$

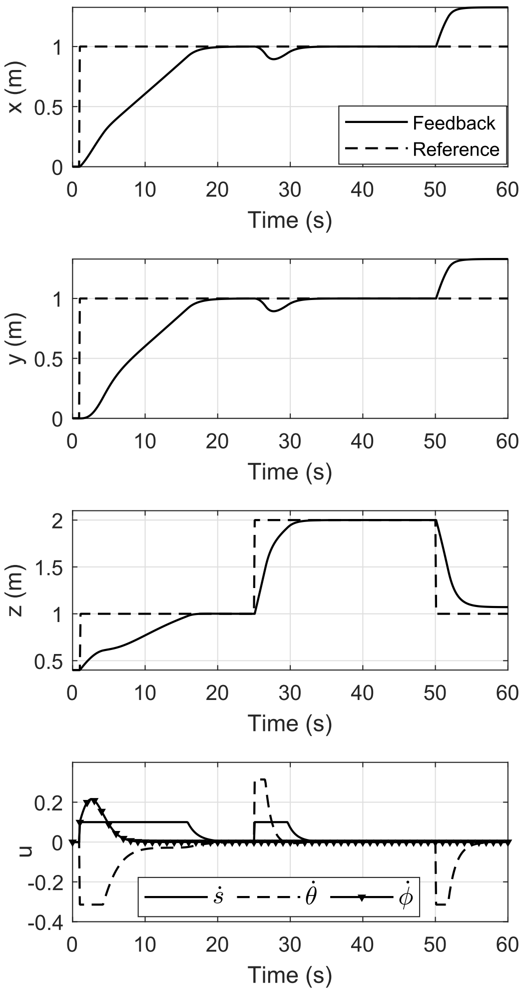

FIGURE 4. Results of point stabilization simulation scenarios to evaluate the the proposed NMPC-based growth control.

Figure 4 highlights the tracking performance of the proposed NMPC-based growth controller during the point stabilization scenario. During the first 25 seconds, the controller stabilizes the robot's tip at (1, 1, 1) meters from its base. Satisfactory results in terms of rising time (20 s) are obtained to reach the goal with the shown actuated inputs. The z position of the goal is doubled during the second 25 seconds. This requires the robot to increase its length of s. According to the vine robots kinematics, increasing the robot length to reach a new z position would affect the other two coordinates. That's why while achieving this new goal, both x and y position have been slightly affected as illustrated in Figure 4. To tackle this issue and bring the robot's tip back, the NMPC has actuated the curvature angle θ in the positive direction while simultaneously increasing the robot length s. After a while, only the robot length is increased to compensate for the changed x and y positions. Finally, after 50 seconds of the simulation time, the robot is required to reach a new z goal that is lower than the previous one. This requires the robot to shrink its length. However, due to the irreversible growing process, the robot is constrained having no ability to shrink its grown length. Thus, the NMPC decreased the robot curvature hoping to reach the new desired goal. Although that helped in obtaining a reasonable error in the z coordinate, the other two coordinates have been significantly affected. In all stages, the NMPC satisfies the state and input saturation constraints of the vine-like robot.

