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

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1. Introduction

With the development of industry, the requirement of robotic systems has been remarkably increased, which may play 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
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 addressing 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

\[
\begin{align*}
M(\eta)\ddot{\eta} + C(\eta, \dot{\eta})\dot{\eta} + B(\eta) (F(\eta) + \tau_d) &= B(\eta)\tau + J^T(\eta)\lambda \\
J(\eta)\dot{\eta} &= 0
\end{align*}
\]

where the vector \( \eta = [x, y, \theta]^T \) sequentially represents the position coordinates \( x, y \), the orientation angle \( \theta \). Additionally, \( M(\eta), C(\eta, \dot{\eta}), B(\eta) \) describe the positive-definite symmetric matrix, centripetal and coriolis matrix, respectively; \( F(\eta) \) and \( \tau_d \) 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 \( \sigma \) satisfying \( \dot{s}(t) = S(\eta)\sigma \) leads to the following equality:

\[
\ddot{s} = S(\eta)\sigma + S(\eta)\dot{\sigma}
\]

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

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

\[
S(\eta) = \begin{bmatrix} \cos \theta & 0 \\ -\sin \theta & 0 \\ 0 & 1 \end{bmatrix}
\]

and the vector \( \sigma = [\dot{\theta}, \dot{\omega}]^T \) is obtained from \( \dot{\theta}, \dot{\omega} \) being the linear and angular velocity, respectively.

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

| Parameter | Meaning | Unit |
|-----------|---------|------|
| \( b \)   | Half of distance between left wheel and right wheel | m |
| \( r \)   | The Radius of each wheel | m |
| \( m_0 \) | The platform’s Weight | kg |
| \( l_z \) | The platform’s Inertia Moment with respect to z axis | kgm^2 |
| \( l_{xz} \) | The wheels Inertia Moment with respect to x axis | kgm^2 |
| \( l_{yz} \) | The wheels Inertia Moment with respect to y 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 |
| \( \theta \) | Heading Angle of WMR with respect to x axis | rad |
| \( \theta_l, \theta_r \) | Angular Displacement of each wheel | rad |
| \( v \)   | Velocity of WMR | m/s |
\[ \dot{\eta} = S(\eta) \sigma \]

\[ D(\eta) S(\eta) \dot{\eta} + C^* (\eta, \dot{\eta}) \eta + d^*(t) = B(\eta) \tau \]

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 \( \lambda \) 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 \( \lambda \). 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:

\[
\begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{\theta}
\end{bmatrix} =
\begin{bmatrix}
\cos \theta & 0 & v \\
\sin \theta & 0 & \omega
\end{bmatrix}
\begin{bmatrix}
x_r(t) - x(t) \\
y_r(t) - y(t) \\
\theta_r(t) - \theta(t)
\end{bmatrix}
\]

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:

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

It implies that:

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

where the modified control vector is described as:

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

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 $u_k(t)$.
3. Keep the state 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:

$$\dot{p}_c(\tau | t_k) = f(x_c(\tau | t_k), u_c(\tau | t_k)), \tau \in [t_k, t_k + T]$$

$$p_c(t_k | t_k) = p_c(t_k),$$

$$u(\tau | t_k) \in U$$

$$p_c(t_k + T) \in \Omega$$

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

$$J(p_c(t_k), u_c(t_k))$$

$$= \int_{t_k}^{t_k+N}\Delta L(p_c(\tau | t_k), u_c(\tau | t_k))d\tau + g(p_c(t_k + T | t_k)$$

(10)

with

$$L(p_c(\tau | t_k), u_c(\tau | t_k))$$

$$= p_c^T(\tau | t_k) Q p_c(\tau | t_k) + u_c^T(\tau | t_k) P u_c(\tau | t_k)$$

$$g(p_c(t_k + T | t_k)) = \frac{1}{2} p_c^T(t_k + T | t_k) P p_c(t_k + T | t_k)$$

$$Q = \text{diag} \{q_1, q_2, q_3\}; P = \text{diag} \{p_1, p_2\}$$

$$T = N\Delta; N \in, N > 0$$

(11)

and terminal region $\Omega$ 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 $\Omega$ and the equivalent terminal controller $u^L(\cdot)$ for the tracking model (7) are defined that: if $p_c(t_k + T | t_k) \in \Omega$, then the closed system satisfies the following conditions (12) for any $\tau \in (t_k + T, t_k + 1 + T)$ under the terminal controller $u^L(\cdot)$:

$$\left\{ \begin{align*}
    p_c(\tau | t_k) & \in \Omega; \\
    u(\tau | t_k) & \in U;
    \frac{dg(p_c(\tau | t_k))}{d\tau} + L(p_c(\tau | t_k), u_c(\tau | t_k)) \leq 0
\end{align*} \right. $$

