Formation Control and Tracking of Mobile Robots using Distributed Estimators and A Biologically Inspired Approach

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Abstract
This paper investigates the formation control problem for multiple nonholonomic wheeled mobile robots using distributed estimators and a biologically inspired approach. The formation pattern of the system adopts leader–follower structure and the communication topology among the multi-robot system is modelled by an undirected graph. In our proposed methodology, first, we develop an adaptive trajectory tracking control for the leader robot to follow the desired trajectory. Second, a distributed estimator is designed for each follower mobile robot, which uses its own information to estimate the leader’s states, such as position, orientation, and linear velocity. Then, distributed formation tracking control laws are designed based on the distributed estimator. Furthermore, a bioinspired controller is developed to address the impractical velocity jump problem. The closed-loop system stability is analysed with the Lyapunov stability theory showing that tracking errors are asymptotically converge to zero. Finally, simulation results are provided to demonstrate the effectiveness of the proposed methods.

Keywords Distributed formation control · Nonholonomic mobile robots · Trajectory tracking control · Bioinspired neurodynamic approach

1 Introduction
Owing to the wide range of practical applications in various fields, there has been increasing attention to research on the cooperative control of numerous nonholonomic mobile robots (NMR). In particular, the formation control problem of multiple NMRs has received great focus from researchers because of its potential applications in surveillance and security, object transportation and manipulation, search and rescue, and intelligent transport systems [1–3]. Besides, mobile medical robots have unique the advantage regarding quarantine infectious disease scenarios, such as SARS and COVID-19 and, thus, can significantly reduce the infection rate [4–9].

In general, the formation control strategies for multi-robot formation include the leader–follower method [10], the artificial potential field method [11], the behaviour-based method [12], and the graph theory-based method [13]. Specifically, behaviour-based techniques for formation control considers several desired behaviours such as collision avoidance, formation maintenance, and target searching. The control inputs for each robot are determined by weighing the relative importance of each behaviour. The disadvantage is that the group behaviour cannot be explicitly defined, and it is difficult to analyze the behavioural approach mathematically.

On the other hand, the virtual structure method treats the entire formation as a single structure. This method is robust against the faults of the virtual robot or point but changing the formation shape depending on the environment is challenging. For instance, the artificial potential field approaches is widely applied for the swarm formation of mobile robots with obstacle avoidance. In the leader-following approach to formation control, the leader NMR moves along a predefined trajectory, and follower NMRs are controlled to follow the leader with a fixed relative position in a given reference frame. Although each approach has its share of advantages and disadvantages, the leader–follower approach seems to be most favoured because of its simplicity and scalability.

In the existing works [13–15], the control law is designed for a single NMR robot to follow the reference trajectory in challenging environments. However, compared to the single
NMR, the multiple NMRs control design is quite difficult due to collision avoidance and external disturbances. Moreover, the multi-robot controller is more difficult to provide the desired geometric shape like triangle, square, or circle formation for the multiple NMR. Therefore, the proposed methodology is mainly focused to address the problems of formation control problems for the multiple NMRs.

The control structure for the swarm robot system can be categorized as centralized [14], distributed [15] and layered structures [16]. The centralized control structure is a single computational unit that processes all the information needed to achieve the desired control objectives. The centralized structure is simple and easy to implement, however, it has low flexibility and fault tolerance. In contrast, the distributed control strategies have no central control unit. In this method, each robot is autonomous and makes the decision according to its own tasks. Particularly, this method has high fault tolerance and reliability, however, it is more difficult to coordinate between robots. Therefore, it is much preferable to use a distributed structure than a centralized structure for the formation control of multiple mobile robots. On the contrary, the layered structure is the fusion of centralized and distributed structures, which has the control unit to supervise the whole system and is independent of each robot. The distributed and layered structures can be applied in high dynamic and complex environments. We would like to mention that the proposed formation control approach is developed based on the distribution strategy.

The authors in [17] have proposed an adaptive iterative learning control method for robotics systems to improve the performance of the industrial robot. On the other hand, in [18] a real-time adaptive tracking control for mobile robot have been developed for mobile robots using sliding mode control and a fuzzy neural network. Similarly, the authors in [19] have proposed a new algorithm to improve the connectivity and area convergence by exploiting some robots in the group to change their topology and the position of sensors. Moreover, in [20] rapidly exploring random trees and B-spline curves are combined to solve the path planning problems of the NMRs.

The rest structure of this paper is prearranged as follows: related to works of mobile robot formation and contribution of the work are discussed in Sect. 2. Moreover, Sect. 3 describes the problem formulation and Sect. 4 explains the proposed methodology including backstepping control for trajectory tracking and formation control. In addition, the bioinspired neural dynamics called shunting model is added to the controls to avoid speed jump and chattering issues in the conventional designs of the control strategy. Then, Sect. 5 provides the results and discussions that demonstrate the efficiency and effectiveness of the proposed method. Finally, conclusions and some potential future improvements for the mobile robot formation control designs are discussed in Sect. 6.

