Robust model predictive kinematic tracking control with terminal region for wheeled robotic systems

Phuong Nam Dao & Hong Quang Nguyen

Published online: 18 Oct 2021.

Submit your article to this journal ↗

View related articles ↗

View Crossmark data ↗

Taylor & Francis
Taylor & Francis Group

REGULAR PAPER

Robust model predictive kinematic tracking control with terminal region for wheeled robotic systems

Phuong Nam DAO [a] and Hong Quang NGUYEN [b]

[a]Hanoi University of Science and Technology, Hanoi, Vietnam; [b]Thai Nguyen University of Technology, 251750 Thai Nguyen City, Vietnam

ABSTRACT

This paper addresses the nonlinear model predictive control (MPC) for wheeled mobile robots (WMRs) under external disturbance. The decoupling technique is utilized based on the non-holonomic constraint description for separating the WMR model. This method is able to achieve the under-actuated kinematic sub-system without disturbance and fully-actuated dynamic sub-system in presence of disturbance. Thanks to the decoupling technique, the disturbance is lumped into dynamic sub-system. The novelty lies in that the MPC-based tracking control with fixed initial point guarantees the stability based on a new establishment of terminal region and equivalent terminal controller. The feasibility problem is demonstrated to lead the tracking problem using theoretical analysis. Moreover, the control structure is inserted more the robust nonlinear dynamic controller. The effectiveness and advantages of the proposed control scheme are verified by numerical simulations using Yamip tool.

1. Introduction

With the development of industry, the requirement of robotic systems has been remarkably increased, which may plays important role in effective improvement of labour productivity. Hence, the problem of control design for robotic systems, which contains mobile robots and manipulators, has attracted much attention, and many excellent works have been presented, such as [1–7]. These researches are focused on practical systems [2,3] and back-stepping approach-based nonlinear control schemes [1,4–7]. For robot manipulator systems, several special Lyapunov function candidates are chosen to address challenges, such as varying time delay [6,7]. Additionally, the problem of finite time convergence in not only sliding surface but also tracking error was discussed in [7] by adding a exponential function. In order to develop the back-stepping method, the model of robotic systems is separated using decoupling technique to be described in [4,5]. Moreover, the control design is implemented from outer sub-system to inner sub-system using Lyapunov function candidate to be modified after extending control loop [1,4,5]. It can be seen that the control design of the first control loop is difficult to address because the property of under-actuated systems. Thus, the transformation to a new tracking error model is considered for easily finding equivalent Lyapunov function [1,5]. It can concludes that most of the above nonlinear control schemes are for finding the appropriate Lyapunov function.

For the desire of handling in constraint situation as well as extending the control requirement, model predictive control (MPC) approach is developed [8]–[29]. Because the principle of MPC technique is considered with two steps, including establishing the predictive model and solving the optimization problem, the computational effort is an obstacle. The quadratic programming (QP) method is introduced to address this issue [8,9]. For implementing MPC technique in perturbed systems, due to the difficulty in considering the predictive model, the Neural Network-based MPC was investigated by using Neural Network for estimating the predictive model [12]. Furthermore, the tube-based MPC technique is presented by considering the nominal system to be obtained after eliminating the disturbance [10,14,18,19]. The influence of disturbance is handled by establishing the boundary condition of starting point of optimization problem in unicycle systems [18]. For manipulator systems, the transformation of coordinate was utilized instead of decoupling technique [14]. It leads to the transformation of terminal region as well as terminal controller in considering the convergence effectiveness. The disturbance observer was given to eliminate the disturbance in MPC approach for the purpose of obtaining the fixed initial point-based optimization problem [13]. On the other hand, the tubed MPC approach was developed by considering the addition of predicted size of Tube [28]. Unlike the classical researches [29], the stability of MPC is guaranteed without mentioning the

---

CONTACT Hong Quang NGUYEN ✉ quang.nguyenhong@tnut.edu.vn ⊙ Thai Nguyen University of Technology, 251750 Thai Nguyen City, Vietnam

terminal constraint [16] as well as terminal cost function [25]. Additionally, the nonlinear MPC was also investigated in [20,21] using linearization technique instead of solving directly nonlinear MPC as mentioned in [10,14,18,19]. Consequently, the minimization of upper bound combined with linear matrix inequalities (LMIs) was developed to obtain the appropriate optimization problem for satisfying the tracking effectiveness [21]. The tube MPC was developed not only for continuous time systems but also for discrete time systems with saturated input [23]. A different approach of addressing the constrained MPC is to utilize barrier function for transforming constrained problem to an unconstrained problem [22]. Moreover, nonlinear MPC was considered for whole of autonomous underwater vehicle by distributed implementation without using the decoupling technique [24]. The influence of event-triggering mechanism in MPC and the self-triggered MPC were developed by modified algorithms in [15,26], respectively. On the other hand, it should be noted that the MPC technique is also considered for multi agent systems, such as leader–follower configuration [17] and multi-vehicle systems [11,27]. The approaching method was developed using distributed MPC with appropriate optimization problem for each vehicle [11,27]. The distributed MPC was investigated for only kinematic sub-system [11] and whole model of AUV [27].

