Flocking Model for Self-Organized Swarms

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***Abstract*— The algorithms of self-organized swarm control refer first to two basic behaviors, these are aggregation and flocking. The present work focuses its research on coordinated movement behavior that is defined as the ability of a group of individuals (usually composed of hundreds or thousands) to move and maneuver in a coordinated manner as if they were a single structure. Such behavior refers us to studies carried out in the field of trajectory control and aggregation behavior, both being keys for the development of a coordinated movement control algorithm. Therefore, control of the system starts from the combination of these studies. The control is a leading robot model which can be designated for any unit according to the assigned task. On the other hand, all robots except the leader keep the group attached and keeping a safe distance. The simulations of the system were developed for three units and later for twelve, observing the cohesion and uniformity of the swarm in movement.**

Keywords— Mobile Robot, Non Linear Control, Coordinated Movement, Robotic Swarm, Aggregation, Multiple Control, Trajectory Control.

I. INTRODUCTION

The collective behaviors of a group of individuals which share similar characteristics have become a field of study that has exceeded the limits of biology and natural sciences. Lately they have joined scientific fields in technological research.

These behaviors, naturally present in insects, birds, fish and even mammals, represent a natural phenomenon that provides a new focus in engineering research areas. Thus, the collective approach, governed by a level of coordination and appropriate organization, has shown great efficiency in the execution of tasks with a high degree of complexity.

Robotics is not an exception for this new engineering focus. Swarm robotics is characterized by emphasizing aspects of natural swarms in order to promote a global behavior that allows the execution of a complex task [17].

This study field uses several simple units instead of a single highly complex robot. The cooperation is the fundamental tool for the accomplishment of tasks collectively. This also implies that the capabilities of robots are limited. The complexity of the swarm lies in their collective behavior and not in the complexity of the individual units.

Nowadays, robotic swarms have meant a research field that has become important. However, the main problem remains to translate the swarm natural phenomenon into a quantifiable logic that allows robots to imitate such behavior. Therefore, swarm robotics does not only pose the minimum characteristics required for individual robots (such as sensors, actuators or processing capability), but also control models which emphasize natural swarm behaviors.

For this work, we are going to focus on one specific behavior.

Flocking is predominant behavior in several types of natural swarms. This is a characteristic present in groups of animals whose global movement is born as a result of interactions of individuals with each other [17].

II. MATH MODEL OF A DIFFERENTIAL TYPE ROBOT

Based on the Aranda's research [1], we can describe the mathematical model for a differential robot in the following way:

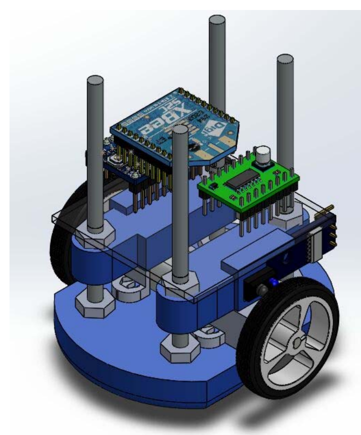

Fig. 1. Differential type robot.

This unit is a vehicle that has two identical rear wheels, left and right, non-deformable and joined by an axis. In addition, it uses an omnidirectional front wheel that ensures that the robot platform is on a plane.

Assuming a movement only in XY plane and slideless wheels roll, robot model can then be defined as:

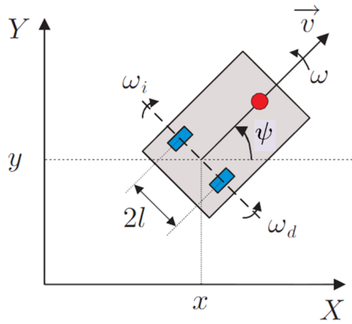

Fig. 2. Mobile robot diagram [16]

Where equations can be defined as:

$$\dot{x} = v\,cos(\psi)$$
$$\dot{y} = v\,sin(\psi)$$
$$\dot{\psi} = w \tag{1}$$

Where (*x, y*) represent the position located on the middle of the wheels. This point also represents the position of the robot with respect to the fixed reference axes (*X, Y*). The orientation angle of the robot in the plane with respect to the *X* axis is defined as ψ. The linear velocity of the robot oriented towards an angle ψ is defined as *v*, while angular velocity is defined as *w*.