2 Related Works

Over the past few years, the trajectory tracking control problem for a single mobile robot has been studied extensively [10, 21–23]. The authors in [21] proposed a backstepping approach to the trajectory tracking control of a mobile robot. Ref. [22] introduced a novel torque controller for a mobile robot and integrated the kinematic controller and a neural network torque controller for an NMR. Ref. [23] proposed the receding horizon tracking control on the wheeled mobile robots, which uses the optimized method to accelerate the convergence speed of errors. In [10], a controller based on the relative position in the global reference frame is developed for unicycle-type robots with input constraints. During the last decade, the interaction between chaos theory and mobile robots has been studied intensively [24–34]. For instance, the authors in [24] have developed a chaotic motion controller for autonomous mobile robots.

Tracking control is one of the fundamental issues in the control of mobile robots, which is concerned to design the tracking controller to force the robot to reach and follow a prescribed trajectory over time. There have been numerous studies on tracking control of NMRs over the past years. In particular, existing tracking control methods can be classified into four categories: (1) sliding mode control [35]; (2) linearization [36] (3) backstepping-based control [37] and (4) neural networks and fuzzy systems [38]. For instance, the tracking control algorithms designed using sliding mode methods are difficult to implement for real-time robots which are computationally expensive. Technically, the generated velocity commands with respect to time are not smooth curves, which leads to nonuniformity in the robot velocities [35]. On the other hand, the linearization-based methods are accomplished by converting input–output nonlinear control systems into input–output linear control systems through the linearization of the static and dynamic state feedback [36]. Among the above methods, the backstepping tracking method is the most commonly used method for tracking control [37]. By using the backstepping technique, the tracking controllers can be simple and the system stability can be guaranteed by Lyapunov stability theory. Moreover, some of the backstepping based controllers can deal with arbitrarily large initial errors. However, the generated robot velocity commands using the backstepping control approaches start with a very large value and suffer from velocity jumps when sudden tracking errors occur, i.e., the required accelerations and forces/torques are infinitely large at those velocity-jump points, which is not practically possible.
In particular, the neural network approach is an efficient way to deal with large velocity jumps. However, this approach requires online/offline learning that helps NMRs to perform well, and it is difficult to prove the stability of the system. In contrast, the fuzzy tracking control for NMRs does not require online learning like the neural network approach which can deal with velocity issues in backstepping control [38]. But this rule-based approach is difficult to set up the rules, which are highly dependent on trial and error and often require knowledge from experts. Moreover, in the backstepping approach, the numerical derivatives of virtual velocity control signals have to be calculated, which makes the tracking controller computationally complicated. The very few recently developed robust controllers consider the adaptive robust control and finite-time control in the mobile robot system. However, it may be difficult to measure the angular and/or linear velocities of the mobile robot system accurately in practice. Among all the above-mentioned tracking control strategies, [39] proposed a novel backstepping controller inspired by a biological neural system which can generate continuous smooth control signals with zero initial velocities for the mobile robot. This method resolved velocity jumps in conventional backstepping control, and this biologically inspired backstepping control method is relatively simple to implement. Inspired by this method, the authors in [40] have proposed tracking control for underactuated surface vehicles to avoid the inherent complexity of the virtual control signals in the backstepping control.

In addition, the authors in [41] have designed a novel tracking controller by incorporating the bioinspired neurodynamics method into the backstepping control to handle the velocity jumps of the multiple robots system. A topologically organized bioinspired neurodynamics method based on the grid map was proposed [42] to represent the dynamic environment and reduce the sharp jumps of the initial values. From, [39, 41] and [42], it can be seen that the bioinspired neurodynamics method has a better ability to handle the external noise/disturbance, such that the system performance is improved. Because an ion-channel-model-based biodynamic neural network is provided by the bioinspired neurodynamics model, it can be employed to reduce the sharp jumps of the initial values. Moreover, the smooth bounded outputs are obtained by employing the bioinspired neurodynamics method. To our best knowledge, there are few works of literature considering the adaptive robust control and bioinspired neurodynamics method for the mobile robot with unmeasurable angular velocity and multiple time-varying bounded disturbances.

Authors in [43] proposed the concept of leader-toformation stability to examine the stability properties of mobile agent formations based on the leader-following approach. Moreover, a decentralized controller has developed a mobile robot in [44] to solve the problem of formation-tracking control to follow straight paths. In [45], the formation control NMRs subject to diamond-shaped input constraints were considered, and novel control laws were designed. A distributed nonlinear controller has been designed for unicycle type robots [46] without considering the global position measurements. A novel distributed control law is developed in [46] to achieve leader–follower formation of multiple nonholonomic vehicles subject to velocity constraints. Later in [47], a distributed event-triggered control method has been proposed for multi-robot systems under fixed topology and switching topology. Recently, the authors in [48] have proposed a distributed control strategy for the leader-following formation control of multiple NMRs using distributed estimators. Compared to the different existing control methods [49–53], the distributed control strategy provides a better solution for the leader-following formation control problems.

