# Multi-Agent Consensus of Wheeled Mobile Robots via Beyond-Pairwise Interaction Frameworks

**Shyam Krishan Joshi**
*AI Research Centre*
Woxsen University, Hyderabad, India
shyam.krishan@woxsen.edu.in

**Manjeet Rege**
*Dept. of Software Engineering and Data Science*
University of St. Thomas, MN, USA
rege@stthomas.edu

**Ojashwini Dubey**
*AI Research Centre*
Woxsen University, Hyderabad, India
ojashwini.dubey_2028@woxsen.edu.in

**Palak Dwivedi**
*AI Research Centre*
Woxsen University, Hyderabad, India
palak.dwivedi_2028@woxsen.edu.in

**Hemachandran K**
*AI Research Centre*
Woxsen University, Hyderabad, India
hemachandran.k@woxsen.edu.in

**Raul Villamarin Rodriguez**
*AI Research Centre*
Woxsen University, Hyderabad, India
raul.rodriguez@woxsen.edu.in

**Abstract-** In this study, we address the consensus formation problem in multi-agent systems, specifically focusing on wheeled mobile robots (WMRs). The paper proposes a hybrid consensus framework that integrates both pairwise and higher-order interactions among robots, aiming to model real-world scenarios involving dense formations and multi-agent group coordination. The framework accounts for non-holonomic constraints of WMRs and incorporates a non-smooth Lyapunov function for stability analysis. By extending classical consensus models with group-level feedback and proving stability using the upper Dini derivative, the proposed solution ensures robust consensus even in the presence of contrarian agents and dynamic environments. The simulation results demonstrate the effectiveness of the proposed model in achieving synchronization and convergence across a network of WMRs.

**Keywords:** Consensus, Wheeled Mobile Robot, Non-smooth Lyapunov Function, Multi-agent Systems, Higher-order Interactions, Group Coordination, Stability Analysis.

## I. Introduction

Driven by the increasing deployment of wheeled mobile robots (WMRs) across many industries, including warehouse logistics, industrial automation, search-and-rescue operations, and even planetary exploration, mobile robotics has seen tremendous expansion recently. Their simple mechanical design, excellent manoeuvrability, and capacity to successfully negotiate both organized and unstructured settings [1] make these robots highly prized. Coordinated behaviour among many robots becomes even more important as robotic systems progress from single-agent designs to sophisticated multi-agent networks [2]. This coordination depends on consensus building, in which a group of autonomous robots, over time, agree on particular states, such as position, velocity, or orientation. For many activities, including formation control, cooperative manipulation, distributed sensing, and synchronized navigation, this capacity is basic [3]. Consensus algorithms have historically been built on pairwise interactions, in which each robot modifies its state depending on local information communicated with its nearby neighbours. Often drawn from graph theory and Laplacian dynamics, these models have succeeded in simpler, more ordered networks [4]. Real-world robotics, however, may show more complicated situations. In dense robot configurations, for example, robots could concurrently impact and be influenced by subgroups instead of individual neighbours. These scenarios call for a more sophisticated knowledge of higher-order interactions, in which the flow of information and control spans groups of three or more agents rather than just between pairs of robots [5].

We propose hypergraphs to represent these intricate multi-robot interaction patterns. A hypergraph is a modification of a conventional graph wherein hyperedges, that is, edges, may link any number of nodes, not just two. Hypergraphs allow wheeled mobile robots to model beyond-pairwise interactions, in which three or more robots may coordinate concurrently as a group entity. This modelling system allows WMRs to depict real-world communication and control topologies with greater richness and accuracy.

A wheeled mobile robot network is shown hypergraphically in Fig.1. Every robot is shown as a node (named a, b, c, d, e); the coloured areas show hyperedges linking clusters of robots. Unlike conventional graphs, in which edges link just two nodes, these hyperedges capture the core of higher-order coordination required for stable consensus in complicated contexts by encapsulating multi-robot interactions [6]. Particularly with advances in network research and synchronizing theory, higher-order interactions—also known as beyond-pairwise connections—have attracted growing interest

