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CONTROL OF MULTIPLE MOBILE AGENTS VIA ARTIFICIAL POTENTIAL FUNCTIONS AND RANDOM MOTION

Manish Kumar

Dept. of Mechanical, Industrial, and Nuclear Engineering, University of Cincinnati, Cincinnati, OH

Devendra P. Garg

Dept. of Mechanical Engineering and Materials Science, Duke University, Durham, NC 27708

Randy Zachery

Army Research Office, RTP, NC, USA

ABSTRACT

This paper investigates the effectiveness of designed random behavior in cooperative formation control of multiple mobile agents. A method based on artificial potential functions provides a framework for decentralized control of their formation. However, it implies heavy communication costs. The communication requirement can be replaced by onboard sensors. The onboard sensors have limited range and provide only local information, and may result in the formation of isolated clusters. This paper proposes to introduce a component representing random motion in the artificial potential function formulation of the formation control problem. The introduction of the random behavior component results in a better chance of global cluster formation. The paper uses an agent model that includes both position and orientation, and formulates the dynamic equations to incorporate that model in artificial potential function approach. The effectiveness of the proposed method is verified via extensive simulations performed on a group of mobile agents and leaders.

INTRODUCTION

Formation control of multiple autonomous vehicles has received attention of several researchers working in the area of mobile robotics because of its potential applications in a number of fields including cooperated search and rescue operation, surveillance, reconnaissance, and boundary protection. Advancement in communication and sensing technologies, and in computing resources have made it possible to coordinate the movement of several autonomous vehicles working cooperatively to achieve a certain mission. One of the very first applications of artificial formation was behavioral simulation of flocks of birds, herd of animals and schools of fish for computer graphics by Reynolds [1]. He stated three simple behaviors that lead to flocking in birds and fish: collision avoidance, velocity matching, and flock centering (in decreasing order of precedence). In artificial systems, these three behaviors become objectives of the controller to achieve flocking. The biggest merit of Reynolds' behavior-based approach was that these behaviors were based on observations of environment and interactions on a local scale that could be fully implemented in individual agents. These local interactions among agents resulted in global flocking, schooling, and herding behaviors which were totally scalable.

Drawing inspiration from Reynolds' approach, many researchers have focused on designing decentralized controller for achieving flocking behavior. Balch and Arkin [2] described a behavior-based decentralized controller using a number of motor-schemas and simple control laws. They applied these control laws to mobile robots; however they did not offer any stability guarantee of such control methods. In [3,4], the authors proposed a decentralized controller for control of formations of non-holonomic mobile robots which used local sensor information in a leader-follower motion. However, they did not discuss scalability issues and the effect of sensor limitations/uncertainties on the performance of the strategy.

In [5], the authors described a model-independent coordination strategy for multi-agent control and showed that if the tracking errors were bounded, the formation error was stabilized. They used formation constraint and virtual leaders/

beacons to formulate the problem. In [6], the authors proposed a Lyapunov function approach to multi-agent coordination. They used Lyapunov function to prove formation maintenance, task completion time, and formation velocity. In [7,8], the authors considered double integrator dynamics for designing control laws using graph theory for both fixed and dynamic topology of flocks. This work was extended to experimental implementation in [9]. In [10], the authors described a distributed control system for multiple autonomous vehicles for formation stabilization. Based on graph rigidity theory, they used natural potential functions obtained from structural constraints of a desired formation. However, they did not discuss the stability issues under uncertain connections or due to the sensing uncertainties.

The concept of *artificial potential* has been used in robotics by many researchers. Artificial potential has been used for path planning [11], manipulator control [12], robot navigation [13], and obstacle avoidance [14]. Leonard and Fiorelli [15], in their work, proposed a distributed control system to coordinate multiple autonomous vehicles using artificial potential functions and virtual leaders. Virtual leaders were used to manipulate group geometry and control the group motion. The use of artificial potentials resulted in interaction forces between the agents (and the virtual leaders). Using kinetic and artificial potential energies of vehicles, they constructed a Lyapunov function to prove stability and robustness of group motion.