Based on the aforementioned investigations, it is assumed that the state information of the leader robot is accessible to all follower robots. In case, if the number of robots in the group is increasing, then the communication between the leader and the followers is very difficult. With the limitation in communication bandwidth and range, it is reasonable to assume that the information of the leader is available only to a subset of followers. Therefore, the proposed methodology, suggests a new distributed leader-following formation control strategy based on the distributed estimation of the leader’s states.

Motivated by the observations made above, we investigate the leader–follower formation and tracking control problem for nonholonomic mobile robots in this paper.

The main contribution of this study is summarized when compared with existing works as below:

1. In this work, we design the trajectory tracking control laws for the leader robot such that the leader robot can track the reference trajectory.
2. For the proposed model, a distributed estimation law is developed for each follower robot to estimate the state information of the leader robot including the position, orientation, and linear velocity.
3. Then, the distributed formation controllers are designed based on the distributed estimators such that the desired formation pattern is achieved.
4. We incorporate a bioinspired neurodynamics based approach according to the backstepping technique for the leader–follower formation to solve the impractical velocity jumps problem.
5. Simulation results are provided to demonstrate the efficiency of the developed controller which shows that the follower robots keep the desired formation with respect to the leader trajectory.
### 3 Preliminaries and Problem Formulation

#### 3.1 Algebraic Graph Theory

The interactions among the nonholonomic wheeled mobile robots can be represented using an undirected graph. In this paper, we consider an undirected graph $G = (V, E, A)$ consisting of set $V = \{1, 2, ..., n\}$, edge set $E \subseteq V \times V$. The adjacency matrix $A \in \mathbb{R}^{n \times n}$ with nonnegative elements. Specifically, in the communication topology, a directed edge denoted by $(j, i)$ means that node $i$ has access to node $j$. Moreover, the elements of adjacency matrix $A = [a_{ij}]_{n \times n}$ are defined as follows: If $(j, i) \in E$, then $a_{ij} > 0$; otherwise, $a_{ij} = 0$. Assume that at least one follower can receive leader’s information. Otherwise $a_{ii} = 0$ for all $i$. On the other hand, when matrix $A$ has symmetric weights, i.e., $a_{ij} = a_{ji}$ for all $i, j \in V$, then the graph is undirected.

The Laplacian matrix $L = [l_{ij}]_{n \times n}$ is defined as

$$l_{ij} = \begin{cases} -a_{ij} & i \neq j, \\ \sum_{j=1, j \neq i}^{n} a_{ij} & i = j. \end{cases}$$  

(1)

In order to solve the leader-following problem we assume that the virtual leader, labeled as 0 and the follower robots in the range 1 to $n$. Moreover, the communication among the leader and the followers can be characterized by the adjacency weights $a_{0i} > 0$ if the leader is a neighbor of follower $i$, and $a_{0i} = 0$ otherwise. Denote $a = [a_{10}, a_{20}, ..., a_{n0}]^T$ to be the weights representing the interactions among the leader and the followers corresponding to $G$. To achieve the control objective, the following assumptions are needed.

**Assumption 1:** The reference signals $v_r$ and $\omega_r$ are bounded. In addition, the following conditions hold.

(1) The signal $v_r(t)$ is persistently exciting, i.e., there exist $T, \mu > 0$ such that $\forall t \geq 0$;

$$\int_{t}^{t+T} |v_r(s)| ds \geq \mu.$$  

(4)

(2) The signal $\dot{v}_r(t)$ is bounded, i.e., there exist constants, $\gamma > 0$ such that

$$\max_{t \geq 0} |\dot{v}_r(t)| \leq \gamma.$$  

(5)

Let $G = (V, E, A)$ be the undirected graph that represents the interactions among the $n$ follower robots. Let $a = [a_{10}, a_{20}, ..., a_{n0}]^T$ be the weights representing the interactions among the leader and the followers corresponding to $G$. To achieve the control objective, the following assumptions are needed.

**Assumption 2:** The undirected graph $G$ is connected, and at least one $a_{0i} > 0$.

Now, the destination of leader–follower formation control of multirobot system in this paper is defined as follows.

First, consider the leader robot $R_0$, a sliding adaptive controller needs to be designed such that the following equation is satisfied:

$$\lim_{t \to \infty} (x_0 - x_f) = 0,$$

$$\lim_{t \to \infty} (y_0 - y_f) = 0,$$

$$\lim_{t \to \infty} (\theta_0 - \theta_f) = 0.$$  

(6)

Second, distributed formation controllers should be designed for each follower robot $R_i$, $i \in (1, 2, ..., N)$, such that

$$\lim_{t \to \infty} (x_i - x_f) = 0,$$

$$\lim_{t \to \infty} (y_i - y_f) = 0,$$

$$\lim_{t \to \infty} (\theta_i - \theta_f) = 0.$$  

(7)

**Remark 1:** Equation (6) can ensure that the position of the leader robot $R_0$ is gradually coincident with the virtual robot $R_f$. Equation (7) ensures that all the follower robots can converge to the desired geometric structure. That is to say, if (6) and (7) are satisfied, the desired formation goal can be reached.
Remark 2: In this paper, the leader robot $R_0$ follows a predefined reference path. The leader robot $R_0$ and all follower robots follow the reference trajectory.