(12)

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

Lemma 3.1: The following set:

$$\Omega = \left\{ \begin{align*}
p_c : |x_c| & \geq |y_c|, y_c \theta_c < 0, \\
k_1 & \leq x_c \leq k_1 \frac{v_c \cos \theta_c - v_{\text{max}}}{k_1} \\
& \leq \theta_c \leq \frac{(\omega_{\text{max}} + \omega_r)}{k_2}
\end{align*} \right\}$$

(13)
is a terminal region for the equivalent terminal controller in tracking error system (7):
\[
u^L(t|t_k) = \left[-k_1x_e + v_r \cos(\theta_e) \right] k_2/\theta_e
\] (14)

for any \( \tau \in [t_k + T, t_{k+1} + T] \), where \( k_1 \) and \( k_2 \) are satisfied that \( k_1 - q_1 - p_1k_1 > q_2, \; k_2 - q_3 - p_2k_2 > 0 \).

**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 \( \tau \), it implies that:
\[
\frac{d}{d\tau} p_e(t_k|t_k) = x_e \dot{x}_e + y_e \dot{y}_e + \theta_e \dot{\theta}_e
= -k_1x_e^2 - k_2\theta_e y_e + y_e v_r \sin(\theta_e)
\] (15)

According to (13) and (15), the inequality is obtained \( \frac{d}{d\tau} p_e(t_k|t_k) < 0 \). Hence, the first problem in (12) is determined. Furthermore, because \( p_e(t_k|t_k) \in \Omega \), the following estimation is achieved to complete the Lemma 1 with the third condition of (12):
\[
\frac{d}{d\tau} \left( p_e(t_k|t_k) \right) + L(p_e(t_k|t_k), u_e(t_k|t_k))
= x_e \dot{x}_e + y_e \dot{y}_e + \theta_e \dot{\theta}_e + q_1x_e^2 + q_2y_e^2 + q_3\theta_e^2
+ p_1u_1^2e + p_2u_2^2e
+ (-k_1 - q_1 - p_1k_1)x_e^2 - (k_2 - q_3 - p_2k_2)\theta_e y_e + y_e v_r \sin(\theta_e) + q_2\theta_e^2 < 0
\] (16)

**Proof:** Firstly, the comparison between two Lyapunov function candidates using optimal cost function as \( V(t_k) = \int (p_e^* \dot{p}_e^* + u_e^* \dot{u}_e^*) dt \), \( k = \infty \) in sequentially sampling times is implemented after the intermediate controller as follows:
\[
u(t_k+1) = \begin{cases} u^*(t_k|t_k), & \tau \in [t_{k+1}, t_k + T) \\ u^L(t_k|t_k), & \tau \in [t_k + T, t_{k+1} + T) \end{cases}
\] (17)

It implies that the deviation of the two Lyapunov candidate functions at time \( t_k \) and \( t_k + 1 \):
\[
\Delta V
= V(t_k) - V(t_k)
= \int_{t_k}^{t_k+1} \left( \frac{p_e^2}{Q} + \frac{u_e^2}{p} \right) d\tau
= \frac{1}{2} \int_{t_k}^{t_k+1} \left( \frac{p_e^2}{Q} + \frac{u_e^2}{p} \right) d\tau
\]

Integrating from \( t_k \) to \( t_{k+1} \) with (12), it follows that:
\[
\frac{1}{2} \int_{t_k}^{t_k+1} \left( \frac{p_e^2}{Q} + \frac{u_e^2}{p} \right) d\tau
\leq 0
\]

According to (18) and (19), the following holds:
\[
\Delta V = V(t_k+1) - V(t_k)
\leq -\int_{t_k}^{t_k+1} \left( \frac{p_e^2}{Q} + \frac{u_e^2}{p} \right) d\tau
\]

It can be rewritten that \( V(\infty) - V(0) \leq -\int_{0}^{\infty} \left( \frac{p_e^2}{Q} + \frac{u_e^2}{p} \right) dt \).

**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 perturbed 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
trajectory of WMR to be tracked follows the desired follower in two cases: 1. $v_r = 0.015 \text{(m/s)}; \omega_r = 0 \text{(rad/s)}, \xi_r(0) = [0 \ 0 \ \pi/3]^T$ and 2. $v_r = 0.015 \text{(m/s)}; \omega_r = 0.04 \text{(rad/s)}; \xi_r(0) = [0 \ 0 \ \pi/3]^T$. The disturbance with sinusoidal 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.

Acknowledgments

The authors acknowledge the Thai Nguyen University of Technology for supporting this works.

Disclosure statement

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

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