Decentralized Tribrid Adaptive Control Strategy for Simultaneous Formation and Flocking Configurations of Multi-agent System

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***Abstract*—This paper focuses on the development of a tribrid control strategy for leader-follower flocking of multi-agents in octagonal polygonal formation. The tribrid approach encompasses Reinforcement Learning (RL), centralized and de-centralized control strategies. While the RL for multi-agent polygonal formation addresses the issues of scalability, the centralized strategy maintains the inter-agent distance in the formation and the decentralized strategy reduces the consensus (in position and velocity) error. Unlike the previous studies focusing only on the predefined trajectory, this paper deals with the leader-follower scenario through a decentralized tribrid control strategy. Two cases on initial positions of multi-agents dealt in this paper include the octagonal pattern from RL and the agents randomly distributed in spatial environment. The tribrid control strategy is aimed at simultaneous formation and flocking, and its stability in a shorter response time. The convergence of flocking error to zero in 3s substantiates the validity of the proposed control strategy and is faster than previous control methods. Implicit use of centralized scheme in decentralized control strategy facilitates retention of formation structure of the initial configuration. The average position error of agents with the leader is within the position band in 3s and thus it confirms the maintenance of formation during flocking.**

***Keywords*—Simultaneous; flocking; polygonal formation; decentralized; hybrid; adaptive; control strategy; simulation**

NOMENCLATURE

r_{ox} & r_{oy}	Position of leader along x and y axes respectively
V_{ox} & V_{oy}	Velocity of leader along x and y axes respectively
A_l	System matrix of leader dynamics
r_{ix} & r_{iy}	Position of i^{th} agent along x and y axes respectively
V_{ix} & V_{iy}	Velocity of i^{th} agent along x and y axes respectively
u_{ix} & u_{iy}	Control input of i^{th} agent along x and y axes respectively
ν	Vertices
E	Edges
a_{ij}	Adjacency matrix
N_i^t	Neighbours of i^{th} agent at time t
C_s	Spatial communication range
$R(\emptyset)$	Rotation transformation matrix
$\emptyset$	Rotation angle
d	Inter-agent distance
H, D	Observation matrices of position and velocity, respectively
$a, b, c, \tilde{c}$	Constants

I. INTRODUCTION

The connectivity among mobile agents imposes a challenge for coordination and communication among agents, during flocking. The multi-agents interact with each other using the communication strategy and achieve formation and flocking configuration. This communication strategy encompasses a challenge for the MAS, having both homogeneous and heterogeneous agents. The challenges include interactions with the environment, and the use of various sensors for communication between the homogeneous and heterogeneous agents [1]. For the ease of operation during flocking and formation configuration by multi-agents, either homogeneous or heterogeneous multi-agents are considered. The consideration is due to the mismatch in the communication frequency [2] and may lead to diverging behaviour. The collective operation of communication and control strategies is required to establish coordination among agents. These strategies also enable to obtain cohesion in formation and flocking configurations of MAS.

Many formation and flocking control strategies have been proposed. For example, leader-follower, behavioural and virtual structure [3] for preserving formation among agents. The formation of agents can include a specific pattern: triangle [4, 5], rectangle [6] and ellipse [7]. These patterns are achieved with agent's control reference to the virtual leader trajectory tracking configuration [8]. The agent's position changes dynamically based on the velocity at which the agents are travelling. The agent's position is controlled such that no agents collide with each other to preserve the formation and achieve the stability. The control of agents [9] depends on the dynamics of each agent and the rotational transformation matrix (to transfer the agent's position from the body reference frame to the global frame).

The cyclic pursuit control strategy [10] is suitable to achieve polygonal shape. This control strategy uses a centralized control station for controlling the angle and distance of each agent. The centroid of the polygon is referred to as the virtual leader and controls the position of each agent. If there is non-availability of the virtual leader due to some destruction in the environment, then the centralized control strategy fails. Thus, the formation and stability of the MAS will not be achieved.

The centralized control strategy is also used in trajectory tracking application to control the agents from a single control station. It is challenging with the expansion of several agents and can increase the computation time with energy consumption [1]. The distributed and decentralized control strategies will overcome the disadvantages of the centralized control strategy. However, to operate simultaneous polygon formation and leader-follower flocking of multi-agents, the solitary control strategy is not useful. In this paper, the tribrid approach of a centralized and decentralized control strategy with Reinforcement Learning (RL) is proposed to perform analysis of simultaneous polygon formation and leader-follower flocking of multi-agents.

In the proposed tribrid control strategy, the polygon obtained using RL [11] is utilized along with the transformation technique (centralized control technique) to maintain the formation. The decentralized control strategy is used along with the centralized strategy for simultaneous pattern formation and leader-follower flocking of multi-agents. The proposed tribrid control strategy maintains the initial formation configuration and achieves time-varying flocking configuration at a quicker response time. The rest of this paper is organized as follows. In Section II, the review on centralized and decentralized control strategies are discussed. In Section III, the MAS model and proposed tribrid control strategy are discussed for communication and control of multi-agents, followed by consensus topology. Section V presents the simulation results and analysis for tribrid control strategy. Section VI provides conclusions.

II. Literature Review

The trajectory tracking and formation of multi-agents are research topics of significant importance in MAS. The application of flocking in polygon contour is required in coverage control of multi-agent surveillance systems [12, 13]. The centralized, decentralized and distributed control strategies are used in the formation and flocking configurations of MAS [4, 14, 15]. The centralized control strategy in [9] uses a control strategy to control all agents based on the availability of information of agents as a whole. The control law is designed for decentralized or distributed control strategy based on the neighbourhood information of agents in MAS.