As diagram of Figure 2, the equations of motion can be redefined as:

$$\dot{x} = \frac{r}{2}\,(w_d + w_i)\cos(\psi)$$
$$\dot{y} = \frac{r}{2}\,(w_d + w_i)\sin(\psi)$$
$$\dot{\psi} = \frac{r}{2l}\,(w_d - w_i) \tag{2}$$

Where *r* is defined as the wheel radius and *l* as the length between a wheel into the axis center. Likewise, w_d and w_i are defined as right and left angular velocities respectively.

Thus, expressing the system in term of v and w, we define a matrix that relates (*v, w*) with (w_d, w_i) as:

$$\begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \begin{bmatrix} v \\ w \end{bmatrix} = T\begin{bmatrix} w_d \\ w_i \end{bmatrix};\quad T = \begin{bmatrix} \frac{r}{2} & \frac{r}{2} \\ \frac{r}{2l} & -\frac{r}{2l} \end{bmatrix} \tag{3}$$

Where (u_1, u_2) may be consider as system control variables.

III. Aggregation Control Model

A. Attraction Force

The case of the spring [11] refers to use a visco-elastic force control model that involves position and linear velocity. Then, we can consider the resulting force model as a spring/damper system that depends on distance of robots from influence field.

Thus, visco-elastic vector control force (VVCF) may be defined as:

$$F_{att} = K^s(d_i - d_0) + K^d v_i \tag{4}$$

Where d_i is defined as the current robot position and d_0 as the influence distance under which potential field affect all robots. Likewise K^s is defined as an adjustable elastic constant which controls required force towards an influence field. K^d is defined as an adjustable viscose constant which dissipates energy with respect to robot velocity. Finally, v_i is defined as robot velocity towards influence field.

Thus, in order to guarantee the system stability, we define constants K^s and K^d as:

$$K^s = \frac{k_s}{\sqrt{\|\vec{q}\|}}$$

$$K^d = k_d\sqrt{K^s} \tag{5}$$

B. Repulsion Force

As Khatib [12], we define a force inducing an artificial repulsion from the surface (FIRAS). Repulsion artificial potential field is defined as:

$$U_{rep} = \begin{cases} \frac{1}{2}n\left(\frac{1}{d} - \frac{1}{d_0}\right)^2, & d \le d_0 \\ 0 \quad , & d > d_0 \end{cases} \tag{6}$$

Where d is the distance between robot and the obstacle, d_0 is the influence limit distance where potential field acts, and n is the constant gain in the function.

Then, we define the repulsion force vector as the potential field gradient at a specific point in the plane as:

$$\nabla U_{rep} = \begin{cases} n\left(\frac{1}{d} - \frac{1}{d_0}\right)\frac{1}{d^2}\frac{\partial d}{\partial x}, & d \le d_0 \\ 0 \quad , & d > d_0 \end{cases} \tag{7}$$

Where $\frac{\partial d}{\partial x}$ is defined as partial derivative vector of the distance between the robot and the obstacle.

Then, we define the system by a generic form. If we include a unitary vector in the force function, we have:

$$F_{rep} = \begin{cases} n\left(\frac{1}{d} - \frac{1}{d_0}\right)\frac{(\vec{q}_O - \vec{q})}{d^3}, & d \le d_0 \\ 0 \quad , & d > d_0 \end{cases}$$
(8)

Where $\vec{q}_O$ represents obstacle position vector, and $\vec{q}$ robot position vector. Thus, repulsion force function can be interpreted as a system that interacts in the XY plane.

C. TRANSFORMATION AND CONTROL OF MOVEMENT FUNCTION

This system [5] [19] can be expressed as:

$$u = \begin{cases} \left(o \cdot \frac{f}{\|f\|}\right)U, & o \cdot \frac{f}{\|f\|} \ge 0 \\ 0, & otherwise \end{cases}$$

$$w = K_w(\angle o - \angle f)$$
(9)

Where u and w are defined as linear velocity and angular velocity respectively.

Vector o is the robot current orientation unitary value, while $\frac{f}{\|f\|}$ is the orientation unitary value of the calculated force vector. Additionally, U is the maximum available velocity of the robot.