Inspired by the above discussion and consideration of MPC approach for robotics, this article aims at developing nonlinear MPC-based kinematic trajectory tracking control for wheeled mobile robots (WMRs) by extending the decoupling technique in our previous work [4,5]. Compared to the existing methods, the main contributions of this brief are two-fold:

(1) In comparison with robust MPC method in [12,18–20,24], there is no boundary condition of initial state in the proposed MPC approach, because the disturbance and unknown parameters are lumped into the dynamic sub-system. Thus, a MPC-based kinematic control scheme with easier optimization problem considering fixed initial state and the relevant MPC scheme is pretty simple.
(2) Compared with MPC method in [29], the strict proof concerning the new terminal controller as well as terminal region are proposed using traditional Lyapunov stability theory. Additionally, unlike the MPC approach in [29] only implementing outer sub-system of WMRs, this proposed controller is addressed for more inner WMR sub-system.

The remainder of our paper is organized as follows. The Dynamic modelling and problem formulation are discussed in Section 2. Kinematic Tracking Control Scheme with Model Predictive is presented in Section 3. Subsequently, the simulation results are shown in Section 4. Finally, the conclusions are determined in Section 5.

2. Dynamic modelling and problem formulation

Consider the WMRs system, whose dynamics can be obtained from the classical Euler–Lagrange theory [4,5] and all parameters, variables are shown in Table 1

$$
\begin{cases}
M(\eta)\ddot{\eta} + C(\eta,\dot{\eta})\dot{\eta} + B(\eta)\left(F(\dot{\eta}) + \tau_d\right) \\
= B(\eta)\tau + J^T(\eta)\lambda \\
J(\eta)\dot{\eta} = 0
\end{cases}
\tag{1}
$$

where the vector $\eta = [x, y, \theta]^T$ sequentially represents the position coordinates x, y, the orientation angle θ. Additionally, $M(\eta)$, $C(\eta,\dot{\eta})$ describe the positive-definite symmetric matrix, centripetal and coriolis matrix, respectively; $F(\dot{\eta})$ and τ_d are the vector of friction term and bounded disturbances, respectively; $B(\eta)$ represents the input transformation matrix; $J^T(\eta)\lambda$ is the constraint force in the WMR; and it is controlled by the torque vector $\tau = [\tau_l, \tau_r]^T$ including left and right torque.

Because the number of variables is more than the number of equations, there exists a solution $S^T(\eta)$ of the following equation $S^T(\eta).J^T(\eta) = 0$. Moreover, the existence of a vector σ satisfying $\dot{\eta}(t) = S(\eta)\sigma$ leads to the following equality:

$$
\ddot{\eta} = \dot{S}(\eta)\sigma + S(\eta)\dot{\sigma}
\tag{2}
$$

In the special case of WMRs, the matrix $J^T(\eta)$ and $S^T(\eta)$ are given as:

$$
J(\eta) = \begin{bmatrix} \sin\theta, & -\cos\theta, & 0 \end{bmatrix}
$$

$$
S(\eta) = \begin{bmatrix} \cos\theta & 0 \\ \sin\theta & 0 \\ 0 & 1 \end{bmatrix}
\tag{3}
$$

and the vector $\sigma = [\vartheta, \omega]^T$ is obtained from ϑ, ω being the linear and angular velocity, respectively.

After multiplying on both sides of the dynamic model (1) with $S^T(\eta)$, using the equation $S^T(\eta).J^T(\eta)$

Table 1. Parameters and the meaning of physical variables of WMRs.

Parameter	Meaning	Unit
b	Half of distance between left wheel and right wheel	m
r	The Radius of each wheel	m
m_r	The platform's Weight	kg
I_{rz}	The platform's Inertia Moment with respect to z axis	kgm^2
I_{wz}	The wheels Inertia Moment with respect to z axis	kgm^2
I_{wy}	The wheels Inertia Moment with respect to wheel axis	kgm^2
x	Position of the coordinate with respect to x axis	m
y	Position of the coordinate with respect to y axis	m
θ	Heading Angle of WMR with respect to x axis	rad
θ_r, θ_l	Angular Displacement of each wheel	rad
v	Velocity of WMR	m/s

Figure 1. The Control Structure of a WMR.

