Adaptive sliding mode control for disturbed multirobot systems performing target tracking under continuously time-varying topologies

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Abstract
This article studies coordination control of the multirobot system for target tracking problem with disturbances in time-varying communication environment. An adaptive sliding mode control is designed to complete the target tracking task with the effect of disturbances and continuously time-varying topologies. This means that the communication between the robots is not switching among constant topologies but changes continuously along with time. The continuously time-varying topology is constructed by a set of fixed Laplacian matrices and variable scheduling functions, which is known as polytopic model structure. The designed adaptive sliding mode control can effectively lower the influence of disturbance and improve tracking performance even under the continuously time-varying topology. Furthermore, numerical simulations are given to demonstrate the effectiveness of the obtained results.

Keywords
Multirobot systems with disturbance, time-varying topology, adaptive sliding mode control, target tracking strategy

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Introduction
Collaborative distributed control of multirobot systems, such as swarm, formation, and collective missions, have raised widespread attention in the past decade.\textsuperscript{1–7} Consensus is the basic theory in multirobot coordination control, which is often done by designing a distributed consensus protocol to make a set of robots to agree on a common state.\textsuperscript{8–12} Target tracking is a typical application of multirobot systems, in which the robots’ states reach consensus with the target.\textsuperscript{4–6}

Sliding mode control is known as a powerful tool for handling system operation under uncertain conditions. The corresponding process is divided into two steps. First of all, to achieve the required specifications, a sliding manifold is designed. Secondly, a discontinuous control law is designed so as to make the system trajectory reach the manifold in fixed time and stay close to the equilibrium point near the sliding mode manifold. Due to the effectiveness and simplicity of sliding mode control in practical
application, it has been widely used in many fields and applications.\textsuperscript{13–17} Since disturbance is inevitable in most cases, some scholars have designed sliding-mode controller of multirobot system under disturbance.\textsuperscript{18–20} In the case of modeling and input uncertainty, faced with consistency tracking control problem of second-order multirobot system, a new nonsingular fast-sliding model surface is designed, in which the surface has a bounded convergence time without considering the initial state.\textsuperscript{18} A sliding mode nonsingular terminal distributed protocol is proposed to accomplish consensus tracking problem of second-order multirobot systems in fixed time.\textsuperscript{19} The authors propose a finite-time robust event trigger control strategy based on integral sliding mode with the purpose of solving the fast distributed coordination problem of multirobot systems with limited disturbances.\textsuperscript{20} According to the definition of the new measurement error, the fast approach law is adopted to enhance the convergence speed of the algorithm, and the system triggering conditions suitable for model uncertainty and disturbance are derived.

Due to the limitation of communication technique, the topology of the system may be time varying.\textsuperscript{21–24} Recently, researchers have proposed different methods to deal with control problems with switching network structure. For example, stabilization of Boolean control networks which are switching among different Boolean networks is investigated.\textsuperscript{22} Several new multiple Lyapunov functions are constructed to solve the multirobot tracking control system with switching topologies.\textsuperscript{23} There also have been some results on the adaptive sliding mode control of the system with switching topologies. Specifically, under switching topologies, an adaptive sliding mode control approach for multirobot systems is presented, in which the model parameters of high-order robots remain unknown.\textsuperscript{25} The results are used to a set of flexible joint multiple single-link manipulators. An adaptive fixed-time distributed consensus protocol with switching topologies for consensus tracking of uncertain high-order multirobot systems is investigated.\textsuperscript{26} The protocol is designed by dynamic surface control technique and backstepping method, making sure that the tracking errors converge although the communication topologies between robots change dynamically as time goes by.

The aforementioned results in the literature are based on fixed or switching topologies, as shown in Figure 1, namely, the communication topology between robots switches among several constant topologies. It is constant during time intervals. However, in real applications, it is possible that the communication topologies are changing continuously along with time, as shown in Figure 2. Therefore, in this article, an adaptive sliding mode control for multirobot systems performing target tracking task with disturbances and continuously time-varying topologies is studied. The continuously time-varying topology is constructed using a set of constant Laplacian matrices and variable scheduling function. This is known as a polytopic model structure. Simulation results are presented to verify the effectiveness of the proposed distributed adaptive control scheme.

