Coordinated Navigation Using Dynamically Varying Velocity Fields

P. Estévez, J. Cappelletto, R. Acuña, F. Alvarez, and G. Fernandez-López

University Simón Bolívar, Mechatronics Group, LabC-302
1080-A Sartenejas, Miranda. Venezuela
pablo.estevez@usb.ve

Abstract. This paper describes a framework for dynamically generated and temporary evolving fields for coordinated robot navigation. The approach based on static fields usually faces the problem of saddle points and local minima preventing the achievement of the goals. This approach overcomes the aforementioned drawbacks by dynamically changing the field definitions through an *insistence schema* where unfulfilled goals increase their effect on robots movements. These algorithm and schema are described and tested to evaluate and compare this idea against classical field approaches. The results show an improvement on the capabilities of the system to deal with the proposed tasks, thus validating this approach.

1 Introduction

The research of potential fields for the resolution of navigation problems with obstacle avoidance began with Khatib, by introducing FIARS (Force Inducing an Artificial Repulsion from the surface). It was originally developed as an on-line collision avoidance approach on unknown environments, focusing on real time-efficiency, rather than on guaranteeing the achievement of the goal [Kha80,Kha86]. During following years different approximations and applications of this concept appeared, like hormone inspired work of Shen [She02] and the Passive Velocity Field Control (PVFC) developed mainly by Li and Horowitz in Berkley [PLi95]. Most recent works try to deal with dynamic environments, like those describe by W. Medina in [Med07], where fields are dynamically generated based on the measurements of changing environments. Also, the field modification has been studied as in [Joh02] where the Electric Field Approach (EFA) is introduced as a generalization of the potential fields, allowing to use of them as an heuristic for the selection of actions and the robot ability to modify the fields through its actions. L. Parker in [Par00] uses concepts of potential fields with a weighted local force vector approach in order to dynamically control the attractive and repulsive forces, depending on environment configuration. It's widely accepted that the main drawback with static fields approach is the appearance of local minimum and saddle points.

In this work dynamic concepts are introduced into the fields definitions to deal with the previously listed undesired effects, by an *insistence* scheme where unfulfilled goals increase their relative weight in the fields generation. Three testbeds are used to test the static fields approach to coordinated navigation and to compare it with the proposed dynamic definition. The first two are related to formation keeping while navigating with obstacle avoidance. The third test consists of checkpoints that must be periodically visited by a robot. All test configurations are simulated under Matlab®, and in a more realistic environment by using the Webots® application for the first task.

The problem description and basic fields definitions are given in sections 2 and 3. The description of tests performed with static fields is provided in section 4. In sections 5 and 6 are shown details about the solution here proposed using the dynamic approach, and those experiments performed to test it. Specific test with more complete and complex models under Webots™ are described in section 7. Finally, main results and further analysis are shown in section 8, as conclusions based on tests results. The recommendations are given in section 9

2 Problems definition

Even if the proposed approach is meant to solve general coordinated navigation problems, the tests where performed for the 3 following cases. The first task is achieving and keeping a relative arrangement by the robots. A formation is designed offline an expressed as a set of positions relative to a reference point, and the robots are expected to arrange into that formation, and keep it while performing their remaining tasks (navigation, obstacle avoidance, etc). The first problem allows any robot to occupy any position in the formation. The second one includes a leader whose position in the formation is previously fixed, while remaining platforms' positions remain free, yielding to the so known Paparazzi or Bodyguard problem [Jen00]. The third problem is an exploration task, where a certain set of positions in the environment (checkpoints) need to be visited for at least one robot with certain periodicity. Typically, the number of robots is smaller than the number of checkpoints, but enough to keep all of them supervised given their space span and the robots velocity.

The test ran in a Matlab® simulation with hollonomic platforms. For the differential wheels robots test, an environment was set up in Webots™ and a TCP-IP communication channel was developed in order to transfer control signals and measurements between the Webots™ robots controller and the Matlab® algorithm. The Webots™ robots controller use a proportional control loop to keep on the desired velocity both in modulus and angle, but the modulus is scaled by the cosine of the angle error prior to use it as a reference. This is made in order to avoid movements in trajectories perpendicular to the desired one, and to benefit from the backwards movement.

3 Basic Fields Definition

For each goal, a vector is calculated from the environment conditions and parameters. Those vectors are combined to determine the final direction of movement.