$= 0$ and $\dot{\eta}(t) = S(\eta)\sigma$, the cascade structure of two connected subsystems without the term of λ is achieved:

$$\begin{cases} \dot{\eta} = S(\eta)\,\sigma \\ D(\eta)\,S(\eta)\,\dot{\eta} + C^*(\eta,\dot{\eta})\,\eta + d^*(t) = B(\eta)\,\tau \end{cases}$$
(4)

Remark 2.1: It is worth emphasizing that the above decoupling technique using matrix $S(\eta)$ leads to lump the term of unknown parameters and external disturbances into fully-actuated dynamic sub-system $D(\eta)S(\eta)\dot{\eta} + C^*(\eta,\dot{\eta})\eta + d^*(t) = B(\eta)\tau$ and unknown disturbance is eliminated in under-actuated kinematic sub-system $\dot{\eta} = S(\eta)\sigma$.

Remark 2.2: Although this decoupling technique was introduced in robust adaptive control design of mobile robotic systems [5]. However, it can be verified that this method is not appropriate motion/force control objective due to elimination of constraint force factor λ in (4). The proposed method in [30] is able to address motion/force control problem by using the coordination transformation to keep the term of constraint force factor λ. Therefore, the chain form is existed in the model and linear matrix inequalities (LMIs) technique is mentioned to address.

The control objective is to achieve the model predictive control (MPC) (Figure 1) such that not only the trajectory tracking control problem but also the optimization problem are guaranteed. It should be noted that the inner loop controller in Fig.1 can be utilized from the proposed robust control in [1].

3. Kinematic tracking control scheme with model predictive

In this section, we first design the trajectory tracking control law using MPC method and then discuss the feasibility and stability of closed system. For control design of WMRs, according to (3) and (4), in the case of WMRs, the kinematic sub-system $\dot{\eta} = S(\eta)\sigma$ without

disturbance can be expressed as:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos\theta & 0 \\ \sin\theta & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix}$$
(5)

In order to handle the difficulty in existence of trigonometric factor in (5) (Figure 1), the tracking error model of kinematic subsystem is transformed with the desired trajectory $[x_r, y_r, \theta_r]^T$ and equivalent $[v_r, \omega_r]^T$ as follows:

$$\begin{bmatrix} x_e(t) \\ y_e(t) \\ \theta_e(t) \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_r(t) - x(t) \\ y_r(t) - y(t) \\ \theta_r(t) - \theta(t) \end{bmatrix}$$
(6)

It implies that:

$$\frac{d}{dt}p_e = \begin{bmatrix} \dot{x}_e \\ \dot{y}_e \\ \dot{\theta}_e \end{bmatrix} = \begin{bmatrix} \omega y_e - v + v_r \cos(\theta_e) \\ -\omega x_e + v_r \sin(\theta_e) \\ \omega_r - \omega \end{bmatrix}$$
(7)

where the modified control vector is described as:

$$u_e = \begin{bmatrix} u_{1e} \\ u_{2e} \end{bmatrix} = \begin{bmatrix} v_r \cos(\theta_e) - v \\ \omega_r - \omega \end{bmatrix}$$
(8)

Remark 3.1: It can be shown that the distinction in comparison with other works [17–19] is the local coordinate frame of the WMR using the geometrical centre. Moreover, unlike the work in [29] studying MPC controller only for kinematic model of WMRs, this brief considers the perturbed WMR (4) with kinematic and dynamic models. Thanks to the decoupling technique above, the disturbance is avoided in kinematic subsystem (7) and it is lumped into the dynamic model $D(\eta)S(\eta)\dot{\eta} + C^*(\eta,\dot{\eta})\eta + d^*(t) = B(\eta)\tau$. It can be seen that the inner-loop controller (Figure 1) can absolutely utilized the control scheme to be introduced in [4]. Consequently, the MPC controller (in Figure 1) is designed for the kinematic model (7), (8) in the absence of disturbance. Therefore, unlike the work in [18] considering the optimization problem with the initial point being in constraint set, the proposed MPC for kinematic model (7), (8) only investigates for fixed initial point-based optimization problem. Furthermore,

as we have all known, the classical MPC contains two steps, including the consideration of estimating the predictive model and solving the optimization problem. However, thanks to the kinematic model without disturbance is established, the MPC algorithm-based kinematic control is developed without implementing the computation of predicted model.