### 3.2 Problem Formulation

For the leader–follower formation, consider a multirobot system consisting of $n$ mobile robots. A typical model of a nonholonomic mobile robot system is depicted in Fig. 1. The kinematic model of each robot can be expressed as

$$
\begin{align*}
\dot{x}_i &= v_i \cos \theta_i, \\
\dot{y}_i &= v_i \sin \theta_i, \\
\dot{\theta}_i &= \omega_i,
\end{align*}
$$

where $x_i, y_i$ be the position coordinates, $\theta_i$ is the orientation of robot $i$. Moreover, $v_i$ and $\omega_i$ are the linear and angular velocity which are the control inputs.

More specifically, the leader–follower system setup is illustrated in Fig. 2. The leader of the mobile robot system is described by

$$
\begin{align*}
\dot{x}_0 &= v_0 \cos \theta_0, \\
\dot{y}_0 &= v_0 \sin \theta_0, \\
\dot{\theta}_0 &= \omega_0,
\end{align*}
$$

where $x_0, y_0$ be the position coordinates, $\theta_0$ is the orientation of the leader, respectively. The velocities of the leader nonholonomic mobile robot are represented in terms of linear velocity $v_0$ and angular velocity $\omega_0$.

### 4 Formation Control Design

#### 4.1 Trajectory Tracking Controller Design.

The tracking errors in global coordinates can be defined as follows:

$$
\begin{align*}
e_{rx} &= x_0 - x_r, \\
e_{ry} &= y_0 - y_r, \\
e_{r\theta} &= \theta_0 - \theta_r.
\end{align*}
$$

Accordingly, the tracking error dynamics can be further described as:

$$
\begin{align*}
\begin{bmatrix}
\bar{x}_0 \\
\bar{y}_0 \\
\bar{\theta}_0
\end{bmatrix}
&= 
\begin{bmatrix}
\cos \theta_0 & \sin \theta_0 & 0 \\
-\sin \theta_0 & \cos \theta_0 & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
e_{rx} \\
e_{ry} \\
e_{r\theta}
\end{bmatrix}
\end{align*}
$$

Define the tracking errors in local coordinates as

$$
\begin{align*}
\dot{\bar{x}}_0 &= \omega_0 \bar{y}_0 + v_r \cos \bar{\theta}_0, \\
\dot{\bar{y}}_0 &= -\omega_0 \bar{x}_0 + v_r \sin \bar{\theta}_0, \\
\dot{\bar{\theta}}_0 &= \omega_0 - \omega_r.
\end{align*}
$$

#### 4.2 Backstepping Control Algorithm

The formation control law of a typical backstepping technique is given as:

$$
\begin{align*}
v_0 &= v_r \cos \bar{\theta}_0 - k_1 \bar{x}_0, \\
&= -k_2 \bar{\theta}_0 + \omega_r - k_3 \frac{\sin \bar{\theta}_0}{\bar{\theta}_0} v_r \bar{y}_r, \\
\omega_0 &= -k_2 \bar{\theta}_0 + \omega_r - k_3 \frac{\sin \bar{\theta}_0}{\bar{\theta}_0} v_r \bar{y}_r.
\end{align*}
$$
where $k_1$, $k_2$ and $k_3$ are positive control gains.

**4.3 Distributed Estimation of Leader’s State**

In general, the leader-following formation control approaches for mobile robots consider that the leader robot information is available to each follower robots and control laws are designed based on this assumption. But, this assumption is not true which means that the communication between the leader robot and follower robots are basically local, and only a sub-group of followers can access to the leader robot information. Therefore, in this section, we develop a distributed estimation law based on the internal communications to obtain the leader robot information such as position, orientation, and forward velocity.

The variables of the leader that must be estimated are defined as follows:

$$
\kappa_r = [\dot{x}_r, \dot{y}_r, \dot{\theta}_r, \dot{v}_r]^T
$$

where $\kappa_i = [\dot{x}_i, \dot{y}_i, \dot{\theta}_i, \dot{v}_i]^T$ as the estimation of $\kappa_r$ obtained by each robot $i$.

The neighborhood position and orientation estimation errors of robot $i$ can be defined as

$$
e_{ik} = \sum_{j=1}^{n} a_{ij} (\kappa_{ir} - \kappa_{jr}) + a_{io} (\kappa_{ir} - \kappa_r).
$$

Based on the neighborhood errors $e_{ik}$, let us consider the succeeding estimation algorithm for $\kappa_{ir}$:

$$
\dot{\kappa}_{ir} = \frac{1}{\sum_{j=1}^{n} a_{ij} + a_{io}} \left( -\Xi e_i + \sum_{j=1}^{n} a_{ij} \dot{\kappa}_{jr} + a_{io} \dot{\kappa}_r \right)
$$

where $\Xi \in \mathbb{R}^{3 \times 3}$ is a symmetric positive definite matrix.