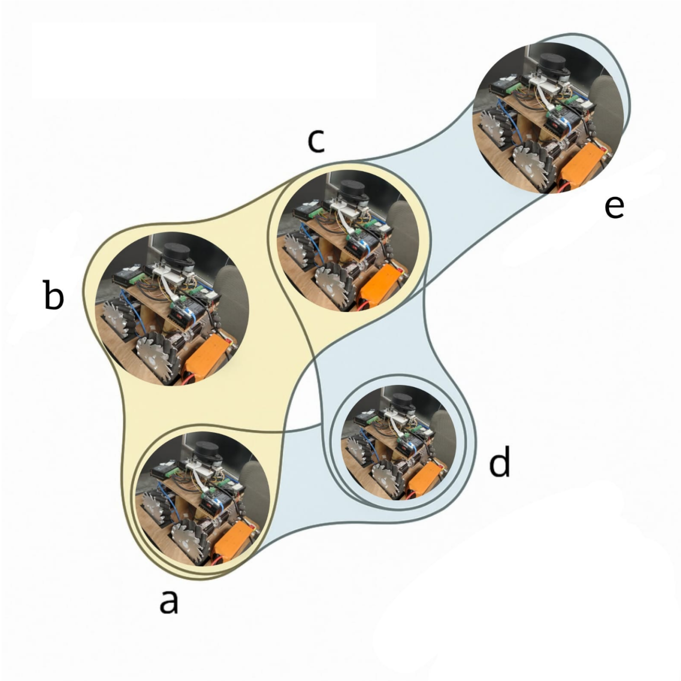


Fig. 1. Hypergraph representation of a wheeled mobile robot network capturing beyond-pairwise interactions among robots (nodes a–e).

in recent years. Inspired by models such as the Kuramoto oscillator network, researchers have shown that integrating group-level interactions may induce synchronization even in cases when some robots operate as contrarians—actively opposing the group's behavior [7]. Particularly in dynamic and uncertain surroundings, these results provide fascinating new opportunities for strong multi-agent control.

Specifically, with wheeled mobile robots, including higher-order interactions in the control method offers some fresh difficulties. WMRs are limited in mobility by nonholonomic motion, unlike that of drones or undersea vehicles. Both velocity and direction regulate their dynamics, so any created control rule must respect these physical limitations [8]. Thus, including complicated interaction topologies while guaranteeing the stability of the system calls for a judicious mix of modelling approaches and analytical tools. This paper presents an original hybrid framework combining Lyapunov-based stability analysis with higher-order interaction modelling in WMRs. Under this framework, every robot is described as a phase oscillator whose dynamics are shaped not only by pairwise couplings but also by triadic interactions—connections between groups of three agents [9]. The consensus protocol allows the system to represent both cooperative behaviours, where robots collaborate, and oppositional behaviours, where certain robots purposefully disrupt the collective behavior [10], by introducing changeable coupling strengths for various kinds of interactions.

Inspired by the most significant deviation among the robot states, a non-smooth Lyapunov function is proposed to ensure that the system converges to a stable solution. Then stability is shown using the upper Dini derivative, a mathematical instrument especially suitable for non-smooth system analysis when conventional calculus-based approaches would not be relevant [11]. This method offers the theoretical framework needed to ascertain the coupling improvements needed to guarantee robot synchronization. Simulations performed using ode45 solver help to confirm the suggested method's efficiency. Incorporating beyond-pairwise interactions not only speeds the convergence process but also helps consensus in situations where conventional pairwise-only models would fail. The suggested control technique effectively directs the system toward a stable, synchronized state even in cases including robots with contrarian tendencies or major starting misalignments [12]. In essence, this study offers a complete framework for obtaining strong multi-robot coordination by combining higher-order consensus models with rigorous Lyapunov-based analysis. This study presents both theoretical insights and practical methods that may be used for the construction of scalable, robust, and intelligent robotic networks capable of working efficiently in complex, real-world environments [13].

## II. Problem Statement

Most consensus control systems for wheeled mobile robots (WMRs) are based on pairwise interactions, in which each robot modulates its state merely depending on its near neighbors in a communication network. This method makes linear behavior and one-to- one interactions assumption. In practical terms, nevertheless, this presumption is usually inadequate. Robots working in dense formations, completing cooperative tasks, or making group-based choices come across circumstances wherein many robots interact concurrently and provide higher-order interactions including triadic feedback.

Furthermore, some robots may act as contrarians—agents who purposefully reject the majority—often because of malfunctioning sensors, conflicting goals, or antagonistic behavior—in dynamic and unexpected surroundings. This may compromise accepted standards and cause system instability or convergence failure.

Furthermore restricting conventional consensus models are their incapacity to include group-level feedback systems. A robot may, for example, change its path depending on the average direction of a subgroup instead of depending on one neighbor. Dealing with these events calls for a model including beyond-pairwise interactions.