The following Optimization Problem is established to develop MPC algorithm:

Algorithm 1: (MPC-based Kinematic/Outer Tracking Algorithm)

(1) At each sampling time t_k, obtaining actual state by a measurement or an observer.
(2) Solve the optimization problem for nonlinear systems (9) without disturbance and with the performance index (10) to achieve the control scheme $u_e(t)$.
(3) Keep the result for the actual WMR system during the interval of sampling time $[t_k, t_k + 1)$
(4) Updating the time instant $t_k \rightarrow t_{k+1}$ and then coming back step 1.

Consider the systems and the boundary condition, constraints of final point, control input as follows:

$$\dot{p}_e(\tau |t_k) = f(x_e(\tau |t_k), u_e(\tau |t_k)), \tau \in [t_k, t_k + T]$$
$$p_e(t_k|t_k) = p_e(t_k),$$
$$u(\tau |t_k) \in U$$
$$p_e(t_k + T) \in \Omega$$
$$(9)$$

where $p_e(t_k)$ is the state obtained from previous step, constraint set of control input $U = \{[v, \omega]^T : 0 \leq v \leq v_{\max}, -\omega_{\max} \leq \omega \leq \omega_{\max}\}$ and the MPC performance index to be minimized is given by:

$$J\left(p_e(t_k), u_e(t_k)\right)$$
$$= \int_{t_k}^{t_k + N\delta} L\left(p_e(\tau|t_k), u_e(\tau|t_k)\right)d\tau + g(p_e(t_k + T|t_k))$$
$$(10)$$

with

$$L(p_e(\tau|t_k), u_e(\tau|t_k))$$
$$= p_e^T(\tau|t_k)Qp_e(\tau|t_k) + u_e^T(\tau|t_k)Pu_e(\tau|t_k)$$
$$g(p_e(t_k + T|t_k)) = \frac{1}{2}p_e^T(t_k + T|t_k)p_e(t_k + T|t_k)$$
$$Q = diag\{q_1, q_2, q_3\}; P = diag\{p_1, p_2\}$$
$$T = N\delta; N \in, N > 0 \qquad (11)$$

and terminal region Ω as well as equivalent terminal controller will be established for proving the stability of the closed system under proposed MPC. Based on MPC problem is mentioned above, the following control algorithm is developed for kinematic sub-system (Figure 1).

Remark 3.2: Different from the work in [18,19,26,28], where the min-max technique was proposed to address the disturbance using minimization of upper bound [28] and tube MPC method was developed based on nominal systems [18,19,26], the proposed MPC tracking control is directly implemented for kinematic sub-system (5) without disturbance and the disturbance is lumped into dynamic model (Figure 1) to address with robust adaptive controller as described in [4].

The following theorem is presented using the Algorithm 1 to determine the Input State Stability (ISS) of closed systems to be introduced in [14] with the convergence to attraction region.

Theorem 3.1: *The closed kinematic control system* (7) *is ISS under the above MPC-based Kinematic Tracking Algorithm*

Because the proof is still developed from traditional Lyapunov control, the Lyapunov function candidate is chosen using the optimal function in each step t_k. However, the comparison in two sequential steps should be addressed with intermediate function being obtained from the definitions of terminal controller and corresponding terminal region.

Definition 3.1: *The terminal region Ω and the equivalent terminal controller $u^L(.)$ for the tracking model* (7) *are defined that: if $p_e(t_k + T|t_k) \in \Omega$, then the closed system satisfies the following conditions* (12) *for any $\tau \in (t_k + T, t_{k+1} + T]$ under the terminal controller $u^L(.)$:*

$$\begin{cases} p_e(\tau|t_k) \in \Omega; \\ u(\tau|t_k) \in U; \\ \dfrac{dg(p_e(\tau|t_k))}{d\tau} + L(p_e(\tau|t_k), u_e(\tau|t_k)) \leq 0 \end{cases} \qquad (12)$$

The following Lemma 3.1 *proposes the equivalent terminal region for the terminal controller to intermediately estimate the inequality between two sequentially sampling times.*

Lemma 3.1: *The following set:*

$$\Omega = \left\{ \begin{array}{c} p_e : |x_e| \geq |y_e|, y_e\theta_e < 0, \\ \dfrac{v_r \cos\theta_e - v_{\max}}{k_1} \leq x_e \leq \dfrac{v_r \cos\theta_e + v_{\max}}{k_1} \\ -\dfrac{(\omega_{\max} + \omega_r)}{k_2} \leq \theta_e \leq \dfrac{(\omega_{\max} - \omega_r)}{k_2} \end{array} \right\}$$
$$(13)$$

is a terminal region for the equivalent terminal controller in tracking error system (7):

$$u^L(t|t_k) = \begin{bmatrix} -k_1 x_e + v_r \cos(\theta_e) \\ k_2 \theta_e \end{bmatrix} \quad (14)$$

for any $\tau \in [t_k + T, t_{k+1} + T)$, where k_1 and k_2 are satisfied that $k_1 - q_1 - p_1 k_1^2 > q_2$, $k_2 - q_3 - p_2 k_2^2 > 0$