Having noted on the above estimation, the linear velocity of the virtual leader $\dot{\nu}_r$ can be estimated if $\dot{\nu}_r$ is known. Based on the Assumption 1, one can know the bounds of velocity $\dot{v}_r$. By using a variable structure approach, the linear velocity $\dot{v}_r$ is estimated. More specifically, the linear velocity estimation error for each follower robot $i$ can be defined as follows

$$
e_{iv} = \sum_{j=1}^{n} a_{ij} (\dot{\nu}_i - \dot{\nu}_{jr}) + a_{io} (\dot{\nu}_i - \dot{v}_r).
$$

Similarly, we can define the estimation law for $v_r$ as follows,$\dot{v}$

$$\dot{v} = -\alpha e_{iv} - \beta \text{sgn}(e_{iv}).
$$

where $\alpha > 0$ and $\beta > \gamma$ are positive constants.

**Theorem 1** Consider the estimation laws (16) and (18). If Assumption 2 holds, then $\kappa_{ir}$ exponentially converges to $\kappa_i$ for all $i$.

**Proof** Initially, we discuss the exponential convergence of $\kappa_{ir}$ to $\kappa_i$. Then, take derivative for $e_{ik}$ with respect to time, we get

$$
\dot{e}_{ik} = \sum_{j=1}^{n} a_{ij} (\kappa_{ir} - \kappa_{jr}) + a_{io} (\kappa_{ir} - \kappa_r).
$$

$$
= \left( \sum_{j=1}^{n} a_{ij} + a_{io} \right) \dot{\kappa}_{ir} - \sum_{j=1}^{n} a_{ij} \dot{\kappa}_{jr} - a_{io} \dot{\kappa}_r,
$$

$$
= -\Xi e_{ik}.
$$

As $\Xi$ is the symmetric positive definite, it is obvious that, $e_{ik}$ exponentially converge to zero.

Moreover, if we denote $e_{kv} = [e_{k1}^T, e_{k2}^T, \ldots, e_{kn}^T]$ and $\kappa = [\kappa_1^T, \kappa_2^T, \ldots, \kappa_n^T]^T$ with $\kappa_i = \kappa_{ir} - \kappa_r$, then (15) can be rewritten as

$$
e_{kv} = (H \otimes I_n) \kappa
$$

where $H \in \mathbb{R}^{n \times n}$ is a matrix defined by $H = L + \text{diag}(a)$.

Since $H$ is a symmetric positive definite matrix when Assumption 2 holds by applying Lemma 1, the exponential convergence of $e_{kv}$ to zero implies exponential convergence of $\kappa$ to zero. This completes the proof.

**4.4 Tracking Error and Error Dynamics**

The tracking errors in global coordinates can be defined as follows:

$$
e_{ix} = x_i - x_{ir},
$$

$$
e_{iy} = y_i - y_{ir},
$$

$$
e_{io} = \theta_i - \theta_{ir}.
$$

Since $x_{ir}, y_{ir}$ and $\theta_{ir}$ exponentially converge to $x_r, y_r$ and $\theta_r$; then the control objectives will be achieved when $\dot{x}_i, \dot{y}_i$ and $\dot{\theta}_i$ converge to zero.

Define the tracking errors in local coordinates as

$$
\begin{bmatrix}
\ddot{x}_i \\
\ddot{y}_i \\
\ddot{\theta}_i
\end{bmatrix} =
\begin{bmatrix}
\cos \theta_i & \sin \theta_i & 0 \\
\sin \theta_i & -\cos \theta_i & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
e_{ix} \\
e_{iy} \\
e_{io}
\end{bmatrix}.
$$

Accordingly, the tracking error dynamics can be further described as:
\[ \dot{x}_i = \omega \dot{y}_i + v_i - v_{ir} \cos \theta_i, \]
\[ \dot{y}_i = -\omega \dot{x}_i + v_{ir} \sin \theta_i, \]
\[ \dot{\theta}_i = \omega_i - \dot{\theta}_ir. \]  

(23)

### 4.5 Backstepping Control Algorithm

The formation control law of a typical backstepping technique is given as:

\[ v_i = v_{ir} \cos \theta_i - k_1 \dot{x}_i, \]  

(24a)

\[ \omega_i = -k_2 \dot{\theta}_i + \theta_{ir} - k_3 \frac{\sin \theta_i}{\dot{\theta}_i} \dot{v}_{ir} \dot{y}_i \]

(24b)

where \( k_1, k_2 \) and \( k_3 \) are positive control gains.

### 4.6 The Bioinspired Neurodynamics Controller Design

The bioinspired neurodynamics model is developed based on the circuit theory which provides an ion-channel-model-based biodynamic neural network to investigate the biological cell membrane potential. Moreover, this biodynamic neural network is a powerful tool to carry out the complex analysis and/or reasoning because the number of biological neurons is huge [55]. In particular, the biodynamic neural network has the great ability to process the nonlinear input signals.