Every goal is represented by a vectorial field or a potential surface whose negative gradient in each point indicates the direction in which the platform should move to accomplish it. In this case, several field definitions are employed in different ways and combined for each goal required to solve any proposed test.

3.1 Gaussian Wells and Hills

The Gaussian wells provide an option for pulling and trapping a platform into a position; it has a limited range of action, a continuous gradient and a zero-gradient in the center. Also, by using a positive weight the Gaussian hills provide a solution for inter-robot repulsion, specially if they have to compete for a Gaussian well. The potential surface and its vectorial field equivalent are defined by Equations [1][2], and can be observed in Figure 1.

$$z(x,y) = w \cdot e^{-\left(\left(\frac{x-x_c}{\sigma_x}\right)^2+\left(\frac{y-y_c}{\sigma_y}\right)^2\right)}; \tag{1}$$

$$\bar{v} = -\nabla z = \begin{cases} v_x = -2 \cdot z(x,y) \cdot \frac{x-x_c}{\sigma_x^2} \\ v_y = -2 \cdot z(x,y) \cdot \frac{y-y_c}{\sigma_y^2} \end{cases} \tag{2}$$

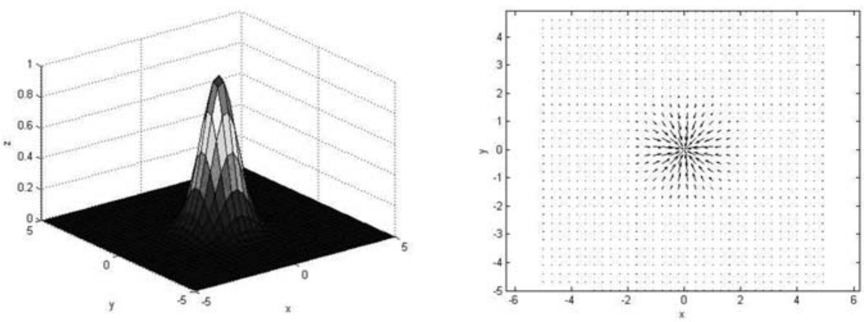


Fig. 1. Gaussian field, $\sigma = 0$, $x_c = y_c = 0$, $w = 1$

3.2 Conical attractors

Conical fields generate a constant radial movement tendency, thus exerting a significant but bounded action even at great distance. Specifically, it can bring distant platforms into a region where more complex field interactions will solve the fine coordination problem. The conical attractors are described by the equation (Eq. 3), and are shown in Figure 2.

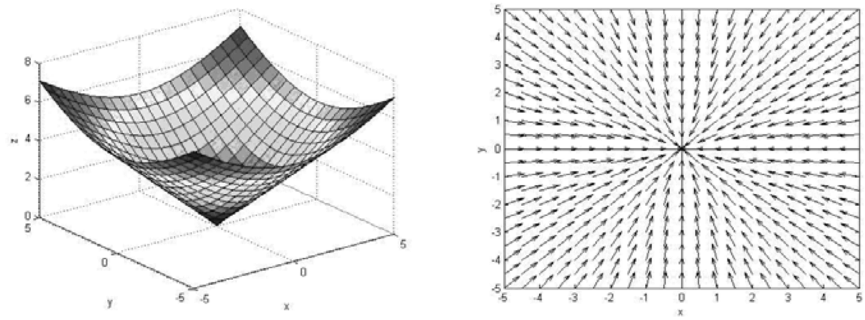


Fig. 2. Conical field, $x_c = y_c = 0$, $w = 0$

$$z(x,y) = w \cdot \sqrt{(x-x_c)^2 + (y-y_c)^2}; \bar{v} = -\nabla z = \begin{cases} v_x = -2 \cdot z(x,y) \cdot \frac{x-x_c}{z(x,y)} \\ v_y = -2 \cdot z(x,y) \cdot \frac{y-y_c}{z(x,y)} \end{cases} \quad (3)$$

3.3 Hyperbolic repulsive field

In obstacle avoidance, it is desired a field with limited range of action for not affecting farthest platforms, increasing values in the mid proximity to deflect potentially unwanted trajectories, and unbounded growing values in the vicinity to avoid imminent collisions. Hyperbolic growing fields with a field intensity inversely proportional to the distance to the robot are used. This field can be modified according the type of obstacles and the sensors involved, but for circular obstacles the shortest distance to the obstacle is used, yielding to the following definition for the potential surface:

$$z(x,y) = \frac{w}{\sqrt{(x-x_c)^2 + (y-y_c)^2} - r} \quad (4)$$

The gradient utilized to describe the associated vector field is defined by Eq. 5, and both definitions are shown in Fig. 3

$$\bar{v} = -\nabla z = -\frac{w}{(\sqrt{(x-x_c)^2 + (y-y_c)^2} - r)^2} \cdot \overrightarrow{((x-x_c),(y-y_c))} \quad (5)$$