Proof: It should be noted that, the constraint condition of terminal controller is guaranteed $u^L \in U$ if $p_e(t_k|t_k) \in \Omega$. ∎

Taking time derivative of $p_e(t_k|t_k) \in \Omega$ with respect to τ, it implies that:

$$\frac{dg(p_e(\tau|t_k))}{d\tau} = x_e \dot{x}_e + y_e \dot{y}_e + \theta_e \dot{\theta}_e$$
$$= -k_1 x_e^2 - k_2 \theta_e^2 + y_e v_r \sin(\theta_e) \quad (15)$$

According to (13) and (15), the inequality is obtained $\frac{dg(p_e(\tau|t_k))}{d\tau} < 0$. Hence, the first problem in (12) is determined. Furthermore, because $p_e(\tau|t_k) \in \Omega$, the following estimation is achieved to complete the Lemma 1 with the third condition of ((12)):

$$\frac{dg(\tilde{p}_e(\tau|t_k))}{d\tau} + L(p_e(\tau|t_k), u_e(\tau|t_k))$$
$$= x_e \dot{x}_e + y_e \dot{y}_e + \theta_e \dot{\theta}_e + q_1 x_e^2 + q_2 y_e^2 + q_3 \theta_e^2$$
$$+ p_1 u_{1e}^2 + p_2 u_{2e}^2$$
$$= -(k_1 - q_1 - p_1 k_1^2)x_e^2 - (k_2 - q_3 - p_2 k_2^2)\theta_e^2$$
$$+ y_e v_r \sin(\theta_e) + q_2 y_e^2 < 0 \quad (16)$$

Proof: Firstly, the comparison between two Lyapunov function candidates using optimal cost function as $V(t_k) = J(p_e^*(t_k), u_e^*(t_k)), k = \overline{1, \infty}$ in sequentially sampling times is implemented after the intermediate controller as follows:

$$u(\tau|t_{k+1}) = \begin{cases} u^*(\tau|t_k), & \tau \in [t_{k+1}, t_k + T) \\ u^L(\tau|t_k), & \tau \in [t_k + T, t_{k+1} + T) \end{cases} \quad (17)$$

It implies that the deviation of the two Lyapunov candidate functions at time t_k and $t_k + 1$:

$$\Delta V$$
$$= V(t_{k+1}) - V(t_k)$$
$$= J(p_e^*(t_{k+1}), u_e^*(t_{k+1})) - J(p_e^*(t_k), u_e^*(t_k))$$
$$\leq J(p_e(t_{k+1}), u_e(t_{k+1})) - J(p_e^*(t_k), u_e^*(t_k))$$
$$= -\int_{t_k}^{t_{k+1}} (\|p_e^*(\tau|t_k)\|_Q^2 + \|u_e^*(\tau|t_k)\|_P^2)d\tau$$

$$+ \int_{t_k+T}^{t_{k+1}+T} (\|p_e(\tau|t_{k+1})\|_Q^2 + \|u_e(\tau|t_{k+1})\|_P^2)d\tau$$
$$+ \frac{1}{2}\|p_e(t_{k+1} + T|t_{k+1})\|^2 - \frac{1}{2}\|p_e^*(t_k + T|t_k)\|^2 \quad (18)$$

Integrating from $(t_k + T)$ to $(t_{k+1} + T)$ with (12), it follows that:

$$\frac{1}{2}\|p_e(t_{k+1} + T|t_{k+1})\|^2 - \frac{1}{2}\|p_e^*(t_k + T|t_k)\|^2$$
$$+ \int_{t_k+T}^{t_{k+1}+T} (\|p_e(\tau|t_{k+1})\|_Q^2 + \|u_e(\tau|t_{k+1})\|_P^2)d\tau$$
$$\leq 0 \quad (19)$$

According to (18) and (19), the following holds:

$$\Delta V = V(t_{k+1}) - V(t_k)$$
$$\leq -\int_{t_k}^{t_{k+1}} (\|p_e^*(\tau|t_k)\|_Q^2 + \|u_e^*(\tau|t_k)\|_P^2)d\tau$$
$$\leq -\int_{t_k}^{t_{k+1}} (\|p_e^*(\tau|t_k)\|_Q^2)d\tau \quad (20)$$

It can be rewritten that $V(\infty) - V(0) \leq -\int_0^\infty (\|p_e^*(t)\|_Q^2)dt$.