This paper suggests a hybrid consensus architecture including both pairwise and higher-order interactions in order to solve these problems. The framework is built to manage the intricate dynamics of multi-robot systems . The nonholonomic restrictions of WMRs are accounted for by the control laws, and a thorough Lyapunov-based analysis guarantees convergence to a stable, synchronised state. Incorporating group-level feedback and showing stability via a non-smooth Lyapunov function, the proposed model extends traditional consensus procedures by convergence proved by the upper Dini derivative.

## III. Proposed Solution

This study advances the consensus control paradigm for wheeled mobile robots by introducing a novel coupling framework that integrates beyond-pairwise interaction dynamics with a rigorous stability analysis utilizing a non-smooth Lyapunov function.

*a) Kinematics of Wheeled Mobile Robots*

The motion of each robot in a two-dimensional Euclidean space is governed by the classical nonholonomic kinematic equations:

$$\dot{x} = v\cos\theta, \quad \dot{y} = v\sin\theta, \quad \dot{\theta} = \omega$$

where $(x, y)$ represent the Cartesian coordinates of the robot, $\theta$ denotes the heading angle, and $v$ and $\omega$ are the linear and angular velocities, respectively. These kinematic constraints restrict instantaneous motion to the robot's heading direction, thereby necessitating specialized control strategies for coordinated movement.

*b) Coupled Dynamics with Beyond-Pairwise Interactions*

To achieve robust and accelerated consensus in multi-agent robotic systems, the proposed framework incorporates two complementary levels of diffusive coupling:

- **Pairwise coupling**, modeling conventional interactions between immediate neighbors.
- **Triadic (higher-order) coupling**, capturing cooperative influences among groups of three robots, thereby extending the interaction topology beyond simple dyadic links.

The coupled dynamics for each agent $i$ are defined as:

$$\dot{x}_i = v_i\cos\theta_i + K\sum_{j=1}^{N}(x_j - x_i) + K\sum_{j=1}^{N}\sum_{k=1}^{N}(x_j + x_k - 2x_i),$$

$$\dot{y}_i = v_i\sin\theta_i + K\sum_{j=1}^{N}(y_j - y_i) + K\sum_{j=1}^{N}\sum_{k=1}^{N}(y_j + y_k - 2y_i),$$

$$\dot{\theta}_i = \omega_i + K\sum_{j=1}^{N}(\theta_j - \theta_i) + K\sum_{j=1}^{N}\sum_{k=1}^{N}(\theta_j + \theta_k - 2\theta_i),$$

where $K > 0$ denotes the coupling gain, and $N$ is the total number of robots in the network.

The introduction of triadic coupling terms enables each robot to respond not merely to individual neighboring agents but to the aggregate behavior of small subgroups. This hierarchical coupling structure fosters richer interaction dynamics, improves disturbance rejection, and enhances the system's resilience to individual agent failures or adversarial behaviors.

*c) Simulation and Validation*

Numerical simulations were performed using MATLAB's `ode45` solver on a network consisting of $N = 4$ wheeled mobile robots, initially set with varied spatial configurations and orientations. The findings show that adding beyond-pairwise interactions and sufficient coupling gains in point robots yields consensus. These results confirm the theoretical claims and emphasize the need for higher-order coupling techniques in developing the area of distributed multi-robot coordination.

## IV. Stability Analysis Using Non-Smooth Lyapunov Function

We investigate the consensus behaviour of the multi-agent system consisting of wheeled mobile robots (WMRs) using non-smooth Lyapunov candidate functions. These functions measure the largest difference between the agent states, and their upper Dini derivatives support the evaluation of system convergence behaviour. Using the Lyapunov stability theorem, we prove the upper Dini-derivative of the Lyapunov function to be negative definite that, in turn, yields sufficient conditions for consensus formation. Consider the following Non-smooth Lyapunov functions as per [14], [15].

$$V(x(t)) = \max\{|x_i - x_j| \mid i,j \in \{1,\dots,N\}\}, \quad (1)$$

$$V(y(t)) = \max\{|y_i - y_j| \mid i,j \in \{1,\dots,N\}\}, \quad (2)$$

$$V(\theta(t)) = \max\{|\theta_i - \theta_j| \mid i,j \in \{1,\dots,N\}\}. \quad (3)$$