3.4 Ramps, punctual attractors, trajectory following fields

Different fields definitions have been proposed to achieve a desired movement pattern or trajectories during navigation. Punctual attractors similar to the conical presented above, with some distance based amplitude modification can be

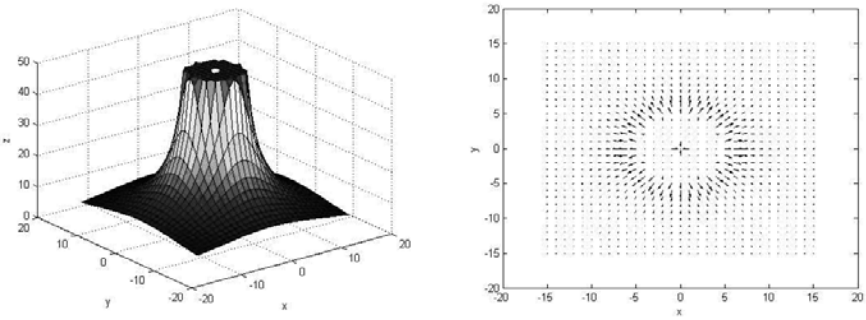


Fig. 3. Hyperbolic repulsive field, $x_c = y_c = 0$, $w = 1$

used to achieve a radial approximation to a goal. Flat pattern tendencies, where the platforms are expected to move into a certain direction are generated by using a tilted plane as potential surface. More complex trajectories can be generated by methods as those proposed in [Med07].

4 Static Fields tests

First, the basic behaviors involved in the navigation problem are presented like fields and tested independently for tuning. The basic navigation path field may be generated by a combination of ramps, attractive/repulsive points and trajectories. In the absence of obstacles or other goals it is no problem to generate different movement patterns over a free space. Since the test only use circular obstacles, obstacle avoidance is attained with repulsive hyperbolic fields. This obstacle avoidance behavior is reinforced for the platforms interaction with a spacing behavior generated by a positive weighted Gaussian hill. The conjunction of both behaviors for a group of 10 robots can be seen in Fig. 4. There, it can be noticed how the platforms are able to follow a pattern created by the addition of a flat tendency and a punctual attractor while avoiding obstacles in their way. Saddle points may exist in some points of the space, but are evaded thanks to the noise in the robots movement and the changes in the field introduced by the inter-robots interaction.

Trapping behavior to keep a robot in a certain absolute or relative position is obtained through a sum of a soft conical attractor and a Gaussian well. Using some of them in fixed positions it is easy to get a behavior where robots come from distant positions to occupy the roles of a formation. Also, locating the traps in positions relative to the average position of the robots is possible, generating a solution to the first proposed problem. Finally, if those positions are taken relative to the position of one specific platform, the second problem is solved. Figures [5][6] show platforms movements for each case. It must be pointed out

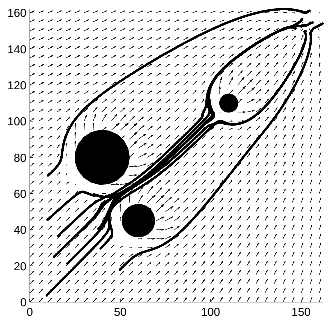


Fig. 4. Static field: Navigation and Obstacle Avoidance

in 6 how the leader trajectory is affected only by the base field and the obstacle avoidance field, while the followers make their best to keep their bodyguard roles.