Likewise, $\angle o$ and $\angle f$ are the current angles of the robot and the calculated force vector respectively. Finally, K_w is adjustable constant gain.

Then, linear velocity and angular velocity must be translated into differential type robot dynamics:

$$N_d = \left(u - \frac{w}{2}l\right)\frac{1}{2\pi r}$$

$$N_i = \left(u + \frac{w}{2}l\right)\frac{1}{2\pi r}$$
(10)

Where N_d and N_i are defined as right and left angular velocities respectively. Likewise, l is defined as the distance between the wheels and r is the radius.

IV. TRAJECTORY CONTROL MODEL

A. CONTROL BY STATIC FEEDBACK LINEARIZATION

If (u_1, u_2) are input variables of the robot cinematic model, this can be expressed as:

$$\dot{x} = u_1 \, cos(\psi)$$
$$\dot{y} = u_1 \, sin(\psi)$$
$$\dot{\psi} = u_2$$
(11)

So, we make structure transformations in the model to define new system outputs.

In this case, we pick x and ψ as output variables by the following way:

$$\begin{bmatrix}\dot{x}\\ \dot{\psi}\end{bmatrix} = \check{A}(\psi)\begin{bmatrix}u_1\\ u_2\end{bmatrix} = \begin{bmatrix}\cos(\psi) & 0\\ 0 & 1\end{bmatrix}\begin{bmatrix}u_1\\ u_2\end{bmatrix}$$
(12)

Such that system control variables are defined as:

$$\begin{bmatrix}u_1\\ u_2\end{bmatrix} = \check{A}^{-1}(\psi)\begin{bmatrix}v_1\\ v_2\end{bmatrix}; \qquad \begin{bmatrix}\dot{x}\\ \dot{\psi}\end{bmatrix} = \begin{bmatrix}v_1\\ v_2\end{bmatrix}$$
(13)

Where (v_1, v_2) are the new system feedback control variables as:

$$\begin{bmatrix}v_1\\ v_2\end{bmatrix} = \begin{bmatrix}\dot{x}_{des} - \alpha\, e_x\\ \dot{\psi}_{des} - \beta\, e_\psi\end{bmatrix}$$
(14)

Such that $e_x(t) = x(t) - x_{des}(t)$ and $e_\psi(t) = \psi(t) - \psi_{des}(t)$, so that $e_x(t), e_\psi(t) \to 0$ when $t \to \infty$, as long as $\alpha, \beta > 0$.

From (13) and (14) we have:

$$\begin{bmatrix}u_1\\ u_2\end{bmatrix} = \check{A}^{-1}(\psi)\begin{bmatrix}\dot{x}_{des} - \alpha\,(x - x_{des})\\ \dot{\psi}_{des} - \beta\,(\psi - \psi_{des})\end{bmatrix}$$
(15)

Such that (u_1, u_2) are expressed as the inputs of the feedback system control where $x \to x_{des}$ and $\psi \to \psi_{des}$.

However, the control model (15) present visible singularity in $\psi = k\pi/2$, $k = \pm 1, \pm 2 \ldots$, where it is evident that u_1 grow without limits in the control system.

Otherwise, the static feedback control model guarantees trajectory tracking x_{des} and ψ_{des}. However, this is a two variable control model where y is not inside. Some authors like Silva [9] have resolved this problem by adapting reference y_{des} in function of x_{des} so that we could predict closely the behavior of y. However, its clear that y cannot be controlled directly.

B. CONTROL BY DYNAMIC FEEDBACK LINEARIZATION

By similar way as the static feedback linearization, it is possible to make a system transformation to obtain a two input and two output system. However, this time by taking x

and y as the new output variables by the following way:

$$\begin{bmatrix}\dot{x}\\ \dot{y}\end{bmatrix} = A(\psi)\begin{bmatrix}u_1\\ u_2\end{bmatrix} = \begin{bmatrix}\cos(\psi) & 0\\ \sin(\psi) & 0\end{bmatrix}\begin{bmatrix}u_1\\ u_2\end{bmatrix} \tag{16}$$

Where initially, it was not possible to linearize the system since this presents matrix singularities in $A(\psi)$ for all values of (x, y, ψ) on the system outputs [7][9].