In this paper, a distributed control model of a multi-agent system using artificial potential functions and virtual leaders [15-16] has been used. In most of the earlier work [7, 8, 10, 15, 16], a particle model has been used to represent mobile agents. These agents were represented by a double integrator dynamic model. This paper extends the concept of particle model to a model with orientation. This model is a better representation of a mobile robot dynamic model, and can be easily implemented on mobile robots. Moreover, the use of artificial potential function based method requires full state information (more precisely, relative position and velocity information) of all agents and leaders at all times. If full state information of agents and leaders are communicated to each agent, this would result in a huge communication overload. This requirement of communication can be overcome by use of onboard sensors. The leaders, in this case, need to be real agents which can be sensed. However, sensors have their own limitations [17-18]. Their measurements are generally noisy, and ranges are limited. With limited range, sensors can provide information about neighboring agents and leaders only. A control system based on the above method should be able to stabilize itself based on local information when the interactions between all of its agents are complete. In other words, if the interaction between agents (and leaders) are modeled as a graph, and if the graph is connected (i.e., no node or group of nodes are isolated), then the above method should be able to find the globally stable equilibrium formation. However, if there is an agent or a group of agents that is not connected to the rest of the graph (i.e., it forms a disconnected subgraph), then the system may not form a globally stable single cluster.

In the formation control problem where the leaders steer the agents, the agents must be connected to the leaders via a chain of links for the group to be able to follow the desired trajectory. Hence, all isolated subgraphs that do not contain leaders as member nodes will follow an arbitrary trajectory, and that group may or may not find any leader to follow. For example, situations can arise when a certain agent cannot find any other agent or leader in its neighborhood. Similarly, even when there are some agents in the neighborhood, if the group of agents find themselves in isolation with no leader in sight, the group would not be able to follow the leader(s). Without the global information, such systems are highly susceptible to fall into local minima (a stable group disconnected from virtual leaders and other agents).

This paper investigates the above scenarios and draws analogies from optimization algorithms where exploration (random component of the search process) plays an important role in the optimization process. It introduces a component representing random motion in the artificial function formulation of the formation control problem. There are a few considerations to be kept in view while designing the random component, for example the randomness should not lead to an unstable formation. The introduction of the random behavior component in agents who do not have leaders in sight results in a better chance of global cluster formation. The analysis uses a model that includes agent orientation and formulates the dynamic equations to incorporate artificial potential function approach. The effectiveness of the proposed method is verified via extensive simulations performed on a group of mobile agents and leaders. The simulations and experiments performed lead to the conclusion that although random behavior does not guarantee better performance in finite time and in every instance, a controlled randomization does improve the chances of system to maintain the group connectedness in presence of sensor uncertainties and limitations resulting in broken links of interactions between members of the group.

The paper is organized as follows: First, the approach for mobile agent formation control using artificial potential function is briefly discussed. Then, the notion of orientation is introduced to the model of the mobile agent, and the corresponding dynamic equations of motions are derived. The concept of random motion is introduced as an approach to overcome the problem of getting stuck in local minima in absence of global information. Some factors to be considered while designing the randomness alongwith an analysis for stability are presented next. A simulation study is then carried out, and results are presented to verify that the proposed technique leads to a better formation, maintenance, and steering of cluster of mobile agents.

ARTIFICIAL POTENTIAL FUNCTIONS BASED CONTROL

This paper utilizes a well formulated approach [15-16] for distributed control of multiple autonomous agents based on artificial potentials and virtual leaders. The artificial potentials are functions of relative distances between the pairs of neighbors. Among a group of autonomous agents, this approach introduces some virtual leaders. In order to extend their method to formation control where agents are equipped with sensors (which have limited range and can detect only neighboring agents/leaders), the leaders have to be real agents controlled independently to steer the group. There are three types of forces acting on each agent – interaction force derived from artificial potential function with other neighboring agents (F^a), interaction force with any neighboring leaders (F^l), and a controlled dissipative force (F^v) (which is zero when the agent is moving with same velocity as its neighbors). The potentials corresponding to F^a and F^l are represented by V^a (potential function due to interaction between two agents) and V^l (potential function due to interaction between agent and leader) respectively. Figure 1 shows the plot of V^a with respect to inter-agent distance. A plot of V^l with respect to agent-leader distance has the same shape as Figure 1.

