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A Flocking Behavior Model with Artificial Potential Fields for the Coordinated Displacement of Robotic Swarms

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Abstract

This paper presents a reactive behavior model for mobile robotic swarms, developed by integrating a biologically inspired method of swarm intelligence known as flocking and an algorithm of artificial potential fields. The resulting reactive behavior model, firstly, prevents collisions between the different agents and constitutes the swarm as a group (flocking model), and secondly, achieves the displacement of the robotic swarm while avoiding the obstacles of the environment (artificial potential fields). This is accomplished without the requirement of a leader or central agent, nor the predefinition of a positioning pattern for the agents. The problem is solved using a simplified swarm behavior model equally programmed in each agent. The proposed model is synthesized such that each agent may calculate its own linear and angular velocities, allowing the implementation of the behavior by introducing those velocities into the kinematic model of each robotic agent.

1. Introduction

The interest in multi-agent systems and the ability to control them is based on their efficiency, cost reduction and robust control [1]. By having partial or global information about their environment, multi-agent systems are able to maintain, reinforce and adapt their position arrangement to carry out their tasks in a successful way. There are tasks for which it is more efficient to have several agents acting simultaneously instead of just one [2]; in addition, the failure of one of the agents does not imply a complete failure of the system, because the rest of them can continue until the task is completed. This multi-agent behavior can be achieved through different types of algorithms such as: behavior-based methods [3], [4], decentralized control methods [5], [6] and local control laws, including control through artificial potential fields [7] and swarm intelligence methods which are adopted by the model developed in this paper.

In this research two different reactive models of behavior are combined, on the one hand, a flocking behavior model is proposed for the agents, allowing them to move simultaneously in the same environment, while maintaining certain integrity as a swarm and avoiding collisions with each other. On the other hand, the concept of artificial potential fields is introduced in order to generate the tendency of the agents to move toward the defined goal by generating an attraction velocity, while, at the same time, avoiding the obstacles located in the environment due to some repulsive effect generated by them.

This paper provides an overview of the model, sections 2 and 3 develop the model that governs the flocking behavior, while section 4 introduces the model implemented for artificial potential fields with the goal and obstacles. Subsequently, section 5 explains how these models are coupled together and section 6 how it may be applied on real robotic swarms. Finally, section 7 highlights the conclusions obtained in this research work, as well as possible future work within this research.

2. Swarm intelligence

Swarm intelligence focuses on the study of the collective behavior of a group of agents that perform tasks or activities together, improving the capabilities that a single agent would have by itself. At first instance, the inspiration for the development of this kind of algorithms comes from the observation of many different types of animals and insects that have a specific organization and behavior that allows them to interact in very large groups and achieve their objectives, such as moving in group from one place to

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another, searching for food or supplies and exploring a specific territory or space [8]-[10].

In [11], D.J.T. Sumpter presents the analysis of different collective biological behavior models like the study of groups of birds, the movement of the ants generating routes to return to the anthill, and even human activities like the applause generated by the crowd after a performance. Each of these behaviors has an operating principle that allows the organization of the group without the need of any particular leader, instead each of the agents finds a way to follow the collective organization from its own individual perception [12], [13]. The movement of groups of birds or fish, for example, can be explained by three basic rules, the repulsion by the nearest neighboring agents, the orientation with the agents that are around them and the attraction from the rest of the group to avoid being isolated from it, this behavior is known as flocking and is developed further in section 3.

According to [14], swarm intelligence should be characterized by the following aspects: a) no general leader that controls the behavior of the swarm from a global knowledge of the system; b) local perception of the environment by each agent, which may lead to a certain level of global knowledge from the shared exchange of information; c) high degree of adaptability to different circumstances which may also change dynamically within time and space.

3. Flocking model

Based on the behavior description proposed by D.J.T. Sumpter [11] this research develops a vectorial model for the application of flocking behavior to mobile robotics operating on a two-dimensional plane and its combination with APF presented in section 4.