The upper Dini derivatives of these functions are given as:

$$D^+V(x(t)) = \dot{x}_{mx} - \dot{x}_{lx}, \quad (4)$$

$$D^+V(y(t)) = \dot{y}_{my} - \dot{y}_{ly}, \quad (5)$$

$$D^+V(\theta(t)) = \dot{\theta}_{m\theta} - \dot{\theta}_{l\theta}, \quad (6)$$

where,

$$\dot{x}_{mx} = \max\{\dot{x}_{mx'}(t) \mid mx' \in \mathcal{I}_{\max}(x(t))\}, \quad (7)$$

$$\dot{x}_{lx} = \min\{\dot{x}_{lx'}(t) \mid lx' \in \mathcal{I}_{\min}(x(t))\}, \quad (8)$$

$$\dot{y}_{my} = \max\{\dot{y}_{my'}(t) \mid my' \in \mathcal{I}_{\max}(y(t))\}, \quad (9)$$

$$\dot{y}_{ly} = \min\{\dot{y}_{ly'}(t) \mid ly' \in \mathcal{I}_{\min}(y(t))\}, \quad (10)$$

$$\dot{\theta}_{m\theta} = \max\{\dot{\theta}_{m\theta'}(t) \mid m\theta' \in \mathcal{I}_{\max}(\theta(t))\}, \quad (11)$$

$$\dot{\theta}_{l\theta} = \min\{\dot{\theta}_{l\theta'}(t) \mid l\theta' \in \mathcal{I}_{\min}(\theta(t))\}. \quad (12)$$

Using these definitions, the upper Dini derivative of $V(x(t))$ becomes:

$$\begin{aligned} D^+V(x(t)) &= \limsup_{h\to 0^+} \frac{V(x(t+h)) - V(x(t))}{h} \\ &= \dot{x}_{mx}(t) - \dot{x}_{lx}(t) \\ &= v_{mv}\cos\theta_{mx} - v_{lv}\cos\theta_{lx} - 3KN(x_{mx} - x_{lx}) \\ &\le 2v_{\max} - 3KN(x_{mx} - x_{lx}). \end{aligned} \quad (13)$$

For Lyapunov stability, $D^+V(x(t)) < 0$ implies:

$$\begin{aligned} 3KN(x_{mx} - x_{lx}) &> 2\|v_{\max}\| \\ K &> \frac{2\|v_{\max}\|}{3N\rho_1}, \end{aligned} \quad (14)$$

where, $||v_{\max}\|$ is the norm of max velocity of the robot $\rho_1 > 0$ is the minimal possible spacing in the $x$-component.

Similarly, the derivative for $V(y(t))$ is:

$$\begin{aligned} D^+V(y(t)) &= \dot{y}_{my}(t) - \dot{y}_{ly}(t) \\ &= v_{my}\sin\theta_{my} - v_{ly}\sin\theta_{ly} - 3KN(y_{my} - y_{ly}), \end{aligned} \quad (15)$$

and for Lyapunov stability:

$$K > \frac{2\|v_{\max}\|}{3N\rho_2}, \tag{16}$$

where $\rho_2 > 0$ is the minimal possible spacing in the $y$-component.

For $\theta$ synchronization, we get:

$$\begin{aligned} D^+V(\theta(t)) &= \dot{\theta}_{m\theta}(t) - \dot{\theta}_{l\theta}(t) \\ &= (w_{m\theta} - w_{l\theta}) - 3KN(\theta_{m\theta} - \theta_{l\theta}), \end{aligned} \tag{17}$$

and for Lyapunov stability:

$$K > \frac{2||w_{\max}||}{3N\rho_3}, \tag{18}$$

where, $||w_{\max}||$ is norm of maximum angular velocity of robot, $\rho_3 > 0$ is the minimal possible spacing in the $\theta$-component. If the coupling gain $K$ satisfies the conditions in equations (14), (16), and (18), then asymptotic synchronization is ensured:

$$(x_i - x_j) \to 0, \quad (y_i - y_j) \to 0, \quad (\theta_i - \theta_j) \to 0 \quad \text{as } t \to \infty. \tag{19}$$

Numerical simulations validating the theoretical results are presented in Section IV. The subsequent sub-section provides an in-depth analysis of the trajectory synchronization performance.