The decentralized control strategy is preferred over centralized control strategy (cyclic pursuit strategy) [5,10] for achieving the flexibility in changing the polygonal formation [9,14,16]. The decentralized control strategy is required to make agents in pattern follow the leader's trajectory for a multi-agent dynamical system with time-varying velocity [15,17]. The distributed control strategy is used for the agents in hexagon to flock along the pre-defined trajectory [8]. The pre-defined trajectory is addressed only for the constant velocity profile. And also, the analysis is not performed for the pattern of agents in leader-follower scenario. The bearing control approach in [18] uses positive gains to obtain formation maneuvering or flocking in a pattern. However, this decentralized bearing control approach has converged flocking error to zero in 20s (larger settling time). The desired bearing angle between the agents is required for formation maneuvering. Any communication failure in maintaining the bearing angle can affect the MAS stability [19, 20]. The switching of formations maneuvering may not be useful for time-varying trajectory [21]. The novelty of this proposed paper is to overcome the disadvantages of bearing angle control approach and use tribrid of centralized and decentralized control strategies to achieve time-varying formation maneuvering with lesser settling time.

III. Multi-agent Dynamics and Control

In this paper, we will consider double integrator system for leader and multi-agent dynamics. The leader dynamics depends on its own states, given by:

$$\dot{r_{ox}} = V_{ox} \quad (1)$$

$$\dot{r_{oy}} = V_{oy} \quad (2)$$

$$\dot{V_{ox}} = g_{11}V_{ox} + g_{12}V_{oy} \quad (3)$$

$$\dot{V_{oy}} = g_{21}V_{ox} + g_{22}V_{oy} \quad (4)$$

where, r_{ox} and r_{oy} represent position of leader along x and y axes respectively. V_{ox} and V_{oy} represents velocity of leader along x and y axes respectively. $A_l = \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}$ is the system matrix of the leader.

The agent dynamics depends on its own state and control input of neighbour states, position consensus terms and velocity consensus terms, given by:

$$\dot{r}_{ix} = V_{\mathrm{ix}}$$

$$\dot{r}_{iy} = V_{\mathrm{iy}} \quad (5)$$

where r_{ix} and r_{iy} are x and y position vector components of the i^{th} agent. V_{ix} and V_{iy} are x and y velocity vector components of the i^{th} agent. i = {1,2,3,….,8}

The velocity vector components of i^{th} agent uses an additional term of control input to perform flocking in leader-follower scenario.

$$\dot{V_{ix}} = g_{11}V_{ix} + g_{12}V_{iy} + u_{\mathrm{ix}} \quad (6)$$

$$\dot{V_{iy}} = g_{21}V_{ox} + g_{22}V_{oy} + u_{\mathrm{iy}} \quad (7)$$

where u_{ix} and u_{iy} are x and y control input vector components of the i^{th} agent.

The distributed control and communication network consisting of eight agents is represented using undirected graph G in Fig. 1.

In the Fig. 1, A represents agent, u represents control input to the agent and C represents centralized control station. The decentralized control inputs {u1, u2,..., u8} to the agents {A1, A2, …. , A8} are used for flocking in the leader-follower configuration.

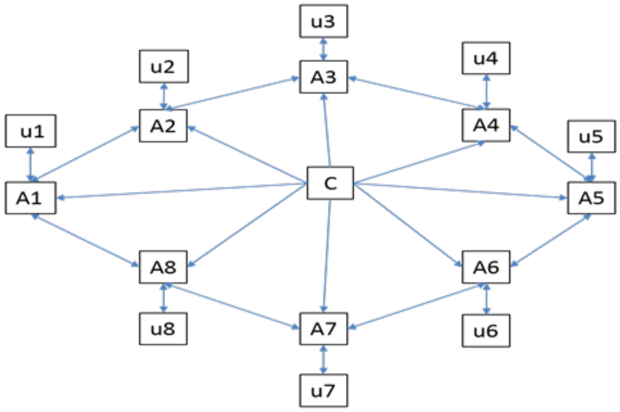


Fig. 1. Proposed Control Configuration for Agents in Octagonal Formation.

A graph, G is defined as: $G = (\nu, E)$, where ν is the set of vertices, $\nu = \{A1, A2, A3, \ldots\ldots, A8\}$ and E is the edges, $E = \upsilon \times \upsilon$, i.e., a pair of vertices in a given spatial environment. Each vertex represents the identity of an agent in the graph. The connection between two agents is bi-directional, represented using the adjacency matrix. The adjacency matrix definition is given in (8).

$$a_{ij} = \begin{cases} 1 \; if \; two \; agents \; are \; connected \\ 0 \;\; otherwise \end{cases} \quad (8)$$

The neighbors of i^{th} agent are given in (9).

$$N_i^t = \left\{ j : \left\| r_j(t) - r_i(t) \right\| \leq C_s, j \in \nu, j \neq i \right\} \quad (9)$$

where C_s indicates the spatial communication range, r_i is the position of i^{th} agent and r_j is the neighbour position of i^{th} agent. The neighbours of the agent are determined for the inter-agents positions lying within the spatial communication range. Apart from the communication strategy to connect the agents, control strategy is required to achieve flocking (trajectory tracking) and formation configuration of MAS.

The centralized control strategy is used in trajectory tracking application to control the agents from a single control station. It is challenging with the expansion of several agents and can increase the computation time with energy consumption [1]. The distributed and decentralized control strategies will overcome the disadvantages of the centralized control strategy. However, to operate simultaneous polygon formation and leader-follower flocking of multi-agents, the solitary control strategy is not useful. In this paper, the tribrid approach of a Reinforcement Learning (RL), centralized and decentralized control strategy is proposed to perform analysis of simultaneous polygon formation and leader-follower flocking of multi-agents.