However, in this case we develop a control technique that allow us to add a new state inside the control model [13].

For this, we can define a new state variable as $\dot{\zeta} = \breve{u}_1$ and $\zeta = u_1$, since only u_1 affects the model. Thus, by adding an integrator in the system dynamics mentioned above, we could calculate u_1. Then, as Oriolo's research [13], we can say:

$$\begin{bmatrix}\ddot{x}\\ \ddot{y}\end{bmatrix} = A_e(\psi,\zeta)\begin{bmatrix}\breve{u}_1\\ u_2\end{bmatrix} = \begin{bmatrix}\cos(\psi) & -\zeta\sin(\psi)\\ \sin(\psi) & \zeta\cos(\psi)\end{bmatrix}\begin{bmatrix}\breve{u}_1\\ u_2\end{bmatrix} \tag{17}$$

In this case, the new decoupling matrix $A_e(\psi,\zeta)$ is not singular as long as $\zeta \neq 0$. Then, we can define the dynamic feedback control system with the new variables as:

$$\begin{bmatrix}\breve{u}_1\\ u_2\end{bmatrix} = A^{-1}(\psi,\zeta)\begin{bmatrix}v_1\\ v_2\end{bmatrix} \tag{18}$$

Where (v_1, v_2) have defined as:

$$\begin{bmatrix}v_1\\ v_2\end{bmatrix} = \begin{bmatrix}\dot{x}_{des} - \alpha_1\,\dot{e}_x - \alpha_0\,e_x\\ \dot{y}_{des} - \beta_1\,\dot{e}_y - \beta_0\,e_y\end{bmatrix} \tag{19}$$

Such that, $e_x(t) = x(t) - x_{des}(t)$, $e_y(t) = y(t) - y_{des}(t)$ equally, $\dot{e}_x(t) = \dot{x}(t) - \dot{x}_{des}(t)$, $\dot{e}_y(t) = \dot{y}(t) - \dot{y}_{des}(t)$. Likewise, $e_x(t)$, $e_y(t) \rightarrow 0$ when $t \rightarrow \infty$, as long as $\alpha_0, \beta_0, \alpha_1, \beta_1 > 0$.

Thus, the controller final output is now:

$$\begin{bmatrix}\breve{u}_1\\ u_2\end{bmatrix} = A^{-1}(\psi,\zeta)\begin{bmatrix}\ddot{x}_{des} - \alpha_1\,(\dot{x} - \dot{x}_{des}) - \alpha_0\,(x - x_{des})\\ \ddot{y}_{des} - \beta_1\,(\dot{y} - \dot{y}_{des}) - \beta_0\,(y - y_{des})\end{bmatrix} \tag{20}$$

This model adjusts the system output so that $x \rightarrow x_{des}$ and $y \rightarrow y_{des}$. Unlike static model, the dynamic model prioritize outputs x and y such that ψ is automatically adjusted by the controller.

We need to say that the system is not singular, thus, it is controllable. However, this cannot function when robot is stopped.

V. Dynamics Control System of Actuators

For the DC motor dynamic model, with a negligible armor inductance, we can define a differential equation as:

$$\frac{dw}{dt} = -C_1 w + C_2 V \tag{21}$$

Where w is motor angular velocity, the source voltage is defined as V. Likewise, C_1 and C_2 are defined as motor internal constants.

Thus, for the motor transfer function, we can define the system as:

$$\frac{w(s)}{V(s)} = \frac{k}{\tau s + 1} \tag{22}$$

Where the parameters k y τ can be found by a motor experimental excitation.

Once found the motor transfer functions, we can design a PID controller for inputs w_{Ddes} and w_{Ides}. In consequence, tracking error can be expressed as:

$$e_D = w_D - w_{Ddes}$$
$$e_I = w_I - w_{Ides} \tag{23}$$

Thus, the PID control model for both motors is defined as:

$$V_D(t) = K_{Dp}e_D(t) + K_{Di}\int_0^t e_D(t)\,dt + K_{Dd}\frac{de_D(t)}{dt}$$
$$V_I(t) = K_{Ip}e_I(t) + K_{Ii}\int_0^t e_I(t)\,dt + K_{Id}\frac{de_I(t)}{dt} \tag{24}$$

Where gains (K_{Dp}, K_{Ip}, K_{Di}, K_{Ii}, K_{Dd}, K_{Id}) can be chosen by Ziegler-Nichols rules.