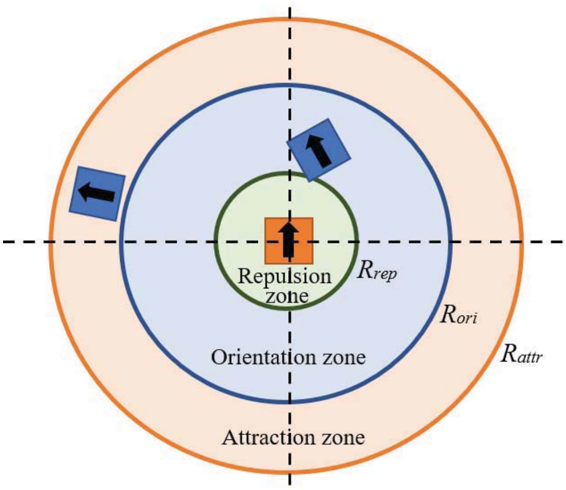

Figure 1. Zones of interaction between agents.

3.1. Zones of interaction between agents

According to [11], flocking is an algorithm that delimits zones of interaction in which the agents involved can distinguish between three different actions: repulsion, attraction, and orientation. The function of this zones is defined as follows:

a) *Repulsion zone:* keeps the integrity of individual agents by avoiding collisions within the swarm.

b) *Attraction zone:* keeps the integrity of the swarm as a whole and prevents the agents from moving away and isolating from each other.

c) *Orientation zone:* adjusts the direction of the agents toward the weighted average of the orientation of the agents in their neighborhood.

3.2. Definition and implementation

In this section the flocking behavior is modeled as a velocity vector field to allow it to be coupled with the APF introduced in section 4 and to be implemented on a kinematic model of robotic agents. This velocity vector field is determined by parts on each of the zones presented in section 3.1 and is normalized and adjusted to avoid abrupt changes at the boundaries of the zones.

Due to the presence of both, linear velocity vector effects (V_F), within repulsion and attraction zones; and angular velocity vector effects (Ω_F), within the orientation zone; the total effect of the flocking model (FM) may be expressed as the addition of both as shown in (1). The linear effect of a particular agent is presented in (2), where V_{F_attr} and V_{F_rep} represent the attractive and repulsive effects of the flocking behavior of agent k.

$$FM = V_F + \Omega_F \tag{1}$$

$$V_{F,k} = V_{F\_attr,k} + V_{F\_rep,k} \tag{2}$$

The V_F may be calculated for each pair of agents located within a specific distance from each other. Thus, it is determined by the addition of the effects that correspond to all the agents located nearby as in (3), where a quantity q of agents is considered located within the interaction zone of one local agent.

$$V_F = \sum_{k=1}^{q} V_{F,k} \tag{3}$$

For the definition of the different zones of interaction between agents, three new variables are introduced that work like boundary radii as shown in

Fig. 1. A first radius called the repulsion radius (R_{rep}), which is the smallest, defines an area identified as repulsion zone; a second radius called orientation radius (R_{ori}), larger than the first one, defines the orientation zone between the repulsion and the orientation radius; and the largest of the three, called the attraction radius (R_{attr}) defines the attraction zone between the orientation and attraction radius. R_{attr} is also the limit range of interaction of the agent with its neighboring agents, so the flocking behavior does not have any effect beyond this attraction radius.

Maximum magnitudes are also defined for the velocity of attraction ($V_{F\_attr\_max}$) and for the velocity of repulsion ($V_{F\_rep\_max}$) in order to avoid any failure with respect to the physical limitations of the agents that make up the swarm.

The distance ($d_{a,k}$), between the local agent k located at (x_k, y_k) and another agent over which the flocking behavior has effect, is calculated as shown in (4).

$$d_{a,k} = \sqrt{(x - x_k)^2 + (y - y_k)^2} \tag{4}$$

3.2.1. Repulsion model. Within the repulsion zone a similar behavior to the one of an obstacle repulsion, presented in section 4.2, is defined around each agent. There, a repulsive velocity vector ($V_{F\_rep,k}$) acts over any other agent located within this zone. It is proposed as to be inversely proportional to the distance between the agents involved, and normalized in such a way that the maximum repulsion velocity is presented when $d_{a,k}$ is zero, and it decreases towards the frontier with the orientation zone, reaching zero when $d_{a,k}$ is equal to R_{rep}. This normalization avoids abrupt changes at the boundary and limits the maximum repulsion velocity. Equations (5) and (6), show how to achieve this for the magnitude and direction, respectively.

$$\left\| V_{F\_rep,k} \right\| = \frac{R_{rep} - d_{a,k}}{R_{rep}} \cdot V_{F\_rep\_\max} \tag{5}$$

$$\angle V_{F\_rep,k} = \arctan\left(\frac{y - y_k}{x - x_k} \right) \tag{6}$$

3.2.2. Orientation model. Within the orientation zone, only an angular velocity is proposed, with a tendency to change the orientation of the local agent in the same direction as the average orientation of the external agents located within this zone. To determine this angular velocity the average of the orientations of the external agents (θ_{prom}) is calculated, if there are no other agents in this zone the angular velocity is zero.