**Preliminaries and problem description**

Consider that there are $n$ robots deployed in the three-dimensional space aiming to track any target in this space. The dynamics of the $i$th tracking robot with disturbances is described by

$$
\begin{align*}
\dot{x}_i(t) &= v_i(t) \\
\dot{v}_i(t) &= f(x_i(t), v_i(t)) + u_i(t) + d_i(t)
\end{align*}
$$

where $x_i(t) = (x_{i1}(t), x_{i2}(t), x_{i3}(t))^T \in \mathbb{R}^3$, $v_i(t) = (v_{i1}(t), v_{i2}(t), v_{i3}(t))^T \in \mathbb{R}^3$, in which $x_{i1}(t), x_{i2}(t), x_{i3}(t)$ and $v_{i1}(t), v_{i2}(t), v_{i3}(t)$ are position and velocity states of the $i$th tracking robot on $x$-axis, $y$-axis, and $z$-axis, respectively.
$f(x_i(t), v_i(t))$ denotes a nonlinear function. $u_i(t) \in \mathbb{R}^3$ is the controller to be designed. $d_i(t)$ describes the disturbances implied on robot $i$ and satisfies the constraint that $d_i(t) \leq d_i^*$, where $d_i^*$ is an unknown constant.

In a target tracking system, the robots are designated to track a target, whose dynamics is assumed to be as follows

$$\begin{align*}
\dot{x}_i(t) &= v_i(t) \\
v_i(t) &= f(x_i(t), v_i(t))
\end{align*}$$

(2)

where $x_i(t) = (x_{i1}(t), x_{i2}(t), x_{i3}(t))^T \in \mathbb{R}^3$, in which $x_{i1}(t), x_{i2}(t), x_{i3}(t)$ are the position states of the target robot on $x$-axis, $y$-axis, and $z$-axis, respectively. $v_i(t) = (v_{i1}(t), v_{i2}(t), v_{i3}(t))^T \in \mathbb{R}^3$, in which $v_{i1}(t), v_{i2}(t), v_{i3}(t)$ are the velocity states of the target robot on $x$-axis, $y$-axis, and $z$-axis, respectively. $f(x_i(t), v_i(t))$ describes the nonlinear force of the target.

In this article, the nonlinear function $f(\cdot)$ satisfies Assumption 1.

**Assumption 1.** The nonlinear function $f(\cdot)$ satisfies the following inequality (3)

$$|f(x_i, x_i) - f(x_i, v_i)| \leq l_x|x_i - x_i| + l_v|v_i - v_i|$$

(3)

where $l_x$ and $l_v$ are positive constants.

We can model the topology of robots and the target as a dynamic graph, with each node representing a robot. Consider the multirobot target tracking system with $n$ robots, $G = \{V, E, \mathcal{A}\}$ is a weighted graph, $V(G) = \{1, 2, \ldots, n\}$ is a set of nodes, $E(G) \subseteq V \times V$ is a set of finite edges and $\mathcal{A} = [a_{ij}] \in \mathbb{R}^{n \times n}$ is a weighted adjacency matrix with non-negative elements. The neighbors of robot $i$ are represented by a set $\mathcal{V}_i = \{jj \in V, (j, i) \in E\}$. If robot $j \notin \mathcal{V}_i$, which implies robot $j$ is not able to get information about robot $i$. In this case, $a_{ij} = 0$, else $a_{ij} > 0$. Considering the following representation $D \triangleq \text{diag}(\sum_{j \in \mathcal{V}_i} a_{ij}, \sum_{j \in \mathcal{V}_i} a_{2j}, \ldots, \sum_{j \in \mathcal{V}_i} a_{nj})$, then the corresponding Laplacian matrix $L = [l_{ij}] \in \mathbb{R}^{n \times n}$ is $L \triangleq D - \mathcal{A}$. $b_i$ is used to describe the connection status between robot $i$ and the target. If $b_i > 0$, we say that the $i$th robot can obtain the target’s information. In other ways, $b_i = 0$. The matrix that describes the connection status of the tracking robots and the target is denoted as $B \triangleq \text{diag}(b_1, b_2, \ldots, b_n)$.