The octagonal formation obtained using a RL technique [15] is maintained using a centralized (transformation technique) control strategy and then is integrated with a decentralized control strategy to obtain a leader-follower flocking configuration of multi-agents. In this proposed control strategy, the agent's position in the polygon is computed using RL and updated with initial position while tracing the leader's trajectory (5). The initial position of formation is computed using (10).

$$\dot{r}_i = R(\emptyset)(r_{i+1} - r_i)$$

where

$$R(\emptyset) = \begin{bmatrix} \cos\emptyset & \sin\emptyset \\ -\sin\emptyset & \cos\emptyset \end{bmatrix}$$

and $\emptyset$ is the rotation angle along z-axis, given by: $0 < \emptyset < \frac{\pi}{N}$, N is the number of agents.

The rotation angle, $\emptyset$ is adjusted to maintain the desired distance between positions of agents. It is given by:

$$\emptyset = \frac{\pi}{N} + g(100 - d)$$

Here 100 is the desired distance and $g = 0.014706$ is the value of gain obtained by trial and error to adjust inter-agent distance (d) between the agents. The distance, d between agents is calculated using,

$$d_{ij} = \| r_i - r_j \|$$

The decentralized control inputs (u_{ix} and u_{iy}) of i^{th} agent for (6) and (7) is described in (11) and (12), respectively.

$$u_{ix} = -d_{11}h_{11}(r_{\mathrm{ix}} - r_{\mathrm{ox}}) - d_{11}h_{12}(r_{\mathrm{iy}} - r_{\mathrm{oy}}) - d_{11}h_{11}(V_{\mathrm{ix}} - V_{\mathrm{ox}}) - d_{11}h_{12}(V_{\mathrm{iy}} - V_{\mathrm{oy}}) + \sum_{j\in n_i} g_{ij}(\|r_j - r_i\|)\left(a - b\, e^{-\frac{\|r_{ij}^2\|}{\check{c}}}\right)(r_{jx} - r_{ix}) + \sum_{j\in n_i} a_{ij}(\|r_j - r_i\|)(V_{jx} - V_{ix}) \quad (10)$$

$$u_{iy} = -d_{21}h_{11}(r_{\mathrm{ix}} - r_{\mathrm{ox}}) - d_{21}h_{12}(r_{\mathrm{iy}} - r_{\mathrm{oy}}) - d_{21}h_{11}(V_{\mathrm{ix}} - V_{\mathrm{ox}}) - d_{21}h_{12}(V_{\mathrm{iy}} - V_{\mathrm{oy}}) + \sum_{j\in N_i} a_{ij}(\|r_j - r_i\|)\left(a - b\, e^{-\frac{\|r_{ij}^2\|}{\check{c}}}\right)(r_{jy} - r_{iy}) + \sum_{j\in N_i} a_{ij}(\|r_j - r_i\|)(V_{jy} - V_{iy}) \quad (11)$$

where $i = 1, 2, \ldots\ldots, N = 8$, r_{ix} and r_{iy} are positions of agent along x and y component respectively. V_{ix} and V_{iy} are velocities of leader along x and y axes respectively. a_{ij} is the adjacency matrix. $H = [h_{11}\; h_{12}] = [0\; 1]$, 8 agents can observe the second (y component) position of leader. $D = [d_{21};\, d_{22}] = [0\; 1]$, 8 agents can observe the second (y component) velocity of leader. $a = 1, b = 20, \check{c} = 0.2$ are constants [17].

IV. Consensus Topology in Leader-follower Flocking Configuration

The MAS consisting of N agents should ensure position and velocity consensus among the agents during flocking and formation of multi-agents. Suppose the network of multi-agents in polygon is connected, the control input (u_{ix} and u_{iy}) ensure semi-global consensus in formation and flocking. For the global consensus of multi-agents, the conditions below are required to be satisfied.

Position Consensus

- For any position of i^{th} agent in the bounded set, i.e., $r_i \subset \Re^n$, position of leader, $r_o \subset \Re^n$, there is an $\mathcal{E}^*$such that, for each $\mathcal{E} \in (0, \mathcal{E}^*)$,

$$\lim_{t\to\infty} || \frac{1}{N} r_i(t) - r_o(t) || = \mathcal{E}^*,$$

$$i = \{1,2,3, \ldots, N; N = 19\}$$

where $\mathcal{E}$ represents small value in r^*

- For any position of i^{th} agent in the bounded set, i.e., $r_i \subset \Re^n$, neighboring agent, $r_j \subset \Re^n$, there is an r^*such that, for each $r \in (0, r^*)$,

$$\lim_{t\to\infty} ||r_i(t) - r_j(t)|| = r^*,$$

$$i = \{1,2,3, \ldots, N = 19\}$$

where r^* is in the band of $[0,10] \times [0, 10]$

Velocity Consensus

The velocity of i^{th} agent is in the bounded set, i.e., $V_i \subset \Re^n$, velocity of leader, $V_o \subset \Re^n$

$$\lim_{t\to\infty} ||V_i(t) - V_o(t)|| = 0,$$

$$i = \{1,2,3, \ldots, N; N = 19\}$$

The above position and velocity consensus terms are substantiated using simulation results of flocking behaviour of multi-agents.

V. Simulation Analysis of Tribrid Control Strategy for Simultaneous Polygonal Formation and Flocking of MAS

The analysis is performed for two cases of initial position of agents: polygon pattern (in Fig. 2, obtained using Reinforcement Learning (RL), [11]) and randomly distributed in the environment (in Fig. 3). The velocity is chosen randomly in the range ($[0, 2] \times [0, 2]$) (in Fig. 4).

The spatial communication or interaction range is 2 and the connectivity is established among all agents with the leader. The cyclic pursuit and the adaptive control strategies are used to achieve synchronization of octagonal formation and tracing the leader's trajectory.