Because $V(\infty) \geq 0$, there exists the finite integral $\int_0^\infty (\|p_e^*(t)\|_Q^2)dt$. Furthermore (20) leads to a finite limitation $\lim_{k\to\infty} V(t_k) = \phi < \infty$. It can be seen that:

$$0 \leq \lim_{k\to\infty} \int_{t_k}^{t_{k+1}} \|p_e^*(t)\|_Q^2 d\tau$$
$$\leq \lim_{k\to\infty} \int_{t_k}^{t_{k+1}} (\|p_e^*(t)\|_Q^2 + \|u_e^*(\tau|t_k)\|_P^2)d\tau$$
$$\leq \lim_{k\to\infty} (V(t_{k+1}) - V(t_k))$$
$$= \phi - \phi = 0. \quad (21)$$

In conclusion, it concludes that $\lim_{k\to\infty} \int_{t_k}^{t_{k+1}} \|p_e^*(\tau)\|_Q^2 d\tau = 0 \Rightarrow \lim_{t\to\infty} \|p_e^*(t)\|_Q^2 = 0$. ∎

Remark 3.3: One of the main differences of our proposed MPC framework in comparison with the work of [12,18–20,29] is the establishment of terminal controller (14) and equivalent terminal region (13). The fact is that the terminal controller and equivalent terminal region in our work are based on the local coordinate frame using the geometrical centre. Moreover, unlike the work in [12,18–20,29] only studying the pertubed kinematic controller, the proposed MPC-based algorithm (Figure 1) can extended for dynamic controller in [4].

4. Simulation results

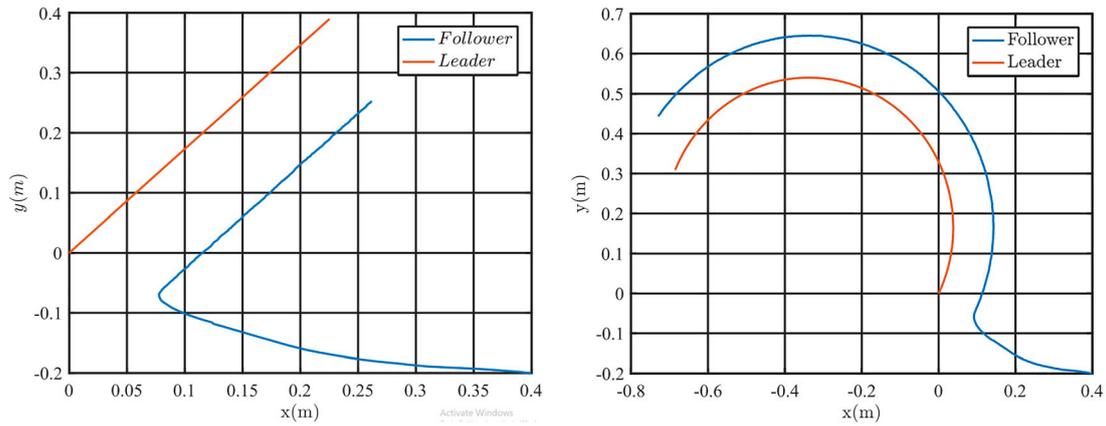The offline simulation is developed by Yalmip tool for MPC-based tracking control (algorithm 1) with the
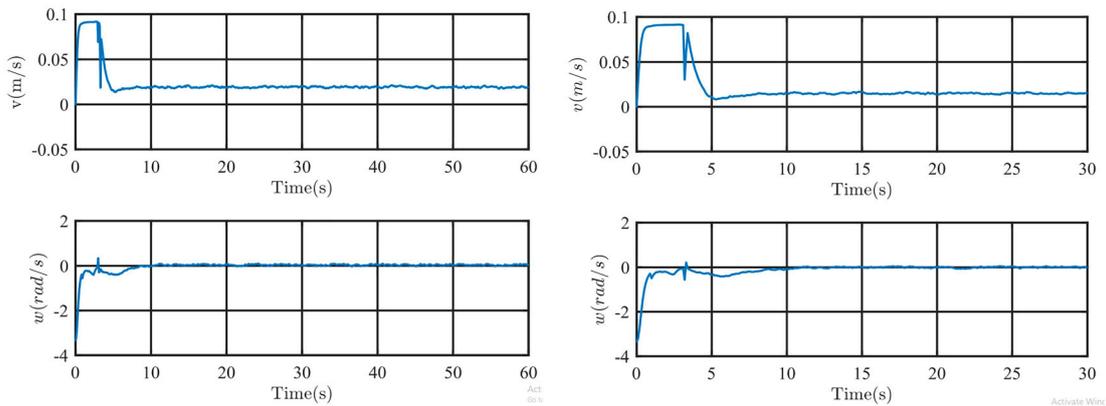
Figure 2. The Trajectory Response in two cases.