The main purpose is to design an adaptive distributed tracking controller that enables the robots to successfully track the target with continuously time-varying topologies. In a continuously time-varying communication topology, the connection between robot $j$ and robot $i$ changes along with time, then, $a_{ij}$ and $b_i$ are denoted as $a_{ij}(t)$ and $b_i(t)$ in this article. Thereafter, the Laplacian matrix then becomes a time-varying matrix $L(t)$. Similarly, the matrix $B$ representing the connection status between robots and the target turns to be $B(t)$. It should be noted that a dynamic graph is called undirected if $a_{ij}(t) = a_{ji}(t)$, otherwise, it is called directed. In this article, we consider the continuously time-varying communication topology to be undirected.

**Polytopic model of Laplacian matrix**

In this article, the continuously time-varying topology is established as a polytopic model. Denote $\mathcal{A}(t) = \mathcal{L}(t) + \mathcal{B}(t)$ as the relative Laplacian matrix of the multirobot system performing target tracking task. The polytopic structure describes the overall time-varying Laplacian matrices as following: $\mathcal{L}(t) = \sum_{k=1}^{N} \alpha_k(t) \mathcal{C}_k$, where $\mathcal{C}_k \in \mathbb{R}^{n \times n}$ are constant matrices, and $N$ is a finite positive constant. The corresponding scheduling functions are $\alpha_k(t) > 0$ and $\sum_{k=1}^{N} \alpha_k(t) = 1$ and the derivative of $\alpha_k(t)$ satisfies $\dot{\alpha}_k(t) \leq \alpha_{dk}$, in which $\alpha_{dk}$ are known constants.

**Remark 1.** Using the proposed polytopic model to describe the continuously time-varying topology has certain advantages. Currently, the results on multirobot systems with continuously time-varying topology in the literature are usually based on the eigenvalues of the corresponding time-varying Laplacian matrix. It requires the eigenvalues of Laplacian matrix to be positive, while the eigenvalues of the derivative of Laplacian matrix to be negative. The proposed polytopic model avoids such conservative constraints in the time-varying topology. However, this structure also suffers some limitations. For example, the time-varying Laplacian matrix is not always easy to be decoupled as appropriate scheduling functions and constant Laplacian matrices.

**Definition 1.** We can say that robot $i$ (1) successfully tracks the target (2) if the following equation exists

$$\lim_{t \rightarrow \infty} \left( \| x_i(t) - x_i(t) \| + \| v_i(t) - v_i(t) \| \right) = 0, i \in V$$

(4)

According to Definition 1, successful tracking is achieved if the tracking errors tend to be zero. Therefore, we reorganize the target tracking multirobot system into an overall tracking error system as follows.

Define the tracking position and velocity errors of the $i$th robot and the target as $e_{xi}(t) = x_i(t) - x_i(t), e_{vi}(t) = v_i(t) - v_i(t)$, respectively. Then, the whole error of $i$th robot with its neighbors and the target is

$$\begin{align*}
e_{xi}(t) &= \sum_{j=1}^{n} a_{ij}(t)(e_{xi}(t) - e_{yj}(t)) + b_i(t)e_{vi}(t) \\
e_{vi}(t) &= \sum_{j=1}^{n} a_{ij}(t)(e_{vi}(t) - e_{yj}(t)) + b_i(t)e_{vi}(t)
\end{align*}$$

(5)

Based on the characteristics of Laplacian matrix $\mathcal{A}(t)$, the tracking error can be reorganized in a compact form (6)
where $C$ is the collective sliding mode surface designed for the multirobot target tracking system. 