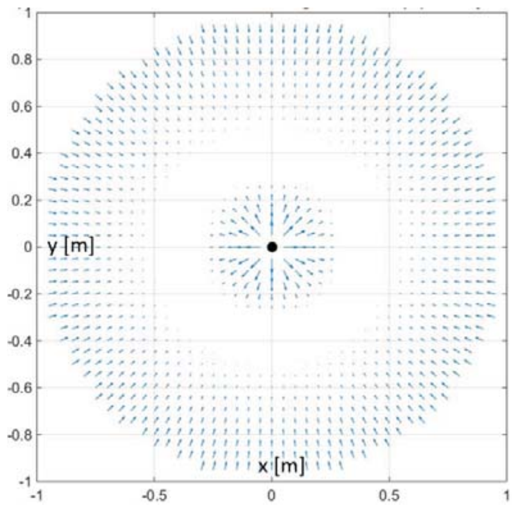

Figure 2. Flocking model linear velocity vector field of repulsion and attraction effects.

In the same way that the distance between the agents is considered and used as reference in the attraction and repulsion models, in this case the difference between the orientation of the agent (θ_a) and the average orientation of the external agents within the orientation zone (θ_{prom}) is used as reference. This difference is denoted by δ_a.

$$\delta_a = \theta_{prom} - \theta_a \tag{7}$$

Thus, the angular velocity vector (Ω_F) is proposed to be proportional to δ_a. Similar to how repulsive and attractive models are adjusted to avoid abrupt behavior changes at the boundaries, here a similar adjustment is made so that the magnitude of the angular velocity generated by the model is zero at both frontiers of the orientation zone. In addition, it reaches its maximum value at the middle between the two boundaries, that is when $d_{a,k}$ is equal to $(R_{rep} + R_{ori})/2$. This is achieved in (8), where a variable γ is included to shift the magnitude of the orientation effect with respect to attraction and repulsion effects.

$$\Omega_F = \frac{\frac{R_{ori} - R_{rep}}{2} - \left| d_{a,k} - \frac{R_{ori} + R_{rep}}{2} \right|}{\frac{R_{ori} - R_{rep}}{2}} \cdot \gamma \cdot \delta_a \tag{8}$$

3.2.3. Attraction model. Within the attraction zone there is a velocity vector due to the flocking model which is also proportional to the distance from the local agent and tends to pull the external agent towards it. This velocity vector is expressed through equations

(9) and (10), where, similar to the previous cases, the magnitude is adjusted to have a value of zero at the boundary with the orientation zone and its maximum value ($V_{F\_attr\_max}$) is produced when $d_{a,k}$ is equal to R_{attr}.

$$\left\| V_{F\_attr,k} \right\| = \frac{d_{a,k} - R_{ori}}{R_{attr} - R_{ori}} \cdot V_{F\_attr\_\max} \quad (9)$$

$$\angle V_{F\_attr,k} = \arctan\left(\frac{y_k - y}{x_k - x} \right) \quad (10)$$

Outside this last repulsion radius no effect is considered among the agents, this taking into account a limit on the range of the agent's sensors and also considering the locality property according to which an agent must be able to make decisions independently, based on what it has detected from the environment and without a global knowledge of the swarm.

4. Artificial Potential Fields

4.1. Overview

Artificial potential fields (APF) were proposed by Khatib in 1985 as a behavioral model for controlling de displacement of an object toward a goal while evading obstacles [15]. This procedure was carried out with a static manipulator, however in recent decades such research has been extended in applications using mobile robots as agents [16].

The APF technique is based on the vector sum of an attraction force toward the goal and the repulsion forces of all the obstacles that may be located within the robot's workspace. The mathematical definition of these forces varies according to the objectives of the research work, but in general the attractive force to the goal is implemented to be proportional to the distance between the agent and the goal, and the repulsive force is implemented to be inversely proportional to the distance between the surface of the obstacle and the agent. Therefore, for each point in space, it is possible to associate a corresponding resulting force which defines the behavior of the agent. In this research those reference distances are adopted, despite of using velocity vectors instead of force vectors to facilitate the application with the kinematic model of the robots.