## IV Numerical Simulations

The robots' behavior during the simulation is summarized in Table I. Before $t = 25$ seconds, all robots move independently without synchronization. At $t = 25$ seconds, coupling is activated, and the robots begin sharing information, adjusting their positions. After $t = 25$ seconds, the robots rapidly converge to a common trajectory. The convergence behavior depends on the coupling gain $K$. A higher $K$ results in faster and sharper synchronization, while a lower $K$ leads to slower but smoother synchronization.

### *1. Convergence in x-state*

Before 25 seconds, each robot moves independently based on its own dynamics, with different initial x-positions and velocities causing divergence. At $t = 25$ seconds, coupling is activated, and the robots start sharing information to adjust their x-positions. After coupling is activated, a sharp transition is observed, with the robots rapidly synchronizing and eventually converging to a common trajectory.

Figures 2 and 3 show the x-state convergence for $K = 1$ and $K = 2$, respectively. As observed, the convergence is faster and sharper for $K = 2$ compared to $K = 1$.

In both cases, after convergence, the robots move together in the x-direction with synchronized dynamics. For $K = 2$, the transition is quicker but more abrupt, while for $K = 1$, the adjustment is smoother but slower.

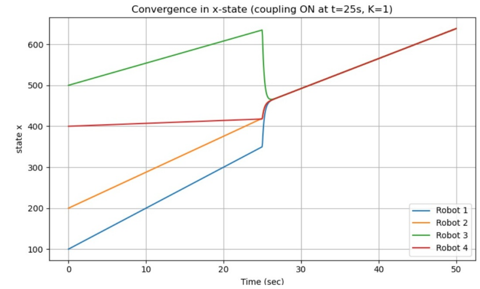


Fig. 2. Convergence in x-state (coupling ON at $t = 25s$, $K = 1$)

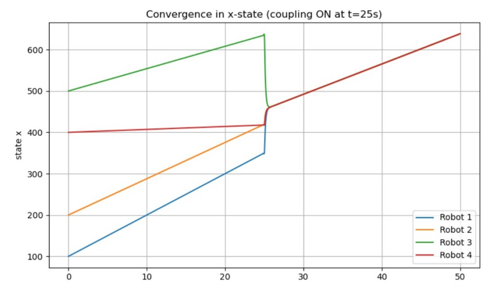


Fig. 3. Convergence in x-state (coupling ON at $t = 25s$, $K = 2$)

### *2. Convergence in y-state*

Similarly, in the y-direction, the robots initially move independently. When coupling is activated at $t = 25$ seconds, they adjust their y-positions.

Figures 4 and 5 show the convergence behavior for $K = 1$ and $K = 2$, respectively. The robots converge faster with higher $K$.

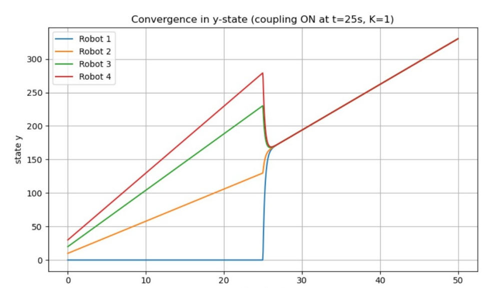


Fig. 4. Convergence in y-state (coupling ON at $t = 25s$, $K = 1$)

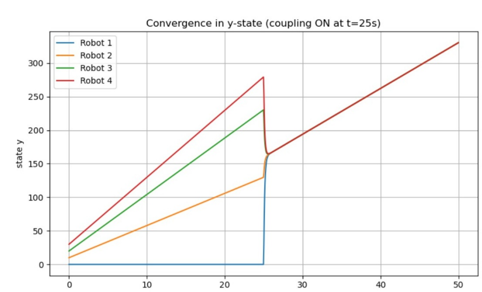


Fig. 5. Convergence in y-state (coupling ON at $t = 25s$, $K = 2$)

Before coupling, robots like Robot 4 move faster, while Robot 1 remains almost stationary. After coupling, all robots adjust their y-positions, aligning quickly for $K = 2$ and more gradually for $K = 1$.

### 3. Convergence in $\theta$-state (Orientation)

The orientation ($\theta$-state) shows a similar trend. Before 25 seconds, robots have different constant headings. Coupling at $t = 25$ seconds causes the robots to adjust and synchronize their orientations.

Figures 6 and 6 illustrate convergence in $\theta$ for $K = 1$ and $K = 2$.