Figure 3. The Control Signals in two cases.

trajectory of WMR to be tracked follows the desired follower in two cases: $1. v_r = 0.015(m/s); \omega_r = 0(rad/s)$, $\xi_r(0) = [\begin{matrix} 0 & 0 & \pi/3 \end{matrix}]^T$ and $2. v_r = 0.015(m/s), \omega_r = 0.04(rad/s); \xi_r(0) = [\begin{matrix} 0 & 0 & \pi/3 \end{matrix}]^T$. The disturbance with sinsoidal function $\sin(0.1t$ is lumped into dynamic controller (fig.1) The parameters of controller are set to be $q_1 = q_2 = q_3 = 0.5, r_1 = r_2 = 0.2, k_1 = 2, k_2 = 1$. Using Algorithm 1 for WMR kinematic sub-system to achieve the tracking trajectory as described in Figure 2. Moreover, the responses of control inputs being velocities and heading angle are shown in Figure 3, respectively. The good behaviours in Figures 2 and 3 validate the high effectiveness of the proposed solution in paper. Furthermore, the computational complexity are easier than the previous works in [12,18–20,29] because of the advantage of fixed initial state in modified optimization problem.

5. Conclusions

In this article, a nonlinear MPC-based kinematic control scheme without the boundary condition of initial state is proposed using the new terminal controller and new equivalent terminal region. The proposed MPC combined with dynamic controller is developed for a whole of WMR with kinematic and dynamic subsystems. Offline simulations are demonstrated to show the effectiveness of the new approach. In our future work, the proposed control scheme will be studied to further improve Multi-Agent systems.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Phuong Nam DAO 🆔 https://orcid.org/0000-0002-8333-5572
Hong Quang NGUYEN 🆔 http://orcid.org/0000-0002-0433-3094

References

[1] Huang J, Wen C, Wang W, Jiang Z. Adaptive output feedback tracking control of a nonholonomic mobile robot. Automatica. 2014;50(3):821–831. doi:10.1016/j.automatica.2013.12.036

[2] Prist M, Cavanini L, Longhi S, Monteri A, Ortenzi D, Freddi A. A low cost mobile platform for educational

robotic applications. In 2014 IEEE/ASME 10th International Conference on Mechatronic and Embedded Systems and Applications (MESA) 2014, September;pp. 1–6. IEEE.

[3] Cavanini L, Benetazzo F, Freddi A, Longhi S, Monteriu A. SLAM-based autonomous wheelchair navigation system for AAL scenarios. In 2014 IEEE/ASME 10th International Conference on Mechatronic and Embedded Systems and Applications (MESA) 2014, September;pp. 1–5. IEEE.

[4] Nguyena T, Hoang T, Pham M, Dao N. A Gaussian wavelet network-based robust adaptive tracking controller for a wheeled mobile robot with unknown wheel slips. Int J Control. 2018;92(11):2681–2692. doi:10.1080/00207179.2018.1458156

[5] Binh N, Tung N, Nam D, Quang N. An adaptive backstepping trajectory tracking control of a tractor trailer wheeled mobile robot. International Journal of Control, Automation and Systems. 2019;17(2):465–473. doi:10.1007/s12555-017-0711-0

[6] Liu Y, Dao P, Zhao K. On robust control of nonlinear teleoperators under dynamic uncertainties with varia ble time delays and without relative velocity. IEEE Transactions on Industrial Informatics. 2020;16(2): 1272–1280. doi:10.1109/tii.2019.2950617

[7] Dao PN, Nguyen VT, Liu YC. Finite time convergence for bilateral teleoperation systems with disturbance and time varying delays. IET Control Theory Applications. 2021;15(13):1736–1748.

[8] Cavanini L, Cimini G, Ippoliti G. Computationally efficient model predictive control for a class of linear parameter-varying systems. IET Control Theory Applications. 2018;12(10):1384–1392.

[9] Cavanini L, Cimini G, Ippoliti G. A fast model predictive control algorithm for linear parameter varying systems with right invertible input matrix. In 2017 25th Mediterranean Conference on Control and Automation (MED) 2017, July; (pp. 42–47). IEEE.