4.2. Definition and implementation

The velocity vector fields generated by the goal (attraction) and obstacles (repulsion), $V(x,y)_{goal}$ and $V(x,y)_{obs}$ respectively, act simultaneously in the same workspace and, therefore, it is possible to add them to generate a resulting velocity vector field, $V(x,y)_{APF}$, which defines the total APF effect at each specific point within the workspace as shown in (11).

$$V(x,y)_{APF} = V(x,y)_{goal} + V(x,y)_{obs} \quad (11)$$

The definition of the attractive and repulsive velocity vector direction is given according to the following considerations:

a) *Repulsive velocity*: is parallel and with the opposite direction to that of the vector that goes from the point evaluated within the workspace to the center of the obstacle.

b) *Attractive velocity*: is parallel and with the same direction to that of the vector that goes from the point evaluated within the workspace to the goal.

Then, the attractive velocity vector's magnitude toward the goal is defined to be proportional to the distance as in (12).

$$\left\| V(x,y)_{goal} \right\| = \mu \cdot d_{goal} \quad (12)$$

Where μ represents a positive constant of proportionality used to shift the magnitude relation between attractive and repulsive effects, and d_{goal} represents the Euclidean distance to the goal defined as shown in (13).

$$d_{goal} = \sqrt{(x_{goal} - x)^2 + (y_{goal} - y)^2} \quad (13)$$

It is also possible to determine a maximum magnitude for attractive velocity vector (V_{goal_max}), such that, if the magnitude given by (12) is larger, the applied magnitude is truncated to that value.

The repulsive velocity vector, $V(x,y)_{obs}$, caused by obstacles located within the workspace is considered to be inversely proportional to the distance between the evaluated point in space and the edge of the obstacle which is closest to the agent, denoted by $d_{obs,i}$. Due to the consideration of the obstacles as solid circles, the distance between each point in space (x,y) and the obstacle i $(x_{obs,i}, y_{obs,i})$ turns to be the distance to its center minus the radius of the obstacle ($r_{obs,i}$).

$$d_{obs,i} = \sqrt{(x_{obs,i} - x)^2 + (y_{obs,i} - y)^2} - r_{obs,i} \quad (14)$$

This research pretends to create a system in which the agents can behave in a reactive way, namely, they do not need to have an absolute knowledge of the surrounding environment to accomplish their goal, instead, they are able to react to their environment as they go through it. Therefore, each agent should not have the ability to perceive an obstacle at every point in the workspace, but only when it is located closed enough within its sensing range. Hence, for sensor simulation it becomes necessary to define a distance called the obstacle's influence range radius (r_{obs_range}). Such that, if an agent is located within that radius distance from an obstacle, the repulsive velocity vector acts on it, otherwise, the repulsive velocity vector must be zero as if the obstacle was not detected.

A normalization is included so that the repulsion velocity vector's magnitude corresponds to its maximum value (V_{obs_max}) when the distance between the agent and the obstacle is zero, and it decreases to zero while the distance approaches the radius of the obstacle's influence range (r_{obs_range}); as shown in (15).

$$\left\| V(x,y)_{obs,i} \right\| = \frac{r_{obs\_range} - d_{obs,i}}{r_{obs\_range}} \cdot V_{obs\_\max} \quad (15)$$

This is referring to the effect of one single obstacle; to generate a total repulsive velocity vector for the effect of all obstacles, the vectors generated at the same point due to the effects of the rest of the obstacles are added up as shown in (16). Where, j represents the total number of obstacles located in the workspace.

$$V(x,y)_{obs} = \sum_{i=1}^{j} V(x,y)_{obs,i} \quad (16)$$

A graphical representation of an APF is presented as a vector field in Fig. 3. Here a minimum potential is observed at the goal, located at the coordinates (3,0), and the effect of two obstacles is presented. The issue of the existence of local minima due to the combination of attractive and repulsive behaviors, which turns evident at the left side of the centered obstacle in Fig. 3, is not treated in this research but has been analyzed in related works as in [16]. However, coupling the flocking behavior model to the APF may have an effect over this issue, since the rest of the agents that constitute the swarm may pull the jammed agent out of the local minima due to the interaction effects between the agents. This research is proposed as future work derived from the current model.