For multirobot system with disturbances (7), an adaptive overall sliding mode control law is designed as 

$$U(t) = \begin{bmatrix} \sum_{k=1}^{N} \alpha_k(t) \end{bmatrix}^{-1} \begin{bmatrix} \varepsilon_1(t) \\ \vdots \\ \varepsilon_n(t) \end{bmatrix} - CE_v(t) - \eta S - \beta \text{sign}(S) - \frac{|S|}{S}\delta$$

where $\delta = [\delta_1, \delta_2, \ldots, \delta_n]^T$ is the estimation of upper bound of disturbances $\delta^* = \sum_{k=1}^{N} \Delta_k$ of disturbances $d_1^*, d_2^*, \ldots, d_n^*$ of disturbances. The adaptive law is 

$$\dot{\delta} = |S|$$

It should be noted that here we use $|S|$, denoting that all the elements are absolute values of the elements in $S$.

The tracking control protocol for the $i$th tracking robot becomes 

$$u_i(t) = \left[ \sum_{j=1, j \neq i}^{n} a_{ij}(t) + b_{ij}(t) \right]^{-1} \left[ \sum_{j=1, j \neq i}^{n} (a_{ij}(t) u_i(t)) - c_{ij} \varepsilon_{ij} - \eta_{ij} - \beta \text{sign}(s_i) - \frac{|s_i|}{s_i}\delta_i \right]$$

Under continuously time-varying topologies constructed by polytopic model structure, the following theorem provides a sufficient condition for disturbed multirobot systems realizing successful target tracking.

**Theorem 1.** Consider the multirobot system (7) with disturbances and continuously time-varying topologies. The designed adaptive sliding mode controller (11) can solve the disturbed target tracking problem (7) if there exists a symmetric positive definite matrix $P_k$ with suitable scale satisfying the condition (12) with known positive constants $\eta, \ell_1, \ell_2, \alpha_d, \beta, \ldots, \alpha_dN$, designed control matrix $C$ and positive definite matrix $Z$ 

$$\Phi_k = \begin{bmatrix} P_k - 2\eta C + C^T Z^{-1} + \ell_1 I \otimes Z \\ \ast \\ -2\eta I + Z^{-1} + P_k Z \end{bmatrix} < 0$$

where $\Phi_{k1} = \alpha_d P_k + \alpha_d P_2 + \cdots + \alpha_dN P_N - 2\eta C + C^T Z^{-1} C + P_k P_k$, for all $k = 1, 2, \ldots, N$, namely the tracking robots (1) are able to successfully track the target (2).

**Proof.** The Lyapunov function is designed as 

$$V(t) = \sum_{k=1}^{N} \alpha_k(t) E_k^2(t) + S^T S + \delta^T \hat{\delta}$$

where $\hat{\delta} = \delta^* - \hat{\delta}$ is the estimation error.

Along the trajectory of the system (7), the derivative of Lyapunov function (13) is 

$$\dot{V}(t) = V_1(t) + V_2(t) + V_3(t)$$

with
\[ V_1(t) = \sum_{k=1}^{N} \alpha_k(t) E_k^T(t) P_k E_k(t) \]
\[ V_2(t) = \sum_{k=1}^{N} \alpha_k(t) [\dot{E}_k^T(t) P_k E_k(t) + E_k^T(t) P_k \dot{E}_k(t)] \]
\[ V_3(t) = S^T \dot{S} + \delta^T \dot{\delta} + \ddot{\delta}^T \dddot{\delta} \]

In the light of the fact that \( \dot{\alpha}_k(t) \leq \alpha_{dk} \), one has
\[ V_1(t) \leq \sum_{k=1}^{N} \alpha_{dk} E_k^T(t) P_k E_k(t) \]

According to system (7), \( V_2(t) \) can be further derived as
\[ V_2(t) = \sum_{k=1}^{N} \alpha_k(t) [E_k^T(t) P_k E_k(t) + E_k^T(t) P_k E_k(t)] \]

Considering the form of sliding mode \( S \) and the system (7), we have
\[ V_3(t) = S^T [CE_v(t) + \sum_{k=1}^{N} \alpha_k(t) \dot{\varphi}_k F(t, e_k(t), e_v(t))] + \sum_{k=1}^{N} \alpha_k(t) \dot{\varphi}_k F(t, e_k(t), e_v(t)) + \sum_{k=1}^{N} \alpha_k(t) \dot{\varphi}_k (U(t) + D(t))] + [CE_v(t) + \sum_{k=1}^{N} \alpha_k(t) \dot{\varphi}_k F(t, e_k(t), e_v(t))] \]