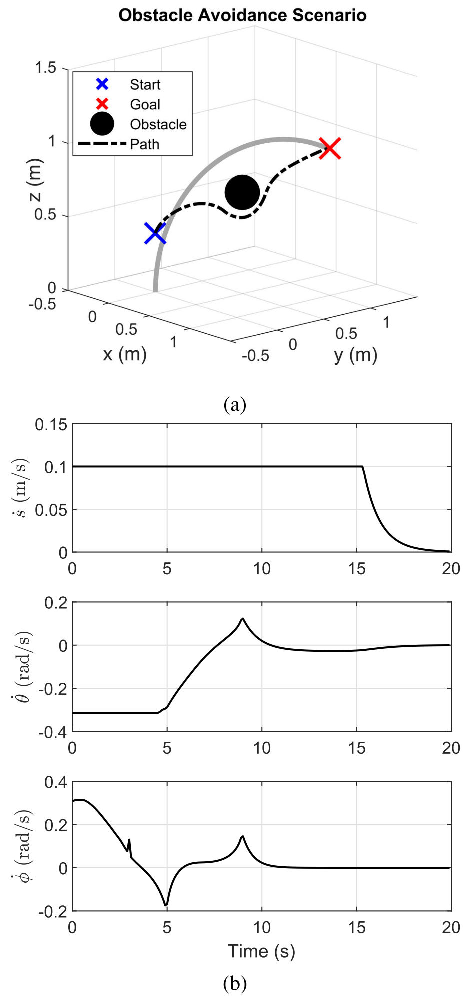

FIGURE 5. (a) The path generated by the proposed NMPC to reach a predefined goal of (1, 1, 1) meters while avoiding an obstacle with a known location. (b) The corresponding actuator inputs generated from the NMPC and applied to the vine-like robot.

B. OBSTACLE AVOIDANCE

In the second simulation scenario, the proposed NMPC is evaluated against avoiding obstacles the could exist in the environment. Thus, a static point obstacle is located at $\boldsymbol{x}_o = [x_o, y_o, z_o]^T$ within the robot pathway from a starting point $\boldsymbol{x}_0$ to the end goal $\boldsymbol{x}_g = [1, 1, 1]^T$ meters away from its base. The prediction horizon at this stage is chosen as $N = 30$, while the sampling time is $T = 0.1$ s. To avoid that obstacle, a new non-linear inequality constraint has been introduced to the optimization problem to retain the Euclidean distance between the robot's tip (x, y, z) and the obstacle's position beyond a certain safe distance $(r_t + r_o)$ as follows,

$$-\infty \leq d_{r,o} + (r_t + r_o) \leq 0 \tag{11}$$

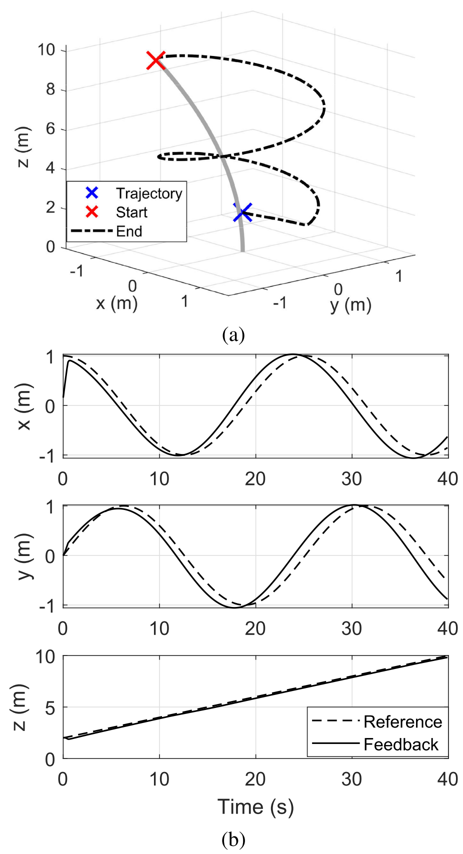

FIGURE 6. **(a) The trajectory tracking performance of the proposed NMPC (b) The corresponding state tracking in x, y and z coordinates.**

where $d_{r,o} = \sqrt{(x-x_o)^2 + (y-y_o)^2 + (z-z_o)^2}$ is the distance between the robot's tip and the obstacle, $r_t = 0.1$ m and $r_o = 0.1$ m are the robot's tip and the obstacle radii respectively. As depicted in Figure 5, the NMPC has succeeded in planning a safe path for the vine robot to avoid the obstacle. The corresponding actuation is shown that the robot has to alter its curvature and bending angle during the navigation to avoid that obstacle. It is worth to mention that this approach in avoiding obstacles could not guarantee that the whole body of the vine robot will avoid that obstacle since it is only the tip position that is considered in Eq. (11). However, this could be tackled in future work by dividing the robot's body into segments that their position could be anticipated from the robot shape parameters. Then, one more constraint could be added to ensure that these segments are away from that obstacle as well.