A. Formation Control using Cyclic Pursuit Strategy

In this paper, the cyclic pursuit strategy (centralized control strategy) is preferred over decentralized control strategy for achieving the flexibility in changing the polygonal formation [15]. The formation of a polygon is described by deviated cyclic pursuit in $\Re^2$ by maintaining the desired distance between positions of agents. In a deviated cyclic pursuit strategy, the rotation angle (in (10)) is adjusted to maintain the desired distance between the agents. The inter-agent distance between the neighbours has converged to maintain a constant value of 100 and is shown in Fig. 5.

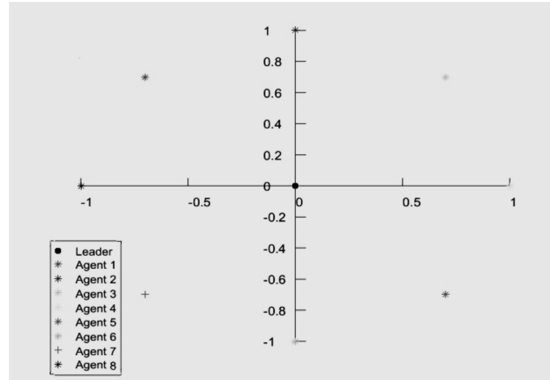


Fig. 2. Initial Position in Octagonal Formation.

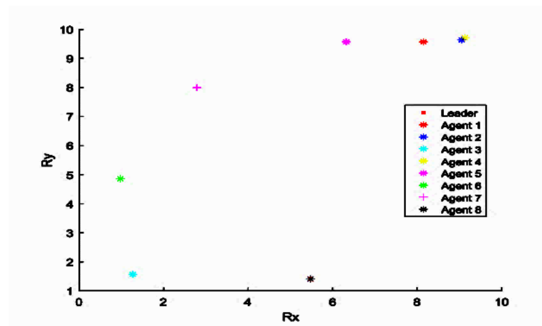


Fig. 3. Random Initial Position of Eight Agents and the Leader.

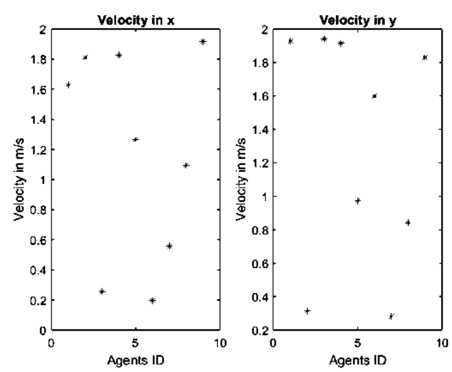


Fig. 4. Initial Velocity of Eight Agents and Leader.

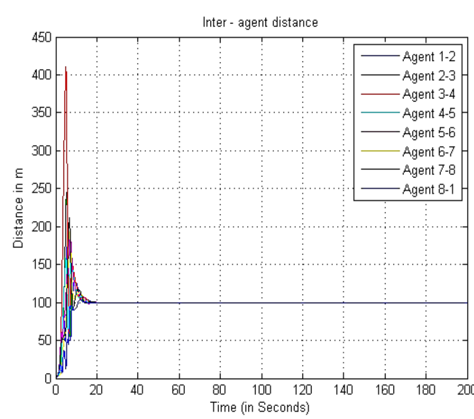


Fig. 5. Inter-agent Distance for All Agents.

The angle is increased to maintain the distance between the agents. Also, a constant multiplying gain factor is adjusted to maintain a constant inter-agent distance between the agents. In Fig. 5, it is observed that, initial transient period is around $9s$ to achieve the steady-state behaviour.

Apart from maintaining the distance, it is also necessary to check whether the formation is maintained. To check that the formation is maintained, all agents should agree to the same point during flocking. This agreement is captured by averaging the positions of agents in x and y axes. The simulation substantiates that all agents have agreed on the position pursuit of interest (shown in Fig. 6) in $20s$. It can be observed that, all agents collectively agree on the same point, $(50, -50)$ i.e., the pursuit point of interest. The rotation angle in (10) is adjusted to maintain the inter-agent distance and angle from the centroid of eight agents. The maintenance of inter-agent distance, angle from the centroid and consensus agreement among agents during the flocking validates the pattern in polygon.

B. Flocking of Agents in Polygon using Adaptive Strategy

The flocking behaviour is obtained by integrating the agent's dynamics with the adaptive controller. The position of agents is updated using the cyclic pursuit strategy (discussed in Section 4A.). The communication or interaction range is 2 and the connectivity is established among all agents with the leader. The cyclic pursuit and the adaptive control strategies are used to achieve synchronization of octagonal formation and tracing the leader's trajectory. The analysis of simultaneous formation and flocking is discussed in two cases:

- The octagonal formation is developed using Q-learning, where the eight agents learn independently in x and y frames. The agents are subjected to follow the leader's trajectory after the octagonal contour is formed. The initial position of the agent is the same as the vertices of the octagon pattern (in Fig. 2) and the velocity is chosen randomly in the range $[0, 2] \times [0, 2]$ (in Fig. 4).

The flocking error is analyzed to match the velocity of agents with the leader and achieve one of the flocking attributes: alignment [21]. The variation in the relative velocity of agents with the leader results in flocking error in leader-follower configuration of MAS. The relative velocity of agents with the leader is shown in Fig. 7. It is observed that the agents in polygon formation follow the leader's trajectory in $1.5s$ (settling time) along x and y axes [shown in Fig. 7(a) and Fig. 7(b)]. The transient time for both axes is around 1s at 0.2 amplitude. This infers that the agents are flocking quickly at less peak amplitude value. The distributed control strategy is used for the agents in hexagon to flock along the pre-defined trajectory [8]. The flocking of the hexagon pattern converges to zero at $5s$ using the distributed control strategy [8]. The proposed strategy is useful to achieve convergence of flocking error to zero, faster than in [8] and is suitable for any polygonal configuration. The cycle change is observed every $20s$ and follows the trajectory of the leader.