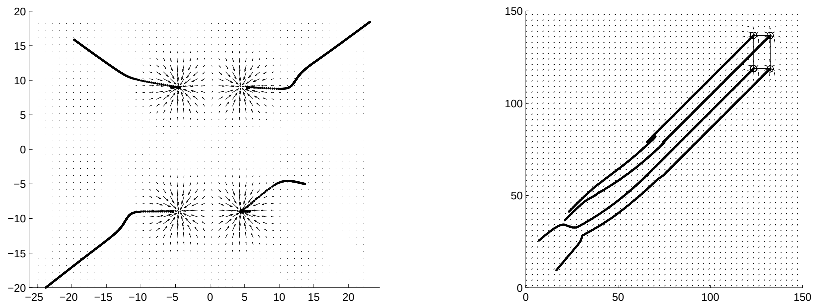


Fig. 5. Formation Generation and Keeping

However, this is not the regular result. For more complicated formations or for a specific initial positions the platforms usually block between themselves, thus creating potential walls for the incoming ones, and impeding them to reach their final positions, as in Fig. 7-a. Also, situations may arise where the whole systems gets into a potential local minimum. The formation shown in 6 has a small potential well in the center. In 7-b where the formation collides with a narrow corridor and due to formation keeping, it remains locked in front of the obstacle. This can be avoided with rigorous tuning, but minor changes in the environment or initial robot positions render useless those adjustments.

The third problem cannot be addressed with the previously described approach. For a number on robots lower than checkpoints number, the robots will

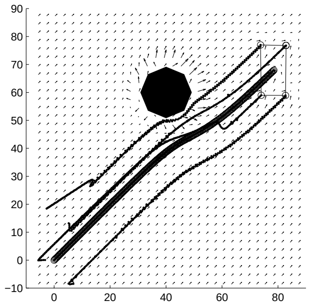
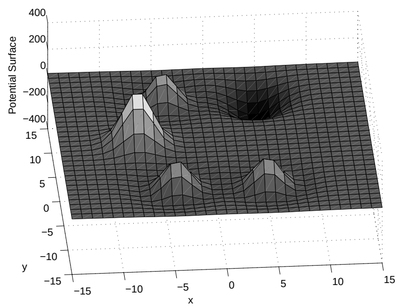


Fig. 6. Papparazzi problem



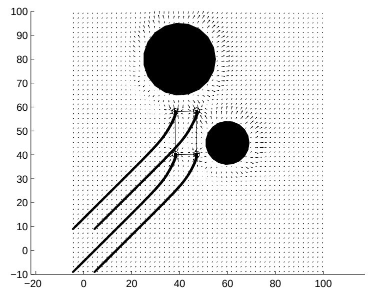


Fig. 7. Limitations of the static fields approach: (a) Potential Wall; (b) Corridor blocking

get trapped in the first reached checkpoint, thus leaving the rest of them unattended.

5 Dynamic parameters definition

The prior tests show one of the main drawbacks of field approaches to navigation problems, which is the appearance of saddle points and local minima. Even if the partial definitions of the fields are monotonically decreasing, their sum can create these wells where the platforms can get trapped. Sometimes the platforms manage to escape from them due to natural dynamical behavior of the environment that changes the field aggregation shape, like other platforms moving or a change on the goals. Also, other dynamic effects can be added to the behavior of the platform in the potential surface in order to avoid this problem, such as inertia, extra energy injection to the system, or even random movements when a trapping like this is identified. For cases where these natural dynamics are not enough to solve the local minima situations, this work introduces the idea of dynamical temporal evolution of the partial fields. When a particular goal is not being attained, shape and weights are modified in an attempt to brake possible potential walls or wells that might be preventing the goal fulfillment. For this purpose, each goal is provided with a metric to measure its success, and with a set of dynamic parameters indicating how to change the field in order to increase it.

In the proposed algorithm (8) the system starts at default field state. For each iteration, goals are monitored and their success metrics calculated. In case of detection of a failure, the system enters into a time interval called the *patience phase*. The field remains unchanged during this period to allow natural dynamics of the system to solve the problem. Then, if there is no significant improvement, the *impatience phase* starts. Here, an *impatience factor* is used to geometrically increase the effect of the field. This process continues until either the success is attained or the *resignation point* is reached. This point refers to the threshold in which the field weight has reached a level without success, thus indicating that the growth process may be useless or even counterproductive. At that point, the insisting goal lowers its weights to a random intermediate value with three purposes. First, the new random value can break the equilibrium between several competing goals. Second, it gives the natural dynamics of the system the opportunity to act by themselves to solve the situation. Third, the sudden change in the fields structure acts as a noise injection to the system helping it to explore the solution space.