In their membrane model, the dynamics of voltage across the membrane \( V_m \) can be described using the state equation technique as

\[ C_m \dot{V}_m = -(E_p + V_m) g_p + (E_{Na} - V_m) g_{Na} - (E_K + V_m) g_K \]

(25)

where \( C_m \) is the membrane capacitance. Here, the parameters \( E_K, E_{Na}, \) and \( E_p \) are the potassium potential, the sodium potential of the membrane, and the passive leakage current of the Nernst potential. Moreover, parameters \( g_K, g_{Na}, \) and \( g_p \) denote the potassium ion, sodium ion and passive channel conductance, respectively. The shunting model and its variants are widely employed in numerous applications.

By setting \( C_m = 1 \) and substituting \( x_i = E_p + V_m, A = g_p, \]
\[ B = E_{Na} + E_p, D = x_i - E_p, S_i^+ = g_{Na} \] and \( S_i^- = g_K \) in (20) the shunting dynamic model is described as

\[ \dot{x}_i = -A_i x_i + (B_i - x_i) S_i^+(t) - (D_i - x_i) S_i^-(t) \]

(26)

where \( x_i \) is the neural activity of the i-th neuron. The parameters \( A_i, B_i, \) and \( D_i \) are non-negative constants that represent passive decay rate, the upper and lower bounds of the neural activity, respectively. The variables \( S_i^+(t) \) and \( S_i^-(t) \) denote the excitatory and inhibitory inputs to the neuron.

The main idea of the proposed control methodology for mobile robots is to exploit the bioinspired neurodynamics model with the existing backstepping control to solve the sudden velocity jumps. Based on the analysis of the controllers designed using backstepping method in [22, 39], it is well known that the velocity-jumps are caused by the sudden changes in the tracking error, particularly \( \dot{x}_i \) and \( \dot{\theta}_i \). Inspired by the smooth neural dynamics of the shunting neural model, a biological tracking controller is proposed to solve the velocity-jumps problem.

Substituting \( A_i = A, B_i = B, D_i = D, x_i = \alpha_i, S_i^+(t) = f_{i1}(\dot{x}_i), S_i^-(t) = g_{i1}(\dot{x}_i) \) we can get,

\[ \dot{\alpha}_i = -A \alpha_i + (B - \alpha_i)f_{i1}(\dot{x}_i) - (D + \alpha_i)g_{i1}(\dot{x}_i). \]

(27)

Similarly, substituting \( x_i = \beta_i, S_i^+(t) = f_{2i}(\dot{\theta}_i), S_i^-(t) = g_{2i}(\dot{\theta}_i) \) we can get,

\[ \dot{\beta}_i = -A \beta_i + (B - \beta_i)f_{2i}(\dot{\theta}_i) - (D + \beta_i)g_{2i}(\dot{\theta}_i) \]

(28)

where the functions, \( f_{i1}(\dot{x}_i), g_{i1}(\dot{x}_i), f_{2i}(\dot{\theta}_i), g_{2i}(\dot{\theta}_i) \) are defined as

\[ f_{i1}(\dot{x}_i) = \max \{ k_i \dot{x}_i, 0 \}, g_{i1}(\dot{x}_i) = \max \{ -k_i \dot{x}_i, 0 \} \]

(29)

\[ f_{2i}(\dot{\theta}_i) = \max \{ k_i \dot{\theta}_i, 0 \}, g_{2i}(\dot{\theta}_i) = \max \{ -k_i \dot{\theta}_i, 0 \} \]

(30)

where \( k_i \) and \( k_j \) are positive constants.

In this section, we design a tracking controller composed of a biologically inspired method and backstepping model. By replacing \( \dot{x}_i \) and \( \dot{\theta}_i \) with \( \alpha_i \) and \( \beta_i \) in (13a) and (13b), the tracking control for each follower robot can be obtained as

\[ v_i = v_{ir} \cos \dot{\theta}_i - k_1 \alpha_i \]

(31a)

\[ \omega_i = -k_2 \dot{\theta}_i + \theta_{ir} - k_3 \frac{\sin \dot{\theta}_i}{\dot{\theta}_i} \dot{v}_{ir} \dot{y}_i \]

(31b)

Substituting (31), into (23), we get

\[ \dot{x}_i = -k_1 \alpha_i + \omega_i \dot{y}_i, \]
\[ \dot{y}_i = -\omega_i \dot{x}_i + v_{ir} \sin \dot{\theta}_i, \]
\[ \dot{\theta}_i = -k_2 \dot{\theta}_i - k_3 \frac{\sin \dot{\theta}_i}{\dot{\theta}_i} \dot{v}_{ir} \dot{y}_i. \]

(32)
4.7 Stability Analysis

A Lyapunov function candidate is chosen as

\[ V = \frac{1}{2} \sum_{i=1}^{n} \left( \ddot{x}_i^2 + \dddot{\bar{y}}_i^2 + \frac{1}{k_3} \dot{\bar{\theta}}_i^2 + \frac{1}{B} a_i^2 + \frac{1}{B} \beta_i^2 \right) \]  \hspace{1cm} (33)