VI. Control Model Links

The studied control model allows us to develop a flocking behavior by the combination of two systems.

Likewise, every robot should be programmed with the two control system. First, an aggregation control system that allows a unit to keep at a closely and secure distance. Second, a trajectory control system that allows a unit go towards a specific point in the plane.

About the aggregation control system, this is essential as long as it allow swarm to be uniformly united. Attraction and repulsion functions calculate the robot desire behavior while the movement control function traduce this in real dynamics.

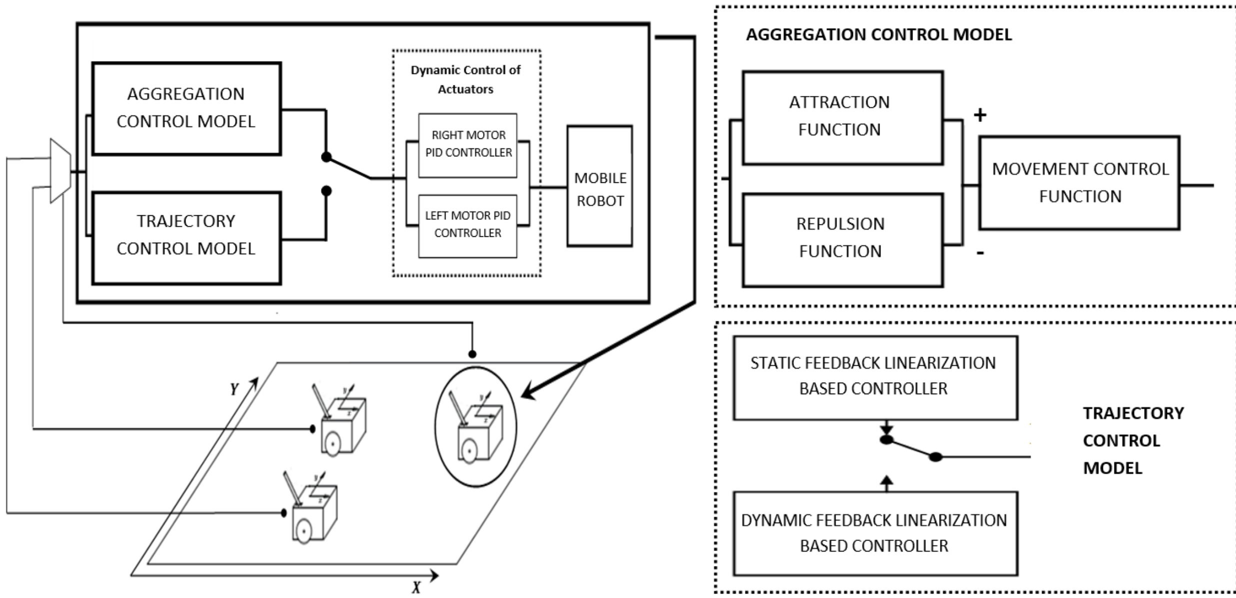

Fig. 3. Control model links of the swarm.

However, aggregation control system only generates movement when robots are closer or farther than potential field distances between each other. It means there is no movement once all robots are aggregated. At the same time, there is no a desire meeting point in the plane. Robots calculate a trajectory by themselves as it shows in Figure 4.

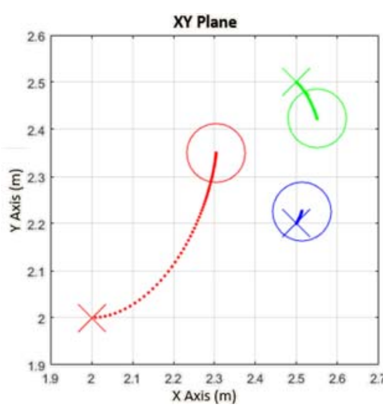

Fig. 4. Aggregation behavior with three robotic units.