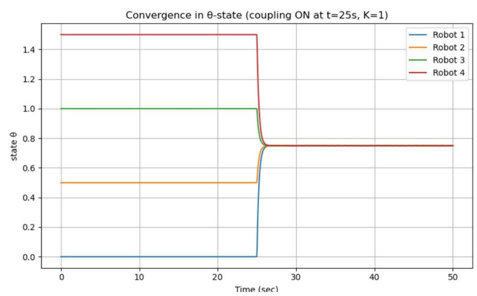


Fig. 6. Convergence in $\theta$-state (coupling ON at $t = 25s$, $K = 1$)

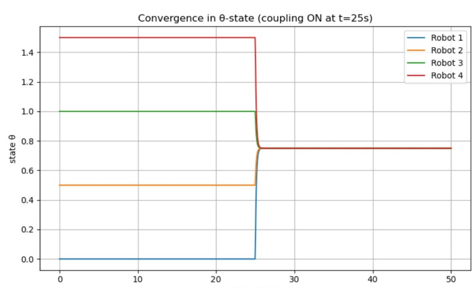


Fig. 7. Convergence in $\theta$-state (coupling ON at $t = 25s$, $K = 2$)

For $K = 2$, the robots quickly align to a common orientation (around 0.78 radians), whereas with $K = 1$, alignment is slower but smoother.

TABLE I
SUMMARY OF ROBOT BEHAVIOR DURING SIMULATION

| Time | Behavior |
|---|---|
| 0–25 seconds | Independent movement without synchronization |
| At 25 seconds | Coupling is activated |
| After 25 seconds | Rapid convergence to a common trajectory (Faster for $K = 2$, Smoother for $K = 1$) |

### Understanding Coupling in Multi-Robot Systems

In multi-robot systems, *coupling* denotes the onset of inter-robot communication and dynamic interaction. Prior to the activation of coupling, each robot operates in an open-loop manner, following its own trajectory independently, without regard to the states of other agents in the network.

TABLE II
COMPARISON OF ROBOT STATES BEFORE COUPLING ACTIVATION

| Aspect | Before 25s |
|---|---|
| **Behavior** | Robots move individually without coordination. |
| **Cause** | No coupling. |
| **Result** | Different trajectories and orientations. |

TABLE III
COMPARISON OF ROBOT STATES AFTER COUPLING ACTIVATION

| Aspect | After 25s |
|---|---|
| **Behavior** | Robots synchronize (in x, y, $\theta$). |
| **Cause** | communication and coordination among robots. |
| **Result** | Same trajectories and orientations |

At the designated coupling time, set to $t = 25$ seconds, the robots transition to a closed-loop regime characterized by information sharing and cooperative control strategies. Specifically, the robots adjust their positions $(x, y)$ and orientations $(\theta)$ to minimize discrepancies relative to their peers, thereby fostering the emergence of coordinated group behavior. The fundamental objective of coupling is to achieve consensus among all robots, leading to collective motion wherein all agents maintain a common velocity vector and orientation. This consensus ensures that the group behaves as a cohesive unit, exhibiting synchronized trajectories and stable formation dynamics.

The coupling intensity is regulated by a gain parameter $K$, defined as:

- For $K = 1$, the coupling force is moderate, resulting in gradual convergence towards consensus.
- For $K = 2$, the coupling force is amplified, promoting rapid convergence and tighter synchronization among robots.

Such coupling mechanisms are fundamental to tasks requiring coordinated behaviors, including formation control, cooperative transportation, and distributed sensing, and are typically analyzed through frameworks such as consensus algorithms, stability analysis, and graph-theoretic modeling of multi-agent networks.

## V. CONCLUSIONS

This study proposed a novel approach employing a hypergraph-based model to include beyond-pairwise interactions and generate consensus in networks of wheeled mobile robots (WMRs). The suggested approach catches more realistic interaction patterns in multi-robot systems running in dynamic and crowded settings by expanding traditional consensus algorithms to incorporate triadic (and higher-order) feedback. We explicitly evaluated the nonholonomic restrictions of WMRs and proved system stability and convergence using a non-smooth Lyapunov function. Stability criteria were obtained using the upper Dini derivative, and it was shown that the system could attain an asymptotic consensus. Apart from improving the dependability of multi-robot systems, the suggested architecture offers a scalable solution for jobs needing sophisticated group coordination. Extending this concept to bigger-scale robot networks and investigating the possible uses in cooperative robotics—such as distributed sensing, cooperative manipulation, and collective navigation—will be the main emphasis of the future work.