Taking the derivative of the Lyapunov function (26) along (25) gives

\[ \dot{V} = \sum_{i=1}^{n} \left( -a_i \dot{x}_i - \frac{k_2}{k_3} \dot{\bar{\theta}}_i \beta_i \right) + \frac{1}{B} \sum_{i=1}^{n} \left( -A a_i^2 - f_1(\bar{x}_i) a_i^2 - g_1(\bar{x}_i) a_i + B f_1(\bar{x}_i) a_i - D g_1(\bar{x}_i) a_i \right) 
+ \frac{1}{B} \sum_{i=1}^{n} \left( -A \beta_i^2 - f_2(\bar{\theta}_i) \beta_i^2 - g_2(\bar{\theta}_i) \beta_i + B f_2(\bar{\theta}_i) \beta_i - D g_2(\bar{\theta}_i) \beta_i \right) \]  \hspace{1cm} (34)

Moreover,

\[ \dot{V} = \frac{1}{B} \sum_{i=1}^{n} \left( -A + f_1(\bar{x}_i) - g_1(\bar{x}_i) \right) a_i^2 
+ \frac{1}{B} \sum_{i=1}^{n} \left( -A f_2(\bar{\theta}_i) / B - g_2(\bar{\theta}_i) \right) \beta_i^2 
+ \frac{1}{B} \sum_{i=1}^{n} \left( -A + f_2(\bar{\theta}_i) - g_2(\bar{\theta}_i) \beta_i \right) 
+ \frac{1}{B} \sum_{i=1}^{n} \left( -\frac{k_2}{k_3} B \theta_i + B f_2(\bar{\theta}_i) - D g_2(\bar{\theta}_i) \right) \beta_i \]  \hspace{1cm} (35)

Choosing the constant \( B = D \) in the shunting Eqs. (27) and (28), we have

\[ \dot{V} = \frac{1}{B} \sum_{i=1}^{n} \left( -A - f_1(\bar{x}_i) - g_1(\bar{x}_i) \right) a_i^2 
+ \frac{1}{B} \sum_{i=1}^{n} \left( -A - f_2(\bar{\theta}_i) - g_2(\bar{\theta}_i) \beta_i \right) 
+ \sum_{i=1}^{n} \left( f_1(\bar{x}_i) - g_1(\bar{x}_i) - \ddot{x}_i \right) a_i 
+ \sum_{i=1}^{n} \left( f_2(\bar{\theta}_i) - g_2(\bar{\theta}_i) - \frac{k_2}{k_3} \dot{\bar{\theta}}_i \right) \beta_i \]  \hspace{1cm} (36)

According to the definitions of \( f_1(\bar{x}_i) \) and \( g_1(\bar{x}_i) \) in (29), whenever \( \bar{x}_i \geq 0 \) and \( \ddot{x}_i < 0 \), we have

\[ f_1(\bar{x}_i) - g_1(\bar{x}_i) - \ddot{x}_i = 0 \]

Similarly, it is easy to obtain that

\[ f_2(\bar{\theta}_i) - g_2(\bar{\theta}_i) - \frac{k_2}{k_3} \dot{\bar{\theta}}_i = 0 \]  \hspace{1cm} (37)

According to the definitions of \( f_1(\bar{x}_i) \) and \( g_1(\bar{x}_i) \) in (29), whenever \( f_1(\bar{x}_i) \geq 0 \) and \( g_1(\bar{x}_i) \geq 0 \). Further, A and B are nonnegative constants, then

\[ \frac{-A - f_1(\bar{x}_i) - g_1(\bar{x}_i)}{B} \leq 0 \]  \hspace{1cm} (34)

Similarly, we have

\[ \frac{-A - f_2(\bar{\theta}_i) - g_2(\bar{\theta}_i)}{B} \leq 0. \]  \hspace{1cm} (35)

Lyapunov function \( \dot{V} \) satisfies the conditions in Lemma 2. Hence, \( \dot{V} \) is uniformly continuous in \( t \). It follows from the Barbalat’s lemma that \( V \to 0 \) as \( t \to \infty \) from which it can be deduced that, \( \alpha_i \to 0 \), \( \beta_i \to 0 \) and \( \ddot{x}_i \to 0 \) as \( t \to \infty \). By using (27), (28) and the input–output property of the shunting model, it infers that if the output converges to zero, the input is supposed to go to zero, that is to say \( \bar{x}_i \to 0 \) and \( \bar{\theta}_i \to 0 \) while \( \alpha_i \to 0 \) and \( \beta_i \to 0 \). Therefore, the tracking controller (31) can guarantee the closed-loop

![Flow chart of proposed method](image-url)

Fig. 3 Flow chart of proposed method
dynamics system (32) to be globally asymptotically stable. The flowchart of the proposed method is shown in Fig. 3.

5 Simulation Results and Discussions

In this section, simulation results are performed to show the effectiveness of proposed method. The proposed control methodology is applied on a group of mobile robots. The communication topology among the multirobot systems adopts an undirected graph, which is shown as Fig. 4. The simulation includes two parts. The first part is mainly to validate the effectiveness of the designed trajectory tracking controllers for the leader robot. The second part is to demonstrate the effectiveness of leader’s controller and distributed formation controllers at the same time. By default, all following variables are in SI units.