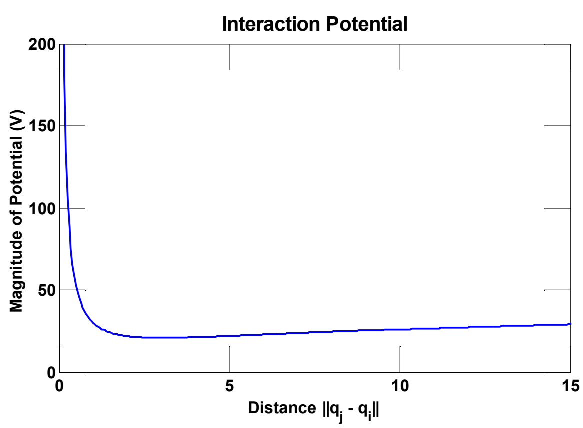

Figure 1: Interaction Potential versus Inter-Agent Distance

Artificial potential function due to interaction between two agents *i* and *j* can be expressed as:

$$V_{ij}^{a} = \begin{cases} a(\ln(q_{ij}) + \dfrac{d_0}{q_{ij}}) & 0 < q_{ij} < d_1 \\ a(\ln(d_1) + \dfrac{d_0}{d_1}) & q_{ij} > d_1 \end{cases} \qquad (1)$$

where, a is a scalar control gain, $q_{ij} = \left\| q_j - q_i \right\|$ is inter-agent distance.

Similarly, for agent-leader interaction between agent *i* and leader *k*, the artificial potential function is given by:

$$V_{ik}^{l} = \begin{cases} b(\ln(q_{ik}) + \dfrac{h_0}{q_{ik}}) & 0 < q_{ik} < h_1 \\ b(\ln(h_1) + \dfrac{h_0}{h_1}) & q_{ik} > h_1 \end{cases} \qquad (2)$$

where, b is a scalar control gain, and q_{ik} is the distance between agent *i* and leader *k*. The parameters d_0 and h_0 represent the distance between the agent-agent and agent-leader respectively below which the interaction force is repulsive (negative). The parameters d_1 and h_1 represent the distance between the agent-agent and agent-leader respectively above which there are no interactions, and they can be regarded as the range beyond which sensor cannot see other agents and leader (respectively).
The total artificial potential associated with an agent *i* is given by:

$$V_i = \sum_{j \in N_i^a} V_{ij}^{a} + \sum_{k \in N_i^l} V_{ik}^{l} \qquad (3)$$

where N_i^a is the set containing agents in the neighborhood of agent *i*, and N_i^l is the set containing leaders in the neighborhood of agent *i*.

The group of mobile agents consists of *N* fully actuated robots whose dynamics is given by the double integrator:

$$\dot{q}_i = p_i \qquad (4a)$$

$$\dot{p}_i = u_i \qquad i = 1, \ldots, N \qquad (4b)$$

where q_i and p_i are *m*-dimensional position and velocity vectors respectively of agent *i*. Net control force on an agent *i* can be written as

$$u_i = -\nabla_{q_i} V_i + f_i^v \qquad (5)$$

where the first term represents the gradient descent based on artificial potential functions (due to interactions with other agents and leaders), and the second term represents the damping force which is responsible for achieving consensus among the agents. ∇_{q_i} represents the gradient with respect to coordinates (position) of agent *i*: q_i. The damping term f_i^v is given by:

$$f_i^v = c \sum_{j \in N_i} \left(p_j - p_i \right) \qquad (6)$$

where c is a scalar gain, p_i represents velocity of agent i, and $N_i = N_i^a \cup N_i^l$ is the set of agents and leaders in the neighborhood of agent i. The total potential of the system is given by:

$$V(q) = \sum_{i=1}^{N} V_i = \sum_{i=1}^{N} \left(\sum_{j \in N_i^a} V_{ij}^a + \sum_{k \in N_i^l} V_{ik}^l \right) \qquad (7)$$

where N is the total number of agents, and $q \in R^{Nm}$ is stacked position vector of all agents.