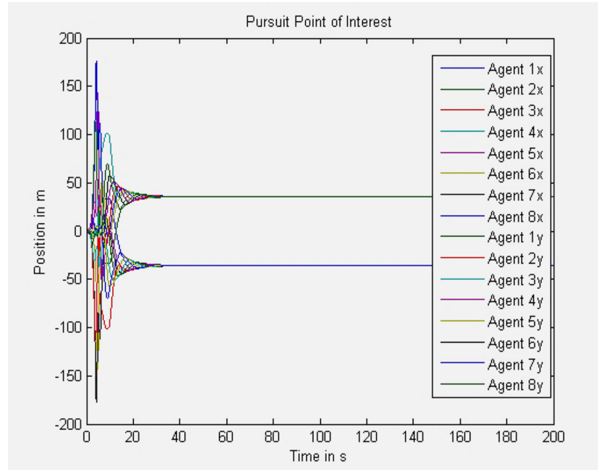
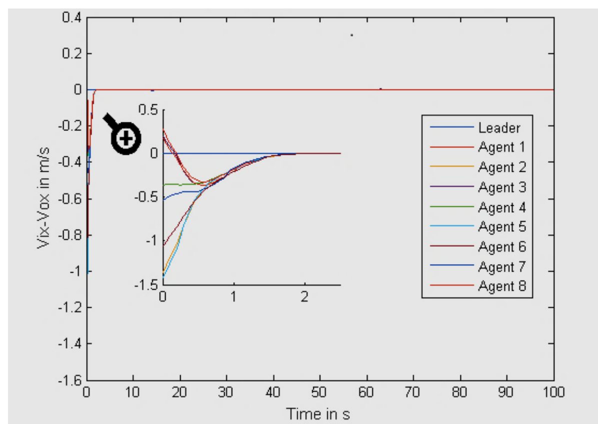
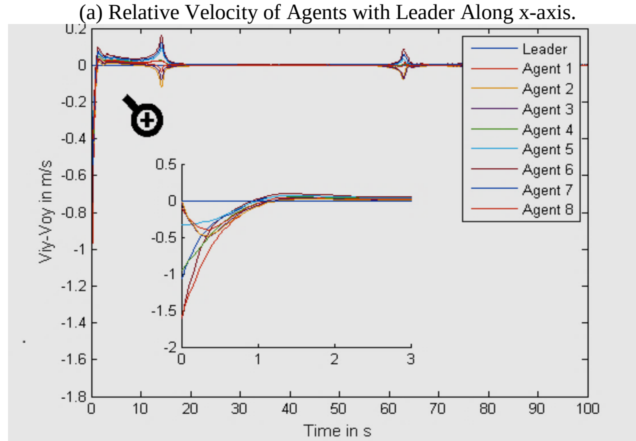


Fig. 6. Consensus Agreement for All Agents.

The robustness of MAS is achieved by maintaining average position error of agents with the leader as minimal as possible (band of $[-1,1] \times [-1,1]$). The robustness of flocking behaviour is analyzed to stay close to nearby agents and avoid the collision. The agents are informed to establish a connection with the leader after updating the position using the cyclic pursuit strategy. The connection indicates that the agents are tracing the leader's trajectory, as shown in Fig. 8.



(a) Relative Velocity of Agents with Leader Along x-axis.



(b) Relative Velocity of Agents with Leader Along y-axis.

Fig. 7. Velocity Consensus of Multi-Agents for the Case 1.

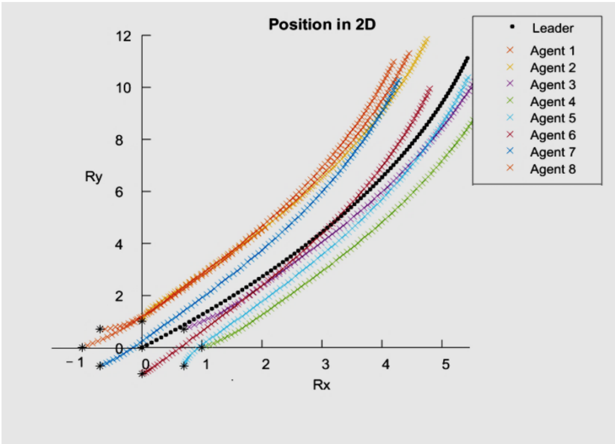
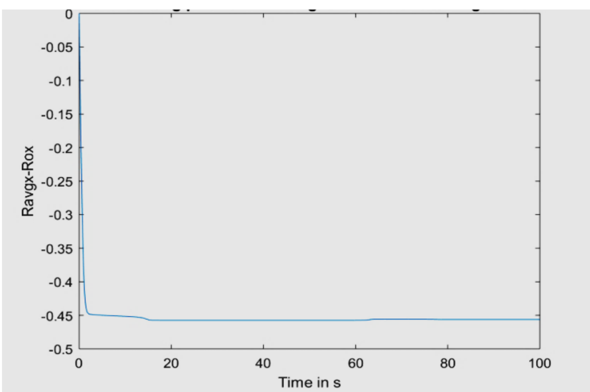


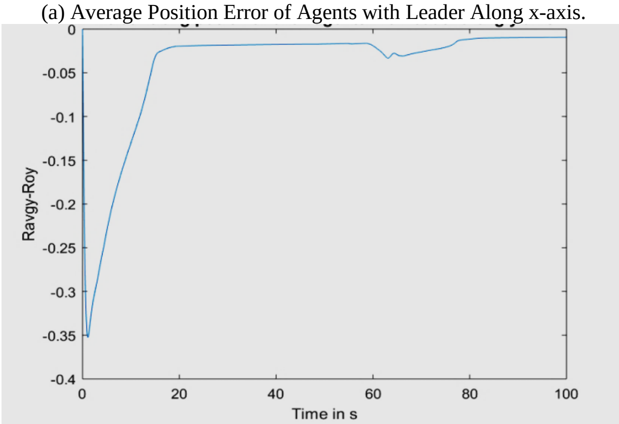
Fig. 8. Trajectory Tracking by Agents in a Closer View using Tribrid Control Strategy for the Case 1.