**Section 1:** The initial position and angle of virtual reference robot $R_r$ is $[0(m), 0(m), \pi/6(rad)]^T$ and the leader $R_0$ starts from $[-0.2(m), -0.15(m), \pi/6(rad)]^T$. The linear and angular velocity of the virtual reference robot $R_r$ is chosen as $(4.25 - (0.5\cos(0.5t)))$ and $2.5\cos(0.5t)$. The parameters for the proposed controllers of leader robot $R_0$ are chosen as $k_1 = 0.15$, $k_2 = 1.25$, $k_3 = 0.90$. Figure 5 shows the trajectory of leader robot $R_0$ and virtual reference robot $R_r$ during 0–350 s, and it can be seen from the figure that the position of leader robot coincides with the virtual reference robot gradually. The tracking errors of leader robot is shown in Fig. 6 that converges to zero. It can be seen from Fig. 7 that the linear velocity and angular velocity of leader robot coincide with the virtual reference robot’s velocities quickly.

**Section 2:** In this section, the effectiveness of the proposed distributed formation controllers based on distributed estimator is verified. The virtual reference robot $R_r$ starts from $[x_r, y_r, \theta_r]^T = [0.5(m), 1(m), \pi/6(rad)]^T$, and the velocities of virtual robot $R_r$ are chosen as $v_r = 3.25 - 0.25\cos(0.24t)(m/s)$.
The initial state of leader robot $R_0$ and all follower robots, $[x_i, y_i, \theta_i], i = 0, 1, ..., N$, set as $R_0 = [2, 2.5, 0.6]$, $R_1 = [5, 2, 0], R_2 = [-3, 3, 0.5], R_3 = [0, 0, -1]$.

The values for each estimators are set to $[1, -0.99, \pi/3], [1, -1, \pi/3], [-1, -1, \pi/3]$. The control parameters of leader robot are chosen as $\omega_r = 0.1 \cos(0.2t) (\text{rad/s})$.

$k_1 = 0.5, k_2 = 1.6, k_3 = 2$, and the control parameters of follower robots are selected as $k_1 = 2, k_2 = 3, k_3 = 5$. The control parameters of leader robot are chosen as $\Xi = I_3, \alpha = 20, \text{and} \beta = 5$; Fig. 8 shows the trajectories of all robots during 0–300 s, it can be seen from the graph that the
multirobot system converges to the desired formation pattern gradually. Similarly, Fig. 9 shows the evolution of the leader robot the three estimators. The estimation errors are shown in Fig. 10. The formation tracking errors of leader robot converge to zero asymptotically are illustrated in Fig. 11. The estimated velocities of the robots are demonstrated in Figs. 12. On the other hand, velocity estimation errors are shown in Fig. 13. Moreover, the linear and angular velocities of the follower robots are displayed in Fig. 14.

More specifically, the proposed controllers is compared with the existing controllers in [56] to show the merit of the proposed method. In this work, the linear velocity and angular velocity of the leader are chosen as follows:

\[ v_0 = 2.2 - 0.3 \cos(t)(m/s) \]

\[ \omega_0 = \cos(0.35t)(\text{rad/s}). \]

Here, the desired formation for the three follower robots is assigned as a triangle. To make fair comparison, we define the total formation error for the robot group as

\[
E(t) = \left[ \sum_{i=1}^{3} \left( \|x_i - x_0\|^2 + \|y_i - y_0\|^2 + \|\theta_i - \theta_0\|^2 \right) \right]^{\frac{1}{2}}
\]

The comparison results among the controllers in [56] and the proposed controller are illustrated in Figs. 15, 16, 17 and 18. From this one can observed that the controller in [56] achieves the best performance; The difficulty of this method is that this method will work efficiently only
when the state of the leader is known to each follower robot. Figures 16 and 18 shows the total error with the controller in [56] and the proposed method. Figure 16 shows the total error of the backstepping controller in which the formation error is quite larger for the first few seconds than that with our proposed controller. On the other hand, the proposed control method uses the estimated state of the leader which results in better performance as shown in Fig. 18.

Apart from that, when comparing with previous research results, the proposed formation control method for wheeled NMRs based on distributed is a significant improvement to achieve better performance. Taking into account, the distributed systems have many advantages over centralized systems, including enhanced scalability and fault tolerance competence. We can conclude that the proposed control scheme has good performance in achieving the desired formation.

6 Conclusion and Future work

In this paper, the distributed estimator-based leader–follower formation control problem for multiple nonholonomic mobile robots has been studied by using a bioinspired technique. Firstly, a trajectory tracking controller is designed for the leader robot to follow the reference trajectory. Secondly, a distributed estimator is designed such that each follower robot can estimate the leader’s states. Then, a distributed control strategy was proposed using a bioinspired neurodynamics-based approach to resolve the impractical velocity jump problem. Finally, the effectiveness of the proposed estimators and controllers are verified by simulation. In future work, obstacle avoidance and the delays associated with communication among nonholonomic mobile robots will be explored. Moreover, we will focus on the extension of the kinematic controllers to a dynamic controller for real-world applications. Hence, future works will take these factors into account.

Declarations

Conflict of interest None declared.

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