The collective dynamics of the system can be given by:

$$\dot{q} = p$$
$$\dot{p} = -\nabla V(q) - \hat{L}(q)p \qquad (8)$$

where $p \in R^{Nm}$ is stacked velocity vector for all agents, and $\hat{L}(q) \in R^{Nm \times Nm}$ is m-dimensional graph Laplacian (see reference [16]). Among other important properties of graph Laplacian matrix $\hat{L}(q)$, it is a positive semi-definite matrix.

In order to carry out stability analysis of the collective motion of agents resulting from the above method, a Lyapunov function can be chosen as the total energy (artificial potential energy and kinetic energy) of the system:

$$\Phi(q,p) = V(q) + \frac{1}{2} p^T p \qquad (9)$$

Lemma: Consider a system of N mobile agents. Each of the agents follows dynamics given by Equation (4), and with feedback control law given by Equation (5). For any initial condition belonging to the level set of $\Phi(q,p)$ given by $\Omega_C = \{(q,p) : \Phi(q,p) \le C\}$ with C>0, and when the underlying graph of the system is connected and cohesive, then the system asymptotically converges to an invariant set $\Omega_I \subset \Omega_C$ such that the points in Ω_I have a velocity that is bounded and velocity of all agents match.

Differentiating with respect to time and using Equation (9) one gets:

$$\dot{\Phi}(q,p) = p^T \nabla V(q) + p^T \dot{p} = p^T \nabla V(q) + p^T \left(-\nabla V(q) - \hat{L}(q)p \right) \qquad (10)$$
$$= -p^T \hat{L}(q) p \le 0$$

since $\hat{L}(q)$ is positive semi-definite matrix.

or, $$\dot{\Phi}(q,p) = -\sum_{(i,j) \in E} \left\| p_j - p_i \right\|^2 \qquad (11)$$

where E is the set of edges in the graph (graph modeling the interconnections between agents) representing interactions between two agents. From Lasalle's Invariance Principle, all solutions of the system starting in Ω_C will converge to the largest invariant set $\Omega_I = \left\{ (q,p) \in \Omega_I : \dot{\Phi}(q,p) = 0 \right\}$, and this happens when the velocities of all agents match. For a detailed proof of this lemma, please see references [16].

AGENT MODEL

The agent, in the previous section, had been modeled as a particle with double integrator dynamics given by Equation (4). This section describes a method by which the double integrator dynamics can be extended to include the orientation of an agent. Figure 2 shows a schematic diagram of the mobile agent or vehicle.

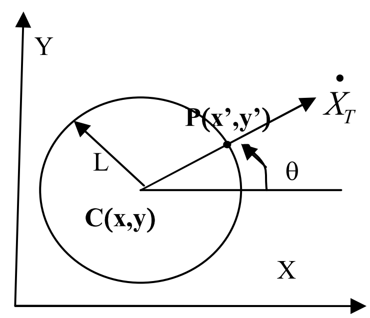

Figure 2: Schematic Representation of a Mobile Agent

For modeling purposes, the agent is assumed to be a two dimensional circular entity with radius L, mass M, and moment of inertia J. Let **C(x,y)** be the center of gravity of the agent, $\dot{X}_T$ be the translational speed of the agent in the direction shown (θ) in the figure. Thus, one can write

$$\dot{x} = \dot{X}_T \cos\theta$$
$$\dot{y} = \dot{X}_T \sin\theta \qquad (12)$$
$$\dot{\theta} = \omega$$

Differentiating Equations (12) gives:

$$\ddot{x} = \ddot{X}_T \cos\theta - \dot{\theta} \dot{X}_T \sin\theta$$
$$\ddot{y} = \ddot{X}_T \sin\theta + \dot{\theta} \dot{X}_T \cos\theta \qquad (13)$$
$$\ddot{\theta} = \dot{\omega}$$

Coordinates of point **P** can be expressed in terms of robot's orientation and coordinates of center of gravity **C**.