Substituting the overall sliding mode control (9) into (18) and considering the fact that \( \delta^* = 0 \), since \( \delta^* \) is constant, equation (19) is derived
\[ V_3(t) = -2S^T \eta S + S^T \sum_{k=1}^{N} \alpha_k(t) \dot{\varphi}_k F(t, e_k(t), e_v(t)) \]

Recalling \( \delta^* = \sum_{k=1}^{N} \alpha_{dk} \dot{\varphi}_k [d_1, d_2, \ldots, d_n]^T \) and combining Lemma 1, it can be obtained that
\[ V_3(t) \leq -2S^T \eta S + S^T Z^{-1} S + \sum_{k=1}^{N} \alpha_k(t) \dot{\varphi}_k (l, e_k(t) + l, e_v(t)) \]

According to the adaptive law (10) and using equation (6), it can be further derived that
\[ V_3(t) \leq -2[CE_v(t) + E_v(t)]^T \eta [CE_v(t) + E_v(t)] + [l, E_v(t) + l, E_v(t)] Z^{-1} [l, E_v(t) + l, E_v(t)] + |S|^T [\delta^* - \dot{\delta}] + [\delta^* - \dot{\delta}]^T |S| - \beta S^T \sigma(S) - \beta (\sigma(S))^T S \]

Given the above inequalities, we are able to organize the derivative of Lyapunov function (14) in a compact form
\[ \dot{V}(t) \leq \sum_{k=1}^{N} \alpha_k(t) [E_v(t)]^T \Phi_k [E_v(t)] - \beta S^T \sigma(S) - \beta (\sigma(S))^T S \]

It is obvious that inequality (12) gives rise to \( \dot{V}(t) < 0 \), which suggests that the overall tracking error system (7) is stable. This implies that the position and velocity errors between the robots and the target tend to zero asymptotically. Then, according to Definition 1, the disturbed robots can track the target successfully with proposed adaptive control even under the effect of continuously time-varying topology. The proof is completed.

**Numerical results**

Numerical examples are conducted to demonstrate the foregoing research result. It is assumed that three robots track a moving target in a three-dimensional space. Numerical comparisons are made to verify the advantages of the designed adaptive control law for disturbed multirobot systems with continuously time-varying topologies.

**Simulation of tracking system with time-varying topology and disturbances**

The target is assumed to start moving at the origin \( x_0(0) = [0, 0, 0] \), with velocity \( v_0(0) = [0.35, 0.8, 0.6] \) in the three-dimensional space. Three tracking robots are initially deployed at positions, \( x_1(0) = [0, 2, -1, 3, 1], x_2(0) = [0.5, 1, 0.7], x_3(0) = [0.8, 0, 1.2] \), with initial velocities...
v_1(0) = [-0.8, -0.2, 0.08], v_2(0) = [0.25, -0.7, 0.2], v_3(0) = [-0.5, 0.8, 0.1], respectively. The following is a description of the nonlinear dynamics

\[
f(x(t), v(t)) = 1.5|x(t)| - 0.26v(t) - 1 \quad (23)
\]

which satisfies Assumption 1. The Lipschitz constants are \( l_x = 1.5 \) and \( l_v = 0.26 \).

In the simulations, the continuously time-varying topology of the system is shown in Figure 3. The left-hand side figures represent the decomposed two constant topologies and the right-hand side figure is the time-varying topology in polytopic model. The corresponding Laplacian matrix is

\[
L(t) + B(t) = \alpha_1(t) \begin{pmatrix} 0.8 & -0.8 & 0 \\ -0.8 & 2.3 & -1.2 \\ 0 & -1.2 & 1.2 \end{pmatrix} + \alpha_2(t) \begin{pmatrix} 1.5 & -0.3 & -0.7 \\ -0.3 & 0.3 & 0 \\ -0.7 & 0 & 1.7 \end{pmatrix}
\]

where the corresponding scheduling functions are \( \alpha_1(t) = 0.3\sin^2(t), \alpha_2(t) = 1 - \alpha_1(t) \).