C. TRAJECTORY TRACKING

A spiral reference trajectory has been considered to assess the proposed NMPC-based growth controller performance against trajectory tracking. This spiral movement could be useful if the robot is required to wrap around a pillar for instance to reach its top. Particularly, the x_{ref}, y_{ref} and z_{ref} coordinates of the reference state $\boldsymbol{x}_{ref}$ has been chosen as:

$$\begin{aligned} x_{ref} &= \cos(0.25t) \\ y_{ref} &= \sin(0.25t) \\ z_{ref} &= 2 + 0.2t \end{aligned} \tag{12}$$

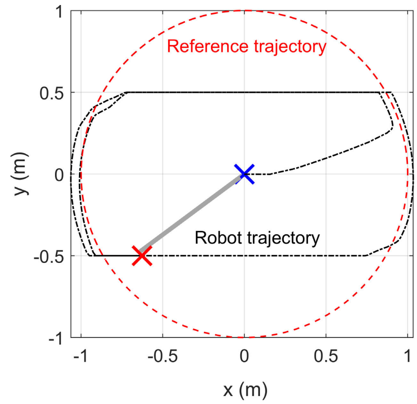

FIGURE 7. **The robot trajectory versus the reference trajectory in the case of work-space constraints.**

The robot starts from an initial state $\boldsymbol{x}_0 = [0, 0, 0.9, 0.9, 0, 0]^T$. The controller time step is chosen to be $t = 0.1$ seconds while the prediction horizon is $N = 20$ with a total simulation time of 20 seconds. The state and input weighting matrices have been chosen as $\boldsymbol{Q} = \text{diag}(10, 10, 1, 0, 0, 0)$ and $\boldsymbol{R} = \text{diag}(0.1, 0.1, 0.1)$ respectively. Figure 6 shows the NMPC performance in terms of the difference between the actual and the reference trajectories. The obtained Root Mean Square (RMS) errors between the reference and the actual robot trajectory are (0.19, 0.193, 0.11) meters respectively in x,y and z directions. As noted in Figure 6, the errors in x and y coordinates are increasing with time. This is because the z coordinate is linearly increasing with time, this requires the robot's length to be increased which subsequently affects the actual x and y tip positions. We believe that properly designed weighting $\boldsymbol{Q}$ and $\boldsymbol{R}$ matrices would tackle this issue. In Figure 7, we imposed an inequality constraint on the robot's state y as a work-space limitation. The proposed NMPC shows satisfactory tracking performance while respecting the imposed constraint beside the other robot's locomotion constraints.

To compare our proposed NMPC-based growth control with attempts found in the literature, we implemented two Jacobian-based trajectory tracking controllers. In the first controller, the irreversible growing process and the limits of the actuator haven't considered while in the second controller these constraints have been considered as saturation blocks. In Jacobian-based trajectory tracking the control action of such a controller is calculated as:

$$\boldsymbol{u} = \boldsymbol{J}^T(\boldsymbol{q})\boldsymbol{K}\boldsymbol{e} \tag{13}$$

where $\boldsymbol{e} = \boldsymbol{x}_{ref} - \boldsymbol{x}$ is the error between the reference trajectory and the feedback state of the robot while $\boldsymbol{K}$ is a positive definite diagonal gain matrix chosen as $\boldsymbol{K} = \boldsymbol{I}$. As shown in Figure 8(a), the performance of the Jacobian-based controller while not considering the process constraints is satisfactory and close to what our proposed NMPC-based growth control achieved. However, if the process constraints are