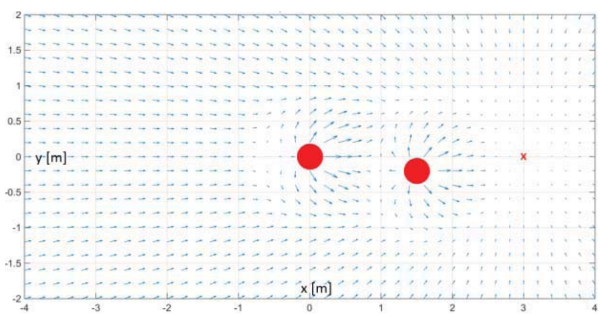

Figure 3. Artificial potential field with a goal located at (3,0) and two obstacles represented as red circles.

Some other limitations to take in mind with this APF model are that the agents are considered as dimensionless points, so the possible extension of the robots is not included in this model; and the obstacles are supposed as to be circular with a specific radius, while in a more general approach they may have different sizes and shapes. Those considerations may be included in future development for improving the model from this research.

5. Flocking model and APF integration

For the integration of both models, APF and flocking behavior, the linear velocity vector resulting from the attraction and repulsion interaction between agents, generated by means of the flocking model, and the velocity vector resulting from the effect of the APF are added as vector sum and are weighted using a constant for each of the models (ρ and σ). This generates a total linear velocity vector for the behavior of the agent as shown in (17). There is also a total angular velocity leading the movement of each agent, given exclusively by the angular component of the flocking model as in (18). So, together, the linear and angular velocities govern the behavior of the agents.

$$V_{Total} = \rho \cdot V_F + \sigma \cdot V_{APF} \quad (17)$$

$$\Omega_{Total} = \Omega_F \quad (18)$$

6. Implementation in mobile robotics

This model was implemented on a real robotic swarm by considering the kinematic model of the robots. Particularly, the robot kinematic model was developed in such a way that it depends directly on the linear and angular velocities and the reactive behavior model was programmed independently on each agent of the swarm. Also, it was tested in both computer simulations and with real differential mobile robots like those shown in Fig. 4. These were tested within an environment instrumented with cameras for fiducial marker recognition. In Fig. 5 the result of a test is presented, in which 3 robotic agents reach a goal while evading an obstacle and keeping a flocking behavior using this model.

7. Conclusions

The reactive model proposed in this paper provides of a mathematical model of the flocking natural behavior presented in [11], which coupled together with the artificial potential fields model allows the displacement of robotic swarms. Experimental results were carried out with 3 differential mobile robots by reaching a goal, meanwhile presenting a flocking behavior when avoiding an obstacle and without colliding between them.

This model was adjusted considering some physical limitations of real robotic agents, such as a limited range of perception, maximum values of linear and angular velocities, and a smooth behavior transition at the boundaries of the flocking model zones. Besides, given that the linear and angular velocities have been computed by the model, this approach can be implemented on different types of robotic agents.

As future work, the detailed analysis and comparison of the implementation of the model in both simulation and real robotic swarms will be reported.

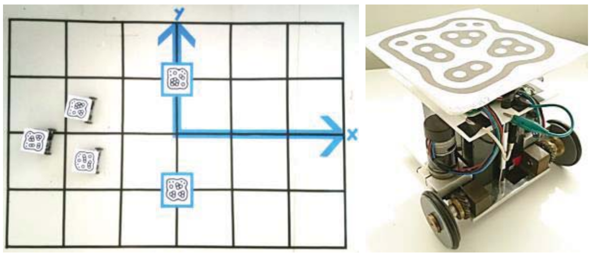

Figure 4. Mobile robots (3) within an environment instrumented with fiducial markers for artificial vision pose recognition (left). Differential mobile robot used fc testing the model (right).

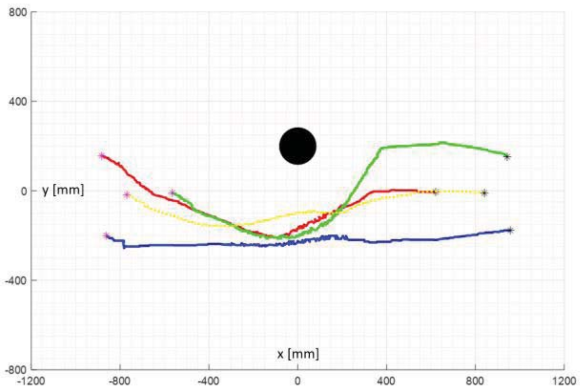

Figure 5. Robotic swarm displacement test with 3 real differential mobile robotic agents and one obstacle, the yellow dotted line represents the centroid of the swarm.

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