Because the agents are following the leader's trajectory, the relative velocity of agents with the leaders is converging to zero. Since the agent's velocity is closely observable with that of the leader, the average position error of the agents with the leader is decreased to a minimum constant value of -0.45 in x axis and -0.02 in y axis in $20s$.

The average position error in $\Re^2$, is shown in Fig. 9(a) and Fig. 9(b), respectively. The error is within the position band and the settling time is, $20s$ as the formation should also be maintained during flocking.



(a) Average Position Error of Agents with Leader Along x-axis.



(b) Average Position Error of Agents with Leader Along y-axis.

Fig. 9. Position Consensus of Multi-Agents for the Case 1.

The octagon formation should be maintained while tracking the leader's trajectory. It is analyzed by using the agent's position at various time and distance between the agents. The distance is maintained at a constant value between 0.19 and 1.18 in $20s$, as shown in Fig. 10.

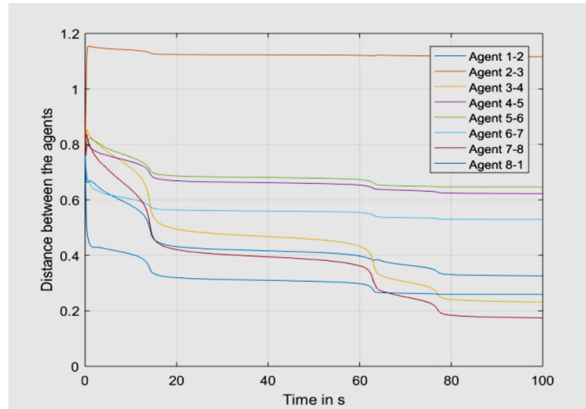


Fig. 10. Inter-agent Distance in Tribrid Strategy for the Case 1.

The structure of the formation is maintained in initial octagonal pattern as shown in Fig. 11. During flocking, the switching in position affects the initial octagonal pattern, as observed in every iteration. The octagonal pattern is achieved in $20s$ (at the iteration $t = 200$). It is observed that in every iteration, two agents are little away from the remaining six agents. It is also inferred in Fig. 11 that inter-agent distance, 2-3, 4-5 and 5-6 are high compared with the other inter-agent distances.

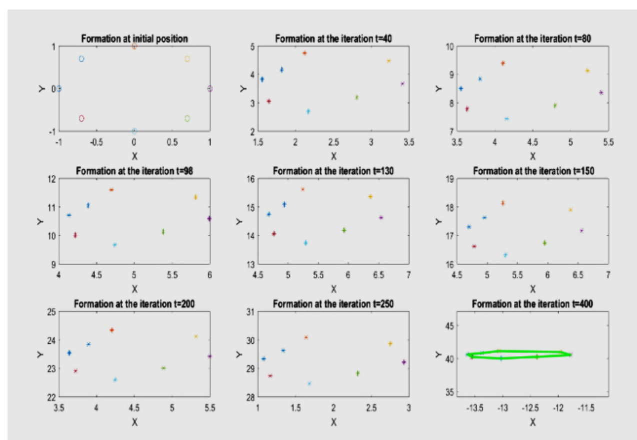


Fig. 11. Formation using Tribrid Control Strategy for the Case 1.

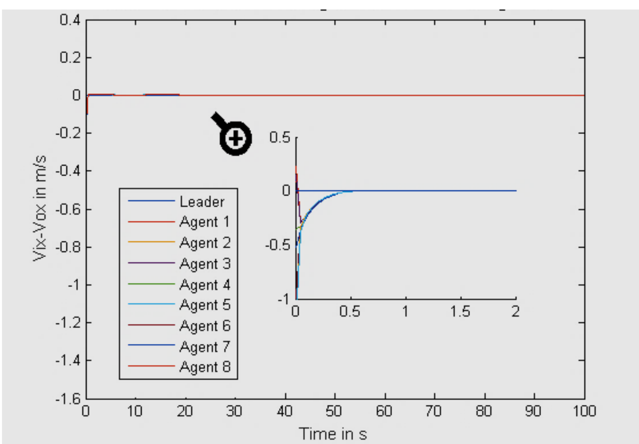
- The agents distributed randomly in space are subjected to follow the leader's trajectory. The initial position of the agent is distributed randomly in the space (in Fig. 3) and the velocity is chosen randomly in the range $[0, 2] \times [0, 2]$ (in Fig. 4).

The variation in the relative velocity of agents with the leader results in flocking error in leader-follower configuration of MAS. The relative velocity of agents with the leader is shown in Fig. 12(a) and Fig. 12(b). It is observed that the agents in octagonal formation follow the leader's trajectory by observing the value of the leader's velocity in $20s$. The cycle change is observed every $60s$ and follows the trajectory of the leader. However, in $3s$, the agents follow the trajectory of the leader with the flocking error of $0.2m/s$.

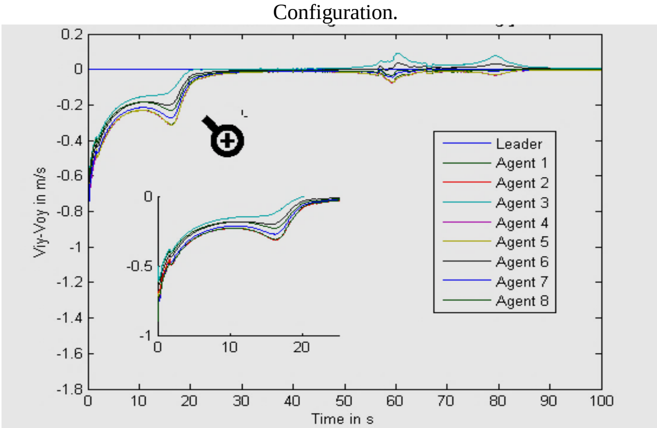
The robustness of MAS is achieved by maintaining average position error of agents with the leader as minimal as possible (band of $[0,10] \times [0,10]$). The robustness of flocking behaviour is analyzed for an agent to stay close to nearby agents and avoid the collision. The agents are informed to establish a connection with the leader after updating the position using the cyclic pursuit strategy. The connection indicates that the agents are tracing the leader's trajectory, as shown in Fig. 13.