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x + L\cos\theta \\ y + L\sin\theta \end{bmatrix} \tag{14}$$

Differentiating Equation (14) twice yields the acceleration of point **P**:

$$\begin{bmatrix} \ddot{x}' \\ \ddot{y}' \end{bmatrix} = \begin{bmatrix} \ddot{x} - L\cos\theta\cdot\dot{\theta}^2 - L\sin\theta\cdot\ddot{\theta} \\ \ddot{y} - L\sin\theta\cdot\dot{\theta}^2 + L\cos\theta\cdot\ddot{\theta} \end{bmatrix} = u = \begin{bmatrix} u_x \\ u_y \end{bmatrix} \tag{15}$$

Also,

$$M\ddot{X}_T = F$$
$$J\ddot{\theta} = T \tag{16}$$

where F is the force, and T is the torque applied to agent.
From Equations (13), (15), and (16):

$$u = \begin{bmatrix} u_x \\ u_y \end{bmatrix} = \begin{bmatrix} \frac{1}{M}\cos\theta & -\frac{L}{J}\sin\theta \\ \frac{1}{M}\sin\theta & \frac{L}{J}s\cos\theta \end{bmatrix} \begin{bmatrix} F \\ T \end{bmatrix} + \begin{bmatrix} -\dot{X}_T\sin\theta\cdot\dot{\theta} - L\cos\theta\cdot\dot{\theta}^2 \\ +\dot{X}_T\cos\theta\cdot\dot{\theta} - L\sin\theta\cdot\dot{\theta}^2 \end{bmatrix} \tag{17}$$

The control inputs F and T can be found as follows:

$$\begin{bmatrix} F \\ T \end{bmatrix} = \begin{bmatrix} \frac{1}{M}\cos\theta & -\frac{L}{J}\sin\theta \\ \frac{1}{M}\sin\theta & \frac{L}{J}s\cos\theta \end{bmatrix}^{-1} \times \left\{ \begin{bmatrix} u_x \\ u_y \end{bmatrix} - \begin{bmatrix} -\dot{X}_T\sin\theta\cdot\dot{\theta} - L\cos\theta\cdot\dot{\theta}^2 \\ +\dot{X}_T\cos\theta\cdot\dot{\theta} - L\sin\theta\cdot\dot{\theta}^2 \end{bmatrix} \right\} \tag{18}$$

The vector $u = \begin{bmatrix} u_x \\ u_y \end{bmatrix}$ is obtained from the artificial forces acting on the mobile agent due to its interaction with neighboring agents and virtual leaders, and is given by Equation (5) for agent 'i'.

RANDOM MOTION STRATEGY

The coordinated control method based on artificial potential functions results in a stable flocking or schooling behavior, which is evident from the analysis shown in the previous section based on Lyapunov function given by Equation (9). The stable flocking or schooling configuration is nothing but an equilibrium condition where the sum of forces acting on each agent arising from artificial interactions between agents and between agents and leaders are zero. In other words, the formation control into a schooling behavior can be seen as an optimization process in agent configuration space where the Lyapunov function is minimized. A negative gradient given by Equation (10) guarantees that the system discussed in the Section entitled "Artificial Potential Functions Based Control" will reach a configuration where the Lyapunov function is minimum, and desired formation is achieved.

The achievement of desired and stable equilibrium configuration mentioned above, however, is based on an assumption that each agent has the knowledge of the position of all other neighboring agents and leaders, and the underlying graph of the whole system is connected. In practical situations, this can be achieved via communicating positional information of all agents and leaders to all agents. However, this kind of strategy will result into huge communication overload. Moreover, the existence of a central sensing system (to determine position of all agents) and central communication system would compromise the decentralized nature of the control system. The use of a central communication system can be avoided if the agents are equipped with sensors which can provide positional information of the neighbors. However, without the use of a communication channel, the concept of virtual leaders cannot be used. The leaders need to be real among the agents which can be sensed by the agents, and which can be separately controlled so that leaders can follow a desired trajectory to steer the agents. The use of onboard sensors has its own limitations. Sensors have limited range, and their measurements can be noisy.