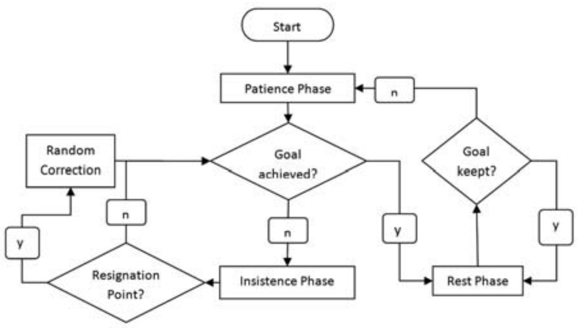


Fig. 8. Decision algorithm

6 Dynamic Fields tests

Tests similar to those in section 4 were performed applying the algorithm here described. Figure 9 shows 14 robots arranged into a complex formation, while navigating and passing through a narrow corridor and surrounding a small obstacle, solving the first task. For this, the dynamic fields approach was applied in several ways. First, the formation keeping field is composed by a set of gaussian and ramp attractors. Each one has a binary success metric associated with having at least one platform within its *conformity ratio*, and when the impatience phase is reached, both sigma and weight of such attractor start growing. Also, the whole formation has a discrete success metric associated with the sum of each position success metric, and this one affects the final sum weight. This general formation goal competes with the base navigation field (flat tendency) whose continuous metric is associated with the average robot velocity.

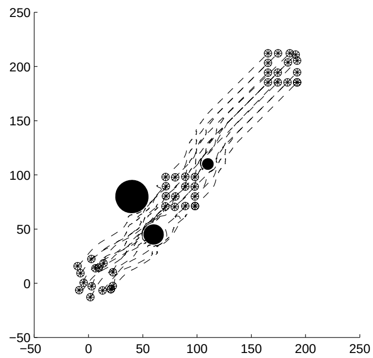


Fig. 9. Dynamic Formation Keeping and Navigation

With a similar approach, the solution for the second task is shown in 10. The trajectory of the leader is shown in dark follows the base navigation field, going to the upper right corner and smoothly avoiding the obstacles, while the bodyguards manage to keep around it.

The basic formation was attained for a variety of initial positions and formation shapes. When added together with the movement pattern and obstacle avoidance fields, the algorithm also shows a good behavior, allowing for the formation to disaggregate during the corridor passing thanks to the impatience pressure from the ramp, and to reunite after doing so. It is important to note that the reagregation process is not always straightforward, needing sometimes to drift and change platforms arrangement before succeeding. Nevertheless, given enough time, the formation is reached in almost all the cases. The same happens in the bodyguard problem.

Fixed Gaussian attractors are employed in the checkpoints for the third test. Their patience time and impatience factor are tuned in a way such that with the required checking periodicity those points compete for the attention of the mobile platforms. The position of the obstacles and checkpoints are shown in Figure 11,

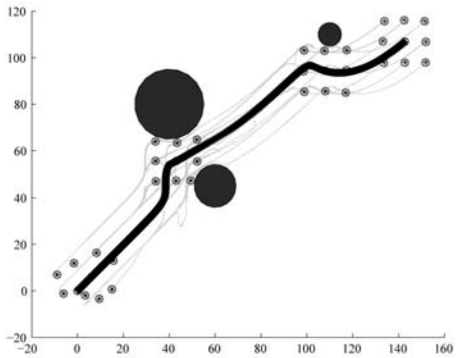


Fig. 10. Dynamic Papparazzi Problem

in whose right side are indicated the timing of visits to the checkpoints by the platforms. The presence of obstacles on the way to some checkpoints decrease their chance of being visited, but the algorithm acts introducing pressure on the robots to attend them. Also, at $t = 2500$ one robot stops in the central position, lowering the team capabilities and acting as a new obstacle. Even though, the system is able to handle the situation.

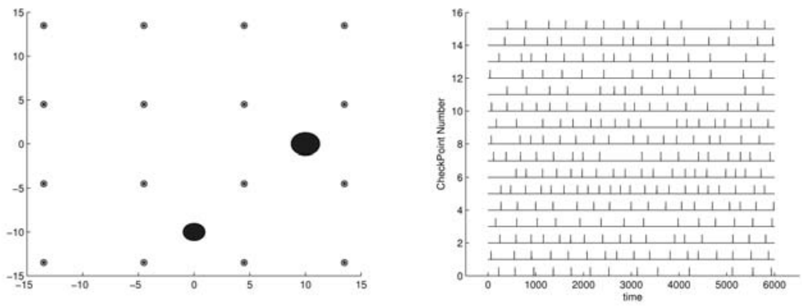


Fig. 11. Checkpoint arrange and visit frequency

7 Webots$^{\text{TM}}$ test

The tests ran using the Webots$^{\text{TM}}$ simulation used the same framework previously tested in the Matlab® ones, except for a less rigid criteria in formation success measurement. This was done to deal with position errors created by the non hollonomic robots while adjusting their orientation. The formation keeping task of Figure 12 shows the robots in formation while surrounding and squeezing through obstacles. Even if their trajectories are a little more curled than those of the Matlab® simulations, the platforms manage to solve the problem. For clarity, a very clear simulation is shown here, but since the approach relies on random changes in order to solve difficult situations and goals confrontations, some simulations yielded oscillations and drifting. Nevertheless, and within a reasonable time, the platforms manage to fulfill their goals.