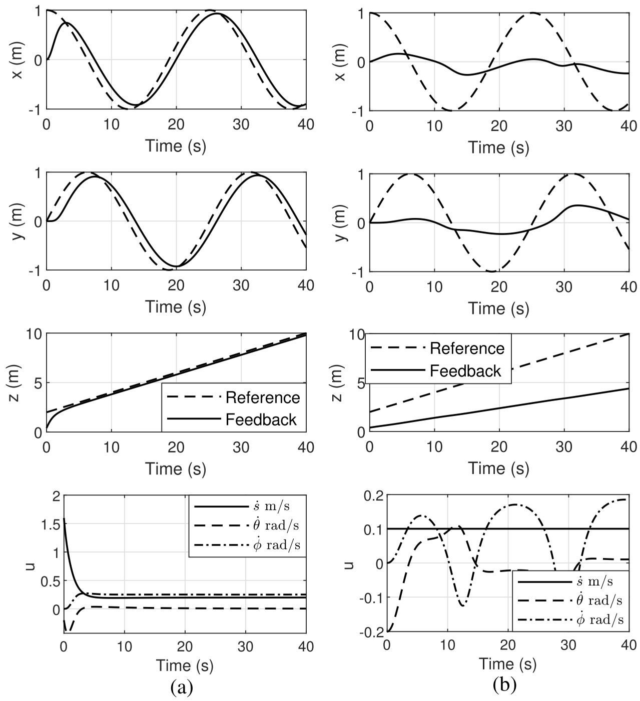

FIGURE 8. **Performance of the Jacobian-based Kinematics control while (a) not considering the irreversible growing and process constraints, and while (b) considering these constraints.**

considered the Jacobian-based control will fail to follow the reference trajectory as highlighted in 8(b). This shows how our proposed trajectory tracking based on the proposed NMPC controller outperforms the Jacobian-based controller when the irreversible process and actuator constraints are considered. This is due to the capability possessed by the MPC controllers to anticipate the future state of the process and plan accordingly while considering any process constraints.

D. ROBUSTNESS ANALYSIS

One of the key factors that ensure the robustness of the MPC control system is to have insignificant levels of discrepancies between the prediction model and the real system under control. Having a nonlinear kinematics model as the prediction model in our proposed NMPC-based growth control of vine robots plays a crucial rule in satisfying such condition. In fact, the system behaviour could be anticipated at each time step in the future relying on the nonlinear prediction model that acts as a replica to the vine robot model under control.

In this experiment, we need to assess the robustness of the proposed NMPC-based growth control over a wide range of input disturbances. Monte Carlo simulations are utilized to evaluate the robustness in terms of tracking performance concerning variation in disturbed model uncertainties. This approach would evaluate the NMPC controller with no need to simulate each parameter variation separately, which could take up significant time.

Thus, 150 values of the variances $\sigma_{\dot{s}}$, $\sigma_{\dot{\theta}}$ and $\sigma_{\dot{\phi}}$ are randomly selected within an allowable uniform distributions

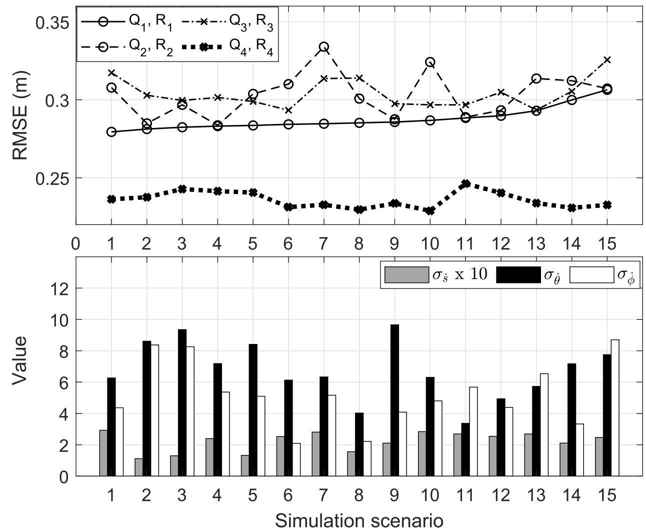

FIGURE 9. **(Top) The RMSE results of the conducted Monte Carlo 15 simulation scenarios at various weighting matrices with the corresponding disturbance values (bottom).**

[0.1, 0.3] m/s, [2, 10] rad/s, and [2, 10] rad/s. These model uncertainties could represent the variation of wind speed effect on the NMPC performance in each control coordinate. The NMPC-based growth control is assessed through the tracking performance of the trajectory proposed in Subsection IV-C by calculating the RMSE at each simulation scenario. In the first set of analysis, the weighting matrices were chosen as $\boldsymbol{Q}_1 = \text{diag}(10, 10, 1, 0, 0, 0)$ and $\boldsymbol{R}_1 = \text{diag}(0.1, 0.1, 0.1)$. Due to limited space, Figure 9 shows the results of 15 scenarios that have been selected and sorted according to the RMSE values. We can interpret that the RMSE has not significantly changed during the various simulated scenarios with the chosen disturbances.