Moreover, the trajectory control system generate movement until a specific point in the plane is reached. The robot generates a trajectory by itself while we define a desire position, but this system cannot link robots by each other.

An example of the trajectory control system shows in Figure 5.

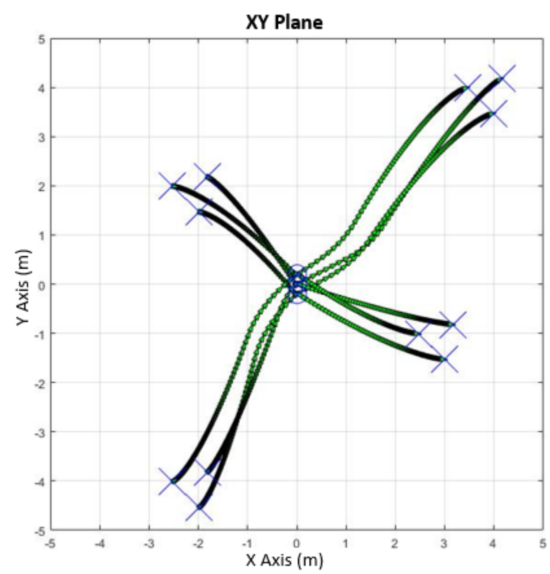

Fig. 5. Trajectory control system with three robotic units

However, for a flocking control model design, it is not necessary to activate both control systems at the same time. As Figure 3 shows, we can switch between both systems in order to generate a specific behavior.

Likewise, if one robot seeks to reach a specific point in the plane by the trajectory control system, the others will follow him as long as they have the aggregation control system activated.

By this way, flocking control model is developed as leader lead system. It is to say, the swarm always is joined, but it does not generate group movement until one unit begins to do it.

Then, all robots are able to be designed as leader. Thus, leader designation may be subject to several considerations (minimal distance with respect a point, center position point of swarm, etc.).

Otherwise, if all robots activate the trajectory control system at the same time, the control model changes, and swarm becomes a multi-robot trajectory system (as Figure 5 showed). This allows robots to generate complex trajectory patterns.

In consequence, these systems combinations can significantly increase the complexity of swarms tasks.

VII. Testing and Simulation of the System

Two simulations were performing in order to observe the linked control model.

First, a test simulation with three robotics units where a leader was appointed. We observe the reaching towards desire point and the following by the other robots.

The Figure 6 shows the behavior graphic results.

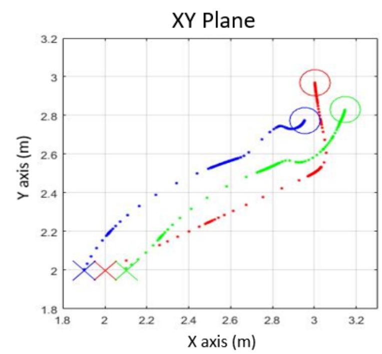

Fig. 6. Flocking system simulation with three robotic units.

Second, a simulation to evaluate the algorithm of twelve linked robotic units. These are joined by groups of three individuals.

As Figure 7 shows, we can observe the aggregation control influence while leader robot reaches a desire point in the plane (red unit in the Figure 5). The linked robots with aggregation control model activated keep closely each other without risk of collision. Likewise, leader robot moves towards desire point temporarily unlinked from other ones.