A formation control system based on artificial potential due to interactions between neighboring agents can essentially be regarded as a particle swarm optimization [19] process where a large number of agents (or particles) are searching for the globally optimal point (or globally stable equilibrium formation). While such a method may be inherently robust to noise in sensor measurements, sensor limitation arising due to range of the sensors will be detrimental. The range limitation of sensors results in agent's partial or local knowledge about the surrounding. A control system based on the above method should be able to stabilize itself based on local information when the interactions between all of its agents are complete. In other words, if the interaction between agents (and leaders) are modeled as a graph, and if the graph is connected (i.e., no node or group of nodes are isolated), then the above method should be able to find the globally stable equilibrium formation. However, if there is an agent or a group of agents that is not connected to the rest of the graph (i.e., it forms disconnected subgraph), then system may not form a globally stable single cluster. In the formation control problem where the leaders steer the agents, agents must be connected to the leaders via a chain of links for the group to be able to follow the desired trajectory. Hence, all isolated subgraphs that do not contain leaders as member nodes will follow an arbitrary trajectory, and that group may or may not find any leader to follow.

In this paper, a random motion has been used as a strategy to find leaders in case such isolation happens. Completely random search techniques may not provide results in a finite time. However, they have been widely used as a component in several deterministic and stochastic search algorithms. For example, evolutionary search algorithms [20] have heavy stochastic components (choice of chromosomes for reproduction, crossover, and mutation are driven by probabilities based on their fitness function). Mutation process, which is a random change in bits representing chromosome (or possible solution), is largely responsible for the global optimization capabilities of evolutionary algorithms. Reinforcement learning techniques [21] have two components: exploitation and exploration. Exploration is nothing but a random walk in the search space that makes the algorithm investigate new regions. Bateson [22] calls the mind as a stochastic system and cognitive learning process a stochastic process. Contemporary cognitive scientists consider mental processes as stochastic processes such as evolutionary algorithms where hypotheses or ideas are proposed, tested, and either accepted or rejected by a population. Random or trial-and-error learning techniques provide ways to create new varieties of solutions for problems. Random behavior is ubiquitous in biological systems. Chaotic behavior of a hooked fish, random behavior among preys for predator avoidance, and zig-zagging of a chased rabbit through a meadow are all examples of existence and heavy use of random behaviors among animals. Lorenz [23], in his intuitive chapter entitled “Oscillation and Fluctuation as Cognitive Functions”, has described the importance of a random behavior in organisms’ motion for search as well as for escaping dangers.

This paper proposes to use this kind of random behavior as a component in the artificial potential function method that can improve the chances that the system reaches the globally optimal configuration. The control force on agent i has now three components, and is given by:

$$u_i = -\nabla_{q_i} V_i + f_i^v + f_i^R \tag{19}$$

where f_i^R is the random component given by:

$$f_i^R = D\xi \tag{20}$$

where ξ is the Gaussian random process of unit variance, and D is the matrix that scales the random component, and $D^T D$ is the covariance of the random component.

There should be a few specific considerations while designing this random component of force. These considerations, as well as corresponding analyses, are provided below:

i. The magnitude of the random component should not be large which can result into unstable and non-cohesive group. In terms of Lyapunov function analysis, this translates to:

$$\begin{aligned}\dot{\Phi}(q,p) &= p^T \nabla V(q) + p^T \dot{p} \\ &= p^T \nabla V(q) + p^T \left(-\nabla V(q) - \hat{L}(q)p + F^R \right) \\ &= p^T \left(-\hat{L}(q)p + F^R \right) \le 0\end{aligned} \tag{21}$$

Or, if $\left(-\hat{L}(q)p + F^R \right) = -\hat{L}'(q)p$ (22)

then $\hat{L}'(q)$ should still be a positive semi-definite matrix, where $F^R \in R^{Nm}$ is a vector of random component of force for all agents.