## REFERENCES


[1] Rubio, Francisco, et al. 'A Review of Mobile Robots: Concepts, Methods, Theoretical Framework, and Applications'. International Journal of Advanced Robotic Systems, vol. 16, no. 2, Mar. 2019, p. 172988141983959. DOI.org (Crossref), https://doi.org/10.1177/1729881419839596.

[2] Almadhoun, Randa, et al. 'A Survey on Inspecting Structures Using Robotic Systems'. International Journal of Advanced Robotic Systems, vol. 13, no. 6, Dec. 2016, p. 172988141666366. DOI.org (Crossref),https://doi.org/10.1177/1729881416663664.

[3] Jadbabaie, A., et al. 'Coordination of Groups of Mobile Autonomous Agents Using Nearest Neighbor Rules'. IEEE Transactions on Automatic Control, vol. 48, no. 6, June 2003, pp. 988–1001. DOI.org (Crossref),https://doi.org/10.1109/TAC.2003.812781.

[4] Joshi, Shyam Krishan. "Synchronization of coupled benchmark oscillators theory and experiments." (2020).

[5] Ogren, P., et al. 'A Control Lyapunov Function Approach to Multi-Agent Coordination'. Proceedings of the 40th IEEE Conference on Decision and Control (Cat. No.01CH37228), vol. 2, IEEE, 2001, pp. 1150–55. DOI.org (Crossref), https://doi.org/10.1109/CDC.2001.981040.

[6] Battiston, F., Cencetti, G., Iacopini, I., Latora, V., Lucas, M., Patania, A., ... and Petri, G. (2020). Networks beyond pairwise interactions: Structure and dynamics. Physics reports, 874, 1-92. https://doi.org/10.1016/j.physrep.2020.05.004

[7] Dorfler, Florian, and Francesco Bullo. 'On the Critical Coupling for Kuramoto Oscillators'. SIAM Journal on Applied Dynamical Systems, vol. 10, no. 3, Jan. 2011, pp. 1070–99. DOI.org (Cross- ref), https://doi.org/10.1137/10081530X.

[8] Li, Xiaolei, et al. 'Jamming-Resilient Synchronization of Networked Lagrangian Systems with Quantized Sampling Data'. IEEE Transactions on Industrial Informatics, 2022, pp. 1–1. DOI.org (Crossref), https://doi.org/10.1109/TII.2022.3148395.

[9] Izadbakhsh, Alireza, and Saeed Khorashadizadeh. 'Robust Adaptive Control of Robot Manipulators Using Bernstein Polynomials as Universal Approximator'. International Journal of Robust and Nonlinear Control, vol. 30, no. 7, May 2020, pp. 2719–35. DOI.org (Crossref), https://doi.org/10.1002/rnc.4913.

[10] Bidram, A., Lewis, F.L., Davoudi, A. and Qu, Z., 2013, May. Frequency control of electric power microgrids using distributed cooperative control of multi-agent systems. In 2013 IEEE International Conference on Cyber Technology in Automation, Control and Intelligent Systems (pp. 223-228). IEEE.

[11] Wang, Conghua, et al. 'Synchronization Control for Networked Mobile Robot Systems Based on Udwadia–Kalaba Approach'. Nonlinear Dynamics, vol. 105, no. 1, July 2021, pp. 315–30. DOI.org (Crossref), https://doi.org/10.1007/s11071-021-06487-z.

[12] Qu, Z., Wang, J. and Chunyu, J., 2007, October. Lyapunov design of cooperative control and its application to the consensus problem. In 2007 IEEE International Conference on Control Applications (pp. 100-107). IEEE.

[13] Chung, Soon-Jo, and Jean-Jacques E. Slotine. 'Cooperative Robot Control and Concurrent Synchronization of Lagrangian Systems'. IEEE Transactions on Robotics, vol. 25, no. 3, 2009, pp. 686–700. DOI.org (Crossref), https://doi.org/10.1109/TRO.2009.2014125.

[14] Joshi, Shyam Krishan , Singh, S. (2024, December). Consensus Formation in Networked Wheeled Mobile Robots. In 2024 IEEE 21st India Council International Conference (INDICON) (pp. 1-5).

[15] Joshi, Shyam Krishan. "Synchronization of Coupled Hindmarsh-Rose Neuronal Dynamics: Analysis and Experiments." IEEE Transactions on Circuits and Systems II: Express Briefs, vol. 69, no. 3, Mar. 2022, pp. 1737–41.