Subsequently, to show the effect of the weighting matrices on the robustness performance, three more Monte Carlo simulations have been conducted with the same chosen disturbances but with different values of $\boldsymbol{Q}$ and $\boldsymbol{R}$ as highlighted in Figure 9. These matrices are chosen as follows,

$$\boldsymbol{Q}_2 = \text{diag}(10, 10, 10, 0, 0, 0), \quad \boldsymbol{R}_2 = \text{diag}(0.1, 0.1, 0.1)$$
$$\boldsymbol{Q}_3 = \text{diag}(10, 10, 1, 0, 0, 0), \quad \boldsymbol{R}_3 = \text{diag}(1, 0.1, 0.1)$$
$$\boldsymbol{Q}_4 = \text{diag}(10, 10, 1, 0, 0, 0), \quad \boldsymbol{R}_4 = \text{diag}(0.05, 0.05, 0.05)$$

As shown in Figure 9, simulations with matrices $\boldsymbol{Q}_4$ and $\boldsymbol{R}_4$ introduces the lowest RMSE, which implies increased states weights compared to the weights of the control inputs. On the other hand, $\boldsymbol{Q}_2, \boldsymbol{Q}_3$ and $\boldsymbol{R}_2, \boldsymbol{R}_3$ have the worst performance compared to others. As noted, these results could suggest the direction of choosing the optimal weighting matrices that give the best performance.

V. CONCLUSION

In this article, a Nonlinear Model Predictive Control (NMPC) scheme is presented, which is capable of automatically driving the tip of the vine growing robot to a spatial target position in the environment. The proposed NMPC-based growth control has succeeded to control the vine robot in a closed-loop while respecting the irreversible growing and actuation constraints. The nonlinear kinematics model of the vine robot is incorporated as the controlled plant where a discrete version has been used as the controller prediction model. The proposed NMPC growth control is simulated over different scenarios ranging from the point stabilization, trajectory following, and obstacle avoidance with satisfactory performance results. Besides, a robustness analysis has been conducted based on Monte-Carlo simulations to evaluate the vine robot growth under various disturbance conditions as well as to guide the direction of choosing the weighting matrices in the control problem in such a way to maximize the tracking performance. In future work, building a Moving Horizon Estimation (MHE) [18] is promising to relax the assumption of full state observability that has been assumed in this research. Also, our work would be possibly extended to a case wherein the dynamics model of vine growing robots is used instead of the kinematics model either a prediction model or as the model of the process under control.

REFERENCES

[1] J. A. E. Andersson, J. Gillis, G. Horn, J. B. Rawlings, and M. Diehl, ''CasADi: A software framework for nonlinear optimization and optimal control,'' *Math. Program. Comput.*, vol. 11, no. 1, pp. 1–36, Mar. 2019.

[2] L. H. Blumenschein, A. M. Okamura, and E. W. Hawkes, ''Modeling of bioinspired apical extension in a soft robot,'' in *Proc. Conf. Biomimetic Biohybrid Syst.* Cham, Switzerland: Springer, 2017, pp. 522–531.

[3] E. F. Camacho and C. B. Alba, *Model Predictive Control*. Springer, 2013.

[4] M. M. Coad, L. H. Blumenschein, S. Cutler, J. A. R. Zepeda, N. D. Naclerio, H. El-Hussieny, U. Mehmood, J.-H. Ryu, E. W. Hawkes, and A. M. Okamura, ''Vine robots: Design, teleoperation, and deployment for navigation and exploration,'' 2019, *arXiv:1903.00069*. [Online]. Available: http://arxiv.org/abs/1903.00069

[5] E. Del Dottore, A. Sadeghi, A. Mondini, V. Mattoli, and B. Mazzolai, ''Toward growing robots: A historical evolution from cellular to plant-inspired robotics,'' *Frontiers Robot. AI*, vol. 5, p. 16, Mar. 2018.