ii. At the same time, this random component should be large enough so as to be able to impart enough energy to the agent (belonging to the sub-group which is stuck in local minimum) to enable it to get out of local minimum valley. The magnitude of random component applied on an agent should depend on how many agents are in the subgroup (subgraph) that the agent is a part of. More the number of agents in the subgroup implies that more deep is the valley created by addition of potentials and more energy is required to break free if an agent needs to break free of this potential barrier. In other words:

$$f_i^R \propto \frac{\left|N_i^a\right|}{N} \tag{23}$$

where $\left|N_i^a\right|$ is the cardinality of set N_i^a which is the set of agents belonging to the neighborhood of agent *i*.

iii. If a subgroup has a leader in it, then the agents belonging to this subgroup should experience lesser magnitude of random component. Lesser magnitude of random component will prevent an agent belonging to such subgroup from breaking free. Providing lesser magnitude of random component can be achieved by adequately inversely scaling the random component with respect to number of leaders in the subgroup. In other words:

$$f_i^R \propto \frac{N^l}{\left|N_i^l\right|} \tag{24}$$

where $\left|N_i^l\right|$ is the cardinality of set N_i^l, which is the set of leaders belonging to the neighborhood of agent *i*, and N^l is the total number of leaders in the system.

SIMULATIONS AND DISCUSSIONS OF RESULTS

The effectiveness of the proposed random motion strategy was verified with the help of simulations carried out on a group of twenty agents (*N*=20) and two leaders ($N^l = 2$). The following parameters were assumed for the simulations:

M=1kg, J=1 kgm^2, L=0.1m, d_0=h_0=5m, d_1=h_1=22m, a_i=a_h=5. The values d_1, h_1 represent the range of sensor beyond which sensor cannot measure.

Simulation results are shown in Figures 3 to 6. Figures 3 to 4 represent the results obtained for simulations carried out when the random motion component was not present (Case 1) in the control strategy. And, Figures 5 to 6 represent the results when the random motion component was present (Case 2).

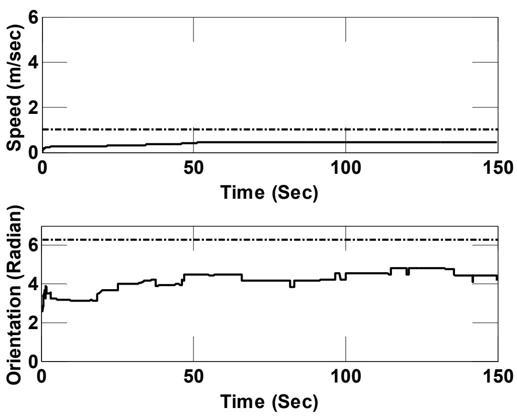

Figure 3: Average Speed (Top) and Average Orientation (Bottom) of Agents (Case 1)

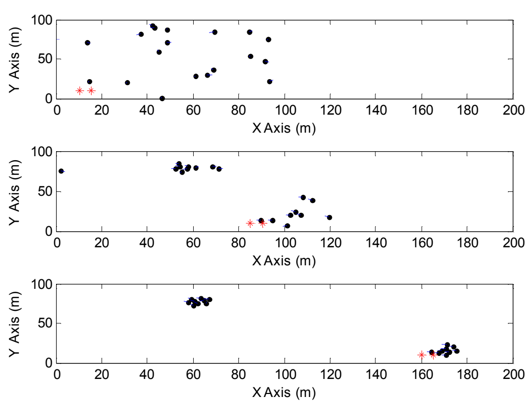

Figure 4: Configuration of Agents and Leaders (Case 1) in X-Y Plane at time T=0 Sec (Top), T=75 Sec (Middle), and T=150 Sec (Bottom)