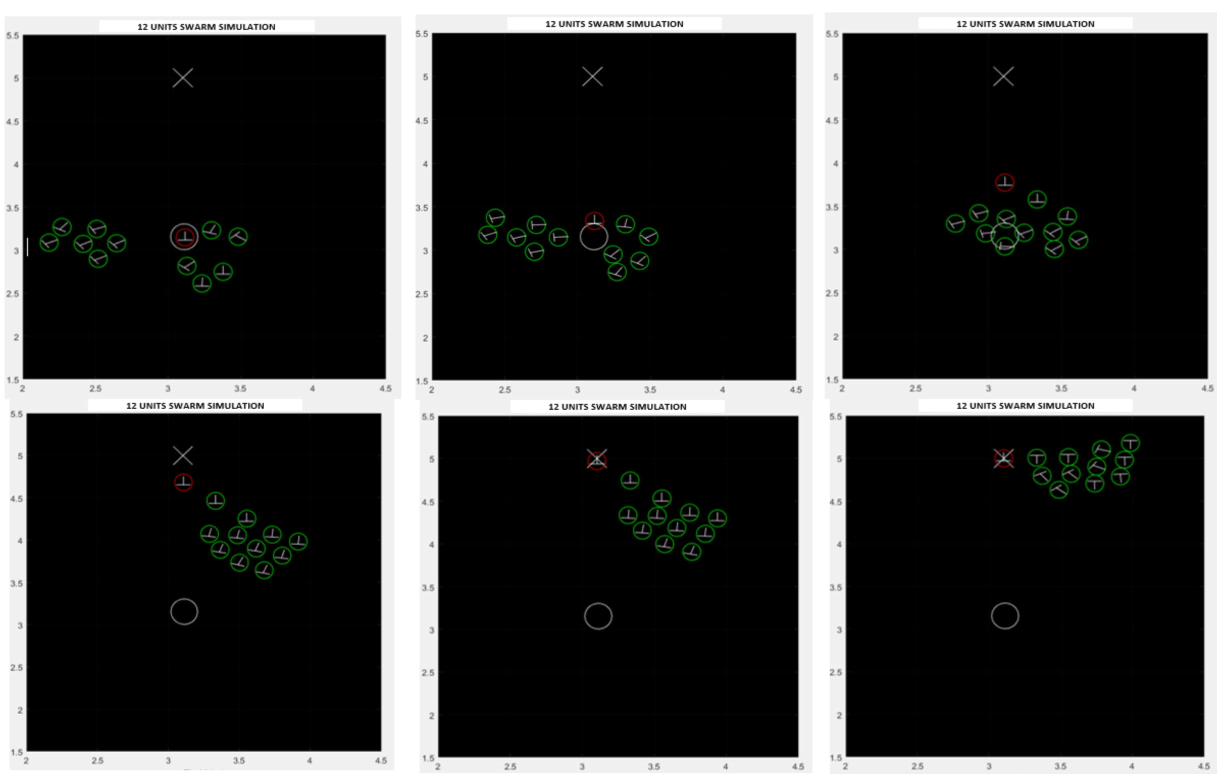

Fig. 7. Flocking behavior simulation for twelve robotic units.

By this way, swarm keeps together while it moves from one point to another.

Otherwise, even leader robot losses the group link, remaining units keep the aggregation behavior. Then, they guarantee uniformity and security of the group.

The simulation parameters were:

PARAMETERS	DESCRIPTION	VALUE
K^s	Elastic constant	1.9 u. force
K^d	Viscous constant	1 u. force
l	Distance between wheels	10 cm
r	Wheels radius	3 cm
n	Repulsion constant	1.75 u. force
L_0	Attraction field limit	20 cm
d_0	Repulsion field limit	20 cm
U	Maximum robot velocity	15 cm/s
K_w	Angular velocity constant	1 s^{-1}
k	Right and left motor gain	0.44
τ	Transfer function motor variable	0.28
α	Static feedback constant on x	0.5
β	Static feedback constant on ψ	0.5
α_0	Dynamic proportional feedback constant on x	0.3
α_1	Dynamic derivative feedback constant on x	4
β_0	Dynamic proportional feedback constant on y	0.4
β_1	Dynamic derivative feedback constant on y	4
K_p	Proportional constant	100
K_I	Integral constant	20
K_D	Derivative constant	0.5

Table 1. Relative parameters of simulations.

VIII. Conclusions

Based on the research on aggregation control models and trajectory control models, it has been possible to design a flocking control system capable for managing the movement of a group of differential type mobile robots.

The aggregation control system has shown effectiveness to keep the swarm joined without risk of collision. At the same time trajectory control system has achieved to reach a desire point in the plane.

The system simulations have shown satisfactory results with respect to the flocking control model. Both, grouping and collision avoidance were achieved.

The development of swarm pattern behaviors that has led to the research and development of control models, reflected in the prior works, have allowed us to study theoretical interpretations of animal swarms in nature. It is foreseed implementation of the control models on groups of real robots, in order to evaluate their respective responses. However, the research presented here tries to become a basic study for the development of more complex swarm behaviors.

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