The derivative of \( \dot{\alpha}_1(t) \) is \( \dot{\alpha}_1(t) = 0.6\sin(t)\cos(t) \). Then, the derivative of \( \dot{\alpha}_2(t) \) is \( \dot{\alpha}_2(t) = -\dot{\alpha}_1(t) \). Thereafter, the assumption \( \dot{\alpha}_k(t) \leq \alpha_{sk} \) is satisfied with \( \alpha_{s1} = \alpha_{s2} = 0.6 \).

In the simulations, \( c_1 = 1.5, c_2 = 2.8, c_3 = 3.5 \) are the selected control parameters and \( \eta = 1.5, \beta = 0.16 \) are the designed reaching parameters. Based on the conditions in Theorem 1 with an identity matrix \( Z \), we can obtain the below feasible solutions for matrices \( P_1 \) and \( P_2 \)

\[
P_1 = P_2 = \begin{pmatrix} 1.3680 & 0 & 0 \\ 0 & 5.3466 & 0 \\ 0 & 0 & 7.2659 \end{pmatrix}
\]

The disturbances of the robots are

\[
d_1 = [1.5\sin(2t), 2\cos(0.8t), 3\cos(1.5t)]
\]

\[
d_2 = 1.5 \times [1.5\sin(2t), 2\cos(0.8t), 3\cos(1.5t)]
\]

\[
d_3 = 0.75 \times [1.5\sin(2t), 2\cos(0.8t), 3\cos(1.5t)]
\]

Now, we conduct the simulation for tracking system under the effect of disturbances (25) and the sliding mode control law (9) without the adaptive part \(-\frac{|S|}{\delta} \). Figure 4 shows the trajectories of the target and tracking robots, while the position and velocity tracking errors are depicted in Figures 5 and 6, respectively. It can be seen that, for target tracking system under continuously time-varying topology, the tracking robots tend to converge to the target under the effect of coordination control without the designed adaptive part. However, it is obvious that the tracking errors fluctuate in a relatively large range.

**Comparison simulation of tracking system with designed adaptive sliding mode control**

In the following, we show the advantage of the proposed adaptive sliding mode control law (9). All the initial configurations of the robots and the target are the same as those in the above simulation. Figure 7 shows the trajectories of the target and three tracking robots with the proposed adaptive control under the same effect of disturbances, as used in the above simulation. Figures 8 and 9 show the robots’ position and velocity tracking errors suffering disturbances
and with the adaptive control law, respectively. Compared to the results in Figures 5 and 6, the tracking errors are significantly reduced. Under the continuously time-varying topology (24), it is shown that the tracking robots can track the moving target successfully.

To clearly show the effectiveness of proposed adaptive sliding mode control for multirobot systems, tracking errors are compared in a quantitative way. The maximum and minimum values of position and velocity errors over time interval $[4s, 10s]$ are tabulated in Tables 1 and 2, respectively. Specifically, for robots 1 and 3, the position tracking errors with adaptive control law are only almost $1/50$ of that without adaptive control law. For robot 2, the position errors are reduced to nearly $1/30$ of the value without adaptive control. In terms of velocity errors, under the effect of adaptive control, they are shrunk to about $1/30$, $1/10$, and $1/70$ of the values without adaptive control for robots 1, 2, and 3, respectively.

Conclusions and discussion
In this work, an adaptive timing consensus tracking method for second-order multirobot systems with disturbances is proposed. The time-varying communication topology between the tracking robot and the target is modeled by constant Laplacian matrices and corresponding time-varying scheduling functions, which is called polytopic model. Through constructing the polytopic model, the tracking strategy is less conservative. Numerical examples show that the proposed adaptive sliding mode control tracking strategy is superior to previous related work. With designed
adaptive sliding mode control, the disturbed robots can effectively track the target with nonlinear dynamic characteristics under continuously time-varying topology.

This article mainly deals with disturbed target tracking systems continuously time-varying topology and some significant results have been presented. However, there are still some issues to be solved in future research. For example, the time delays are existing in most systems since the robots are exchanging information using wireless communication techniques. How the time delays will affect the control performance of designed adaptive sliding mode control method especially with polytopic structure is worth further investigating.

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