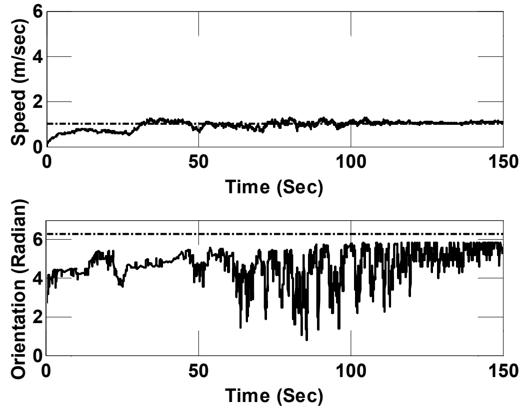

Figure 5: Average Speed (Top) and Average Orientation (Bottom) of Agents (Case 2)

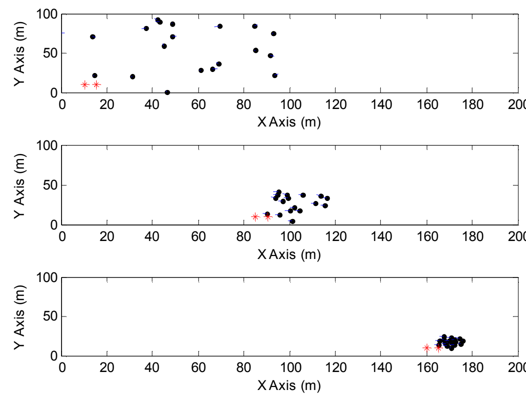

Figure 6: Configuration of Agents and Leaders (Case 2) in X-Y Plane at time T=0 Sec (Top), T=75 Sec (Middle), and T=150 Sec (Bottom)

In Figure 3 and Figure 5, the dashed lines represent the reference trajectory that leaders are following. It can be seen from these figures that, for Case 2, agents on an average align with the reference trajectory better than for Case 1. Similarly, Figures 4 and 6 show the configuration of the mobile agents at times T=0, 75, and 150 seconds. Agents are represented by 'dots' with short tail (showing orientation), and leaders are represented by 'stars'. Initial configuration for both Case 1 and Case 2 are the same. For Case 1, the number of agents with the leaders is 9 (out of total 20). For Case 2, this number is 17 which shows a drastic improvement (which are also evident from Figures 3 and 5.

The above results were based on a single pair of simulations. In order to study the average effect of random motion, fifty (50) pairs of simulations were performed. The number of agents in the group that contained leaders is plotted in Figure 7 for Case 1 and Case 2, for 50 different simulations where each simulation started with a random initial configuration of agents. The average number of agents in the subgroup with leaders for Case 1 is 11.7, and that for Case 2 is 12.98.

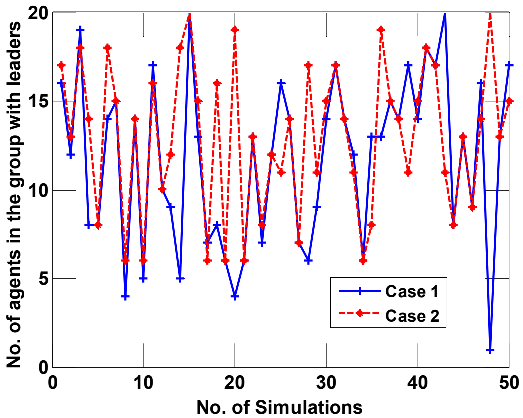

Figure 7: Number of Agents in the Subgroup that Contains Leaders

The component of random motion in the second case leads to better results because random behavior of isolated agent or group of agents makes it more likely that they will find leaders or other agents that are connected to leaders. Although, random behavior does not guarantee better performance in finite time and in every example, a controlled randomization does improve the chances of system providing better performance.

CONCLUSIONS

The paper has presented an innovative mechanism to add designed random behavior to mobile agents which facilitated an effective formation control of multiple mobile agents in presence of sensor range limitations. The range limitation of onboard sensors results in the local information available to mobile agents. Formation of a global and stable cluster based on local information may not be possible due to isolation of agents or group of agents. The proposed method adds a component representing random motion to a method based on artificial potential functions. The random motion is applied to mobile agents by providing random yet designed magnitude of control while taking the stability of the group into consideration. Extensive simulations performed on a group of mobile agents and leaders confirmed that the chances of global formation of cluster following desired reference trajectory with large number of agents are better with the proposed method.

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