[6] C. Della Santina, R. K. Katzschmann, A. Biechi, and D. Rus, ''Dynamic control of soft robots interacting with the environment,'' in *Proc. IEEE Int. Conf. Soft Robot. (RoboSoft)*, Apr. 2018, pp. 46–53.

[7] V. Falkenhahn, T. Mahl, A. Hildebrandt, R. Neumann, and O. Sawodny, ''Dynamic modeling of constant curvature continuum robots using the euler-Lagrange formalism,'' in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Sep. 2014, pp. 453–458.

[8] H. El-Hussieny, U. Mehmood, Z. Mehdi, S.-G. Jeong, M. Usman, E. W. Hawkes, A. M. Okarnura, and J.-H. Ryu, ''Development and evaluation of an intuitive flexible interface for teleoperating soft growing robots,'' in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2018, pp. 4995–5002.

[9] J. D. Greer, L. H. Blumenschein, R. Alterovitz, E. W. Hawkes, and A. M. Okamura, ''Robust navigation of a soft growing robot by exploiting contact with the environment,'' *Int. J. Robot. Res.*, Mar. 2020.

[10] J. D. Greer, L. H. Blumenschein, A. M. Okamura, and E. W. Hawkes, ''Obstacle-aided navigation of a soft growing robot,'' in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2018, pp. 1–8.

[11] J. D. Greer, T. K. Morimoto, A. M. Okamura, and E. W. Hawkes, ''A soft, steerable continuum robot that grows via tip extension,'' *Soft Robot.*, vol. 6, no. 1, pp. 95–108, Feb. 2019.

[12] W. Gu, J. Yao, Z. Yao, and J. Zheng, ''Output feedback model predictive control of hydraulic systems with disturbances compensation,'' *ISA Trans.*, vol. 88, pp. 216–224, May 2019.

[13] E. W. Hawkes, L. H. Blumenschein, J. D. Greer, and A. M. Okamura, ''A soft robot that navigates its environment through growth,'' *Sci. Robot.*, vol. 2, no. 8, Jul. 2017, Art. no. eaan3028.

[14] K. Isaki, A. Niitsuma, M. Konyo, F. Takemura, and S. Tadokoro, ''Development of an active flexible cable by ciliary vibration drive for scope camera,'' in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Oct. 2006, pp. 3946–3951.

[15] B. A. Jones and I. D. Walker, ''Kinematics for multisection continuum robots,'' *IEEE Trans. Robot.*, vol. 22, no. 1, pp. 43–55, Feb. 2006.

[16] P. Liljebäck, K. Y. Pettersen, O. Stavdahl, and J. T. Gravdahl, ''A review on modeling, implementation, and control of snake robots,'' *Robot. Auto. Syst.*, vol. 60, no. 1, pp. 29–40, 2012.

[17] D. Q. Mayne, J. B. Rawlings, C. V. Rao, and P. O. M. Scokaert, ''Constrained model predictive control: Stability and optimality,'' *Automatica*, vol. 36, no. 6, pp. 789–814, Jun. 2000.

[18] M. W. Mehrez, G. K. I. Mann, and R. G. Gosine, ''Nonlinear moving horizon state estimation for multi-robot relative localization,'' in *Proc. IEEE 27th Can. Conf. Electr. Comput. Eng. (CCECE)*, May 2014, pp. 1–5.

[19] D. Mishima, T. Aoki, and S. Hirose, ''Development of pneumatically controlled expandable arm for search in the environment with tight access,'' in *Field and Service Robotics*. Berlin, Germany: Springer, 2003, pp. 509–518.

[20] A. Porat, F. Tedone, M. Palladino, P. Marcati, and Y. Meroz, ''A general 3D model for growth dynamics of sensory-growth systems: From plants to robotics,'' *Frontiers Robot. AI*, vol. 7, p. 89, 2020. [Online]. Available: https://www.frontiersin.org/article/10.3389/frobt.2020.00089, doi: 10.3389/frobt.2020.00089.

[21] A. Sadeghi, A. Mondini, E. Del Dottore, V. Mattoli, L. Beccai, S. Taccola, C. Lucarotti, M. Totaro, and B. Mazzolai, ''A plant-inspired robot with soft differential bending capabilities,'' *Bioinspiration Biomimetics*, vol. 12, no. 1, Dec. 2016, Art. no. 015001.