The agents' velocity is closely observable with that of the leader's velocity. Hence, the average position error of the agents with the leader has decreased to a minimum constant value of -0.065 in x axis and -0.6 in y axis in $20s$. The average position error in $\Re^2$ along x- and y axes is shown in Fig. 14(a) and Fig. 14(b), respectively.

The formation should be maintained while tracking the leader's trajectory. It is analyzed by using the agent's position at various time and distance between the agents. The distance is maintained at a constant value between 1.5 and 9 in $80s$, as shown in Fig. 15.



(a) Relative Velocity of Agents with Leader Along x-axis for Random Configuration.



(b) Relative Velocity of Agents with Leader Along y-axis for Random Configuration.

Fig. 12. Velocity Consensus of Multi-Agents for the Case 2.

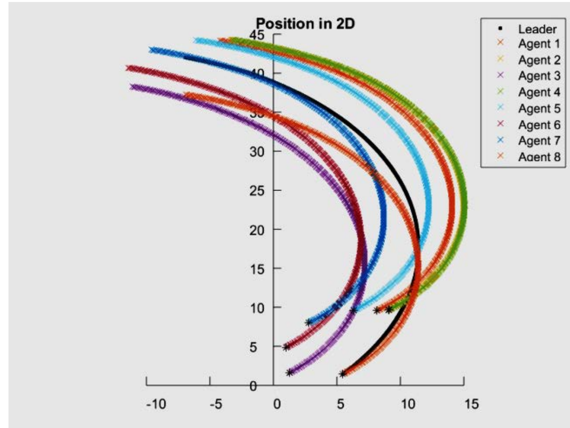
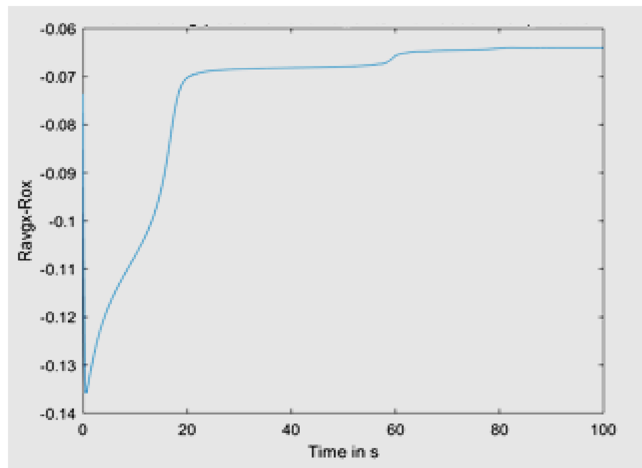
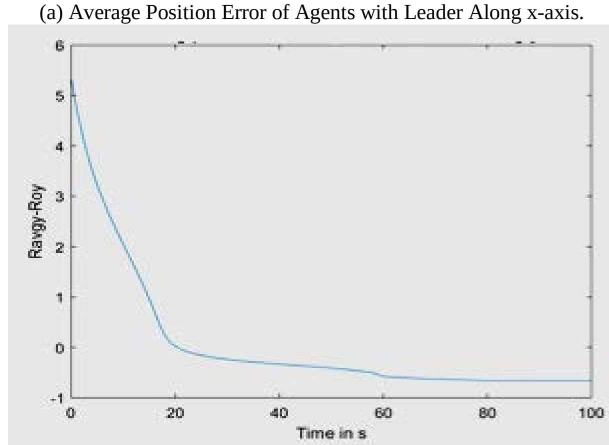


Fig. 13. Trajectory Tracking by Agents in a Closer View using Tribrid Control Strategy for the Case 2.



(a) Average Position Error of Agents with Leader Along x-axis.



(b) Average Position Error of Agents with Leader Along y-axis.

Fig. 14. Position Consensus of Multi-Agents for the Case 2.

The structure of the formation is maintained with the initial pattern as shown in Fig. 16. During flocking, the switching in position affects the initial pattern, as observed in every iteration. The initial pattern is achieved in $20s$ (at the iteration $t = 200$). It is observed that in any iteration, the configuration is the same as the initial pattern.

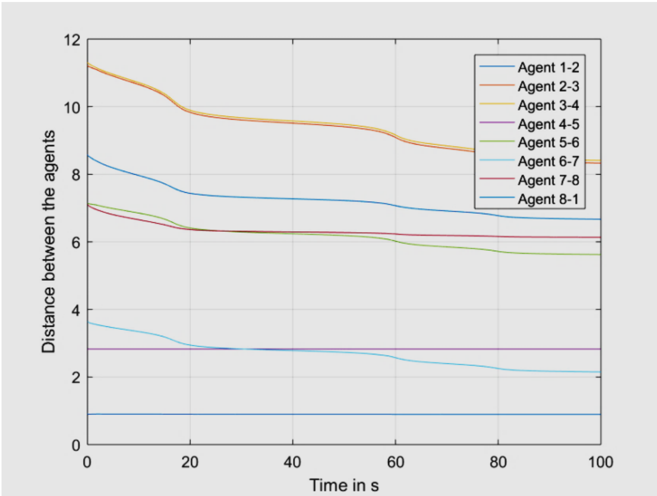


Fig. 15. Inter-agent Distance in Tribrid Strategy for the Case 2.