[10] Bao X, Sheng Z, Dicianno BE, Sharma N. A tube-based model predictive control method to regulate a knee joint with functional electrical stimulation and electric motor assist. IEEE Trans Control Syst Technol. 2021;29(5):2180–2191. doi:10.1109/TCST.2020.3034850

[11] Wang P, Ding B. Distributed RHC for tracking and formation of nonholonomic multi-vehicle systems. IEEE Trans Automat Contr. 2014;59(6):1439–1453.

[12] Kang E, Qiao H, Gao J, Yang W. Neural network-based model predictive tracking control of an uncertain robotic manipulator with input constraints. ISA Trans. 2021;109:89–101.

[13] Sun Z, Xia Y, Dai L, Liu K, Ma D. Disturbance rejection MPC for tracking of wheeled mobile robot. IEEE ASME Trans Mechatron. 2017;22(6):2576–2587. doi:10.1109/tmech.2017.2758603

[14] Dai L, Yu Y, Zhai DH, Huang T, Xia Y. Robust model predictive tracking control for robot manipulators with disturbances. IEEE Transactions on Industrial Electronics. 2020;68(5):4288–4297.

[15] Sun Z, Dai L, Xia Y, Liu K. Event-based model predictive tracking control of nonholonomic systems with coupled input constraint and bounded disturbances. IEEE Trans Automat Contr. 2018;63(2):608–615. doi:10.1109/tac.2017.2736518

[16] Yang H. Trajectory tracking for wheeled mobile robots via model predictive control with softening constraints. IET Control Theory & Applications. 2018;12(2):206–214. doi:10.1049/iet-cta.2017.0395

[17] Sun Z, Xia Y. Receding horizon tracking control of unicycle-type robots based on virtual structure. International Journal of Robust and Nonlinear Control. 2016;26(17):3900–3918. doi:10.1002/rnc.3555

[18] Sun Z, Dai L, Liu K, Xia Y, Johansson K. Robust MPC for tracking constrained unicycle robots with additive disturbances. Automatica. 2018;90:172–184. doi:10.1016/j.automatica.2017.12.048

[19] Wang P, Feng X, Li W, Ping X, Yu W. Robust RHC for wheeled vehicles with bounded disturbances. International Journal of Robust and Nonlinear Control. 2019;29(7):2063–2081. doi:10.1002/rnc.4478

[20] Boccia A, Grne L, Worthmann K. Stability and feasibility of state constrained MPC without stabilizing terminal constraints. Systems & Control Letters. 2014;72:14–21. doi:10.1016/j.sysconle.2014.08.002

[21] Cheng S, Li L, Chen X, Wu J, Wang H-D. Model-Predictive-Control-Based path tracking controller of autonomous vehicle considering parametric uncertain ties and velocity-Varying. IEEE Transactions on Industrial Electronics. 2021;68(9):8698–8707. doi:10.1109/TIE.2020.3009585

[22] Petsagkourakis P, Heath WP, Carrasco J, Theodoropoulos C. Robust stability of barrier-based model predictive control. IEEE Trans Automat Contr. 2020;66(4):1879–1886.

[23] Nguyen HN. Optimizing prediction dynamics with saturated inputs for robust model predictive control. IEEE Trans Automat Contr. 2020;66(1):383–390.

[24] Shen C, Shi Y. Distributed implementation of nonlinear model predictive control for AUV trajectory tracking. Automatica. 2020;115:108863.

[25] Nguyen NT, Prodan I, Lefvre L. Stability guarantees for translational thrust-propelled vehicles dynamics through nmpc designs. IEEE Trans Control Syst Technol. 2020;29(1):207–219.

[26] Su Y, Wang Q, Sun C. Self-triggered robust model predictive control for nonlinear systems with bounded disturbances. IET Control Theory Applications. 2018;13(9):1336–1343.

[27] Wei H, Shen C, Shi Y. Distributed Lyapunov-Based model predictive formation tracking control for auto nomous underwater vehicles subject to disturbances. IEEE Transactions on Systems, Man, and Cybernetics: Systems. 2021;51(8):5198–5208. doi:10.1109/TSMC.2019.2946127

[28] Khler J, Soloperto R, Mller MA, Allgwer F. A computationally efficient robust model predictive control framework for uncertain nonlinear systems. IEEE Trans Automat Contr. 2020;66(2):794–801.

[29] Gu D, Hu H. Receding horizon tracking control of wheeled mobile robots. IEEE Trans Control Syst Technol. 2006;14(4):743–749.

[30] Fu J, Chai T, Su C, Jin Y. Motion/force tracking control of nonholonomic mechanical systems via combining cascaded design and backstepping. Automatica. 2013;49(12):3682–3686. doi:10.1016/j.automatica.2013.09.004