[22] I. A. Seleem, H. El-Hussieny, and S. F. M. Assal, ''Motion planning for continuum robots: A learning from demonstration approach,'' in *Proc. 27th IEEE Int. Symp. Robot Hum. Interact. Commun. (RO-MAN)*, Aug. 2018, pp. 868–873.

[23] I. A. Seleem, H. El-Hussieny, S. F. M. Assal, and H. Ishii, ''Development and stability analysis of an imitation learning-based pose planning approach for multi-section continuum robot,'' *IEEE Access*, vol. 8, pp. 99366–99379, 2020.

[24] H. Tsukagoshi, N. Arai, I. Kiryu, and A. Kitagawa, ''Tip growing actuator with the hose-like structure aiming for inspection on narrow terrain,'' *Int. J. Autom. Technol.*, vol. 5, no. 4, pp. 516–522, Jul. 2011.

[25] H. Tsukagoshi, A. Kitagawa, and M. Segawa, ''Active hose: An artificial elephant's nose with maneuverability for rescue operation,'' in *Proc. IEEE Int. Conf. Robot. Autom. ICRA*, May 2001, pp. 2454–2459.

[26] G. J. Vrooijink, A. Denasi, J. G. Grandjean, and S. Misra, ''Model predictive control of a robotically actuated delivery sheath for beating heart compensation,'' *Int. J. Robot. Res.*, vol. 36, no. 2, pp. 193–209, Feb. 2017.

[27] R. J. Webster and B. A. Jones, ''Design and kinematic modeling of constant curvature continuum robots: A review,'' *Int. J. Robot. Res.*, vol. 29, no. 13, pp. 1661–1683, Nov. 2010.

[28] M. Wooten, C. Frazelle, I. D. Walker, A. Kapadia, and J. H. Lee, ''Exploration and inspection with vine-inspired continuum robots,'' in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2018, pp. 1–5.

[29] M. Yim, K. Roufas, D. Duff, Y. Zhang, C. Eldershaw, and S. Homans, ''Modular reconfigurable robots in space applications,'' *Auto. Robots*, vol. 14, no. 2, pp. 225–237, Mar. 2003.

HAITHAM EL-HUSSIENY received the B.Sc. degree in electronics and communication engineering from the Faculty of Engineering (Shoubra), Benha University, Egypt, in 2007, and the M.Sc. and Ph.D. degrees in mechatronics and robotics engineering from the Egypt-Japan University of Science and Technology (E-JUST), Alexandria, Egypt, in 2013 and 2016, respectively. He is currently working as an Assistant Professor of robotics engineering with the Electrical Engineering Department, Faculty of Engineering (Shoubra), Benha University. Since August 2019, he has been working as a Senior Research Fellow in soft robotics with the University of Salford, Manchester, U.K. His research interests include soft robots, soft haptics, teleoperation, model predictive control, and applied intelligence.

IBRAHIM A. HAMEED (Senior Member, IEEE) received the Ph.D. degree in industrial systems and information engineering from Korea University, Seoul, South Korea, and the Ph.D. degree in mechanical engineering from Aarhus University, Aarhus, Denmark. He is currently a Professor with the Department of ICT and Natural Sciences, Faculty of Information Technology and Electrical Engineering, Norwegian University of Science and Technology (NTNU), Norway, where he is also the Deputy Head of research and innovation. His current research interests include artificial intelligence, machine learning, optimization, and robotics. He is also the elected Chair of the IEEE Computational Intelligence Society (CIS) Norway Section.

JEE-HWAN RYU (Senior Member, IEEE) received the B.S. degree in mechanical engineering from Inha University, Incheon, South Korea, in 1995, and the M.S. and Ph.D. degrees in mechanical engineering from the Korea Advanced Institute of Science and Technology, Daejeon, South Korea, in 1995 and 2002, respectively. He is currently an Associate Professor with the Department of Civil and Environmental Engineering, Korea Advanced Institute of Science and Technology. His research interests include haptics, telerobotics, teleoperation, exoskeletons, and autonomous vehicles.