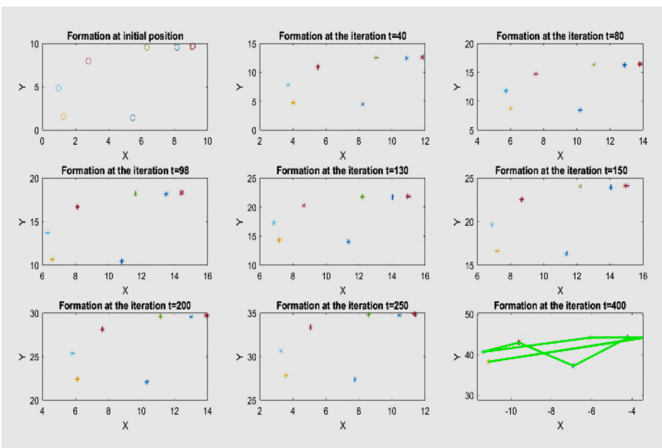


Fig. 16. Formation using Tribrid Control Strategy for the Case 2.

The distributed control strategy is used for proper communication and coordination among agents and avoids a collision while flocking in a pre-defined trajectory [8] and in the leader-follower scenario [17]. The analysis does not focus on simultaneous polygon formation and flocking in the leader-follower scenario. The proposed tribrid control strategy is discussed under two cases: the octagonal pattern from RL and agents distributed in the spatial environment are chosen as the initial position of agents. The comparative analysis for the two cases is given in Table I and Table II.

TABLE I. COMPARATIVE ANALYSIS OF FLOCKING AND FORMATION BEHAVIOUR IN TRIBRID CONTROL STRATEGY

Flocking Configuration					
Cases	Relative Velocity of Agents with the Leader in m/s		Average Position Error of Agents in m		
	Transient Time in s	Settling Time in s	x- coor-dinate	y - coor-dinate	Settling Time in s
Case 1	0.2	1.5	-0.45	-0.02	1.5
Case 2	1	20	-0.065	-0.6	20

TABLE II. COMPARITIVE ANALYSIS OF FORMATION BEHAVIOUR IN TRIBRID CONTROL STRATEGY

Formation Configuration		
Cases	Inter-agent Distance Range	Formation Structure
Case 1	0.19-1.18	Same as initial position
Case 2	1.5-9	Same as initial position

The flocking error of eight agents in the polygon pattern has converged to zero at $1.5s$ for the Case 1 and $20s$ for the Case 2. The distributed control strategy is used for the agents in hexagon pattern to flock along the pre-defined trajectory [8]. The flocking of the pattern converges to zero in $5s$ using the distributed control strategy [8]. Thus, the proposed strategy enables the system to converge faster. The details of comparison of various configurations of flocking at time-varying velocity are described in Table III. As can be observed in Table III, the earlier studies [8,19,22] did consider configurations which have dimensions smaller than octagon configuration to flock at time-varying velocity. In this paper which considers octagonal contour for flocking, the convergence of flocking error to zero has been achieved faster than the existing studies [8, 19, 22].

TABLE III. COMPARITIVE ANALYSIS OF VARIOUS CONTOUR CONFIGURATION FLOCKING AT TIME-VARYING VELOCITY

		Flocking Error
Sl. No.	Contour configurations flocking at time- varying velocity	Settling Time in s
1	Octagonal contour flocking at time-varying velocity (Proposed Tribrid Control Strategy for Case 1)	1.5
2	Square contour flocking at time – varying velocity [22]	5
3	Formation tracking control [19]	2
4	Hexagonal contour flocking at time – varying velocity [8]	5

The settling time is high ($20s$) for the Case 2, compared to Case 1. If the agents are randomly distributed in an environment, then the centroid of agents cannot be maintained with the leader's position. It results in a larger average position error, as observed in Table I. Also it results in larger inter-agent distance range, as observed in Table II. The advantage of the tribrid approach is that the formation structure will remain the same as the initial configuration.

VI. CONCLUSIONS

In this paper, the simulation model of flocking uses the tribrid control strategy for demonstration of two cases: multi-agents distributed randomly in the environment and multi-agents in polygonal formation (obtained from Reinforcement Learning (RL)). The initial positions of multi-agents are varied with the variation of gain value in the cyclic pursuit strategy to maintain the distance between the agents at a constant value. Also, the cyclic pursuit strategy is applied to the multi-agent dynamics to achieve consensus among the agents and to maintain the formation. The analysis of simultaneous formation and flocking is discussed in two cases:

- The agents form polygonal formation using Q-learning and are integrated with cyclic pursuit strategy to maintain the octagonal formation.
- The agents in a randomly distributed environment use cyclic pursuit strategy to achieve and maintain the octagonal formation.

In both the cases, the inter-agent distance and cyclic pursuit interest are achieved in $20s$. The positions of agents are updated using the cyclic pursuit strategy before performing flocking. The flocking error of eight agents in the polygon pattern has converged to zero at $1.5s$ in first case and at $20s$ in the second case, with the proposed tribrid control strategy. The average position error of agents with the leader has increased by 4% for the second case, compared with the first case. In both the cases, the agents in the octagonal polygon configuration follow the leader's trajectory in $0.2s$. To conclude, the proposed tribrid control strategy enables the flocking error of multi-agents to converge faster and is suitable for closed contour configuration of multi-agents. The advantage of the tribrid approach is the facilitation of the retention of formation structure of the initial configuration. The proposed approach has the assumption that all the agents are always connected during flocking and formation. The disconnection leads to diverging behavior of flocking and formation configuration of multi-agents. Hence an analysis for the scenario of loss of connectivity during simultaneous polygonal formation and leader-follower flocking of multi-agents can be of significant importance from both research and system perspectives.

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