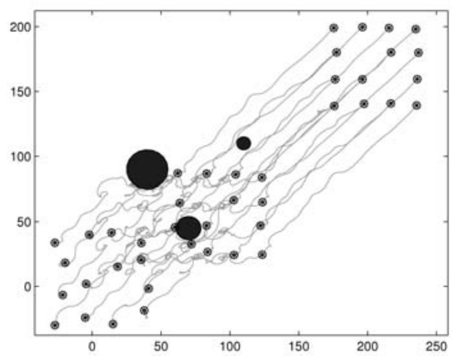


Fig. 12. Webots test

8 Conclusions

The proposed approach shows itself suitable to coordinated navigation problems, in particular for navigation amid obstacles, added to secondary goals. Also, one of the main problems encountered in field based control systems: potential wells, walls and saddle points which usually appear and completely cancel the capability of the systems to solve a goals confrontation, are solved by introducing dynamic behaviors in the fields definitions.

The fact that this approach searches in the configuration space of the system for a solution, simplifies the design phase and makes it robust for a wide range of environmental conditions. Even if work is needed to adapt the idea to a new problem, tuning is not complex and once got the system it copes with different situations. In particular, the performed simulations show the applicability of the approach to formation generation and keeping problems, and to the data logging task. The suggested algorithms gain robustness from the fact that besides the leader, all the roles are free to be taken by any robot. The first two tested tasks confirm this when robots switch positions on the formation. The last one shows a good example of the adaptability of the system to the failure of one platform and its transformation into a new obstacle. Webots^{TM} simulation shows the suitability of the proposed idea to a differential wheels platforms group, given enough information interchange among platforms about self and obstacles positions.

9 Recommendations and future works

Even though the configuration of the system is possible by empirical methods, other approaches should be tested. The use of automated search techniques might improve and simplify the design process, as would also do a rigorous mathematical analysis of the system dynamics. A more classical control approach might be used by identifying the potential surface modifications as an actuator of a control loop, in which the performance metrics are to be monitored and regulated. The idea must be adapted and tested into a wider variety of problems, in order to develop a generalized concept and to asses its versatility. Other simulation environments and conditions, with 3D tasks and physics, would prepare the idea for its final application to real platforms.

References

[Kha80] Oussama Khatib: Commande Dynamyque dans l'Espace Ioerationnel des Robots Manipulateurs en Presence d'Obstacles. Ph.D. Thesis. ENSA, France, 1980

[Kha86] Oussama Khatib: Real-Time Obstacle Avoidance for Manipulators and Mobile Robots. International Journal of Robotics Research, pp 90–98, Vol. 5, 1986

[She02] W. M. Shen, B. Salemi, and P. Will: Hormone-inspired adaptive communication and distributed control for conro self-reconfigurable robots. IEEE Transactions on Robotics and Automation, pp 700–712, October 2002.

[PLi95] P. Li and R. Horowitz: Passive velocity field control of mechanical manipulators. In Proceedings of the 1995 IEEE International Conf. on Robotics and Automation, vol. 3, pp. 2764– 2770, Nagoya, Japan. April 1995.

[Med07] W. Medina-Meléndez, L. Fermín, J. Cappelletto, C. Murrugarra and G. Fernández-López: Vision based dynamic velocity field generation for mobile robots. 6th International Workshop on Robot Motion and Control (ROMOCO 2007). Poznan, Poland. 2007.

[Joh02] S. Johansson and A. Saffiotti: Using the Electric Field Approach in the RoboCup Domain. Birk, Coradeschi, Tadokoro (eds) RoboCup 2001, Springer-Verlag, 2002.

[Par00] L. Parker and C. Touzet: Multi-robot learning in a cooperative observation task. In Proceedings of Fifth International Symposium on Distributed Autonomous Robotic Systems (DARS). 2000.

[Jen00] M. Jenkin and G. Dudek: The Paparazzi Problem. In Proceedings of IEEE/RSJ IROS 2000, Takamatsu, Japan. 2000