

Particle diffusion model applied to the swarm robots navigation

Modelo de difusión de partículas aplicado a la navegación de un enjambre de robots

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Fecha de recepción: 28 de Julio de 2012

Clasificación del artículo: Investigación

Fecha de aceptación: 1 de Octubre de 2012

Grupo de Investigación: ARMOS

Key words: Autonomous robots, bio-inspired system, Brownian motion, hybrid automaton, robot navigation, swarm robotics.

Palabras claves: Enjambre de robots, hybrid automaton, movimiento Browniano, navegación robótica, robots autónomos, sistema bio-inspirado

ABSTRACT

The robots today become very powerful tools that support many human tasks. However, the trend of development has often been separated from its application. The use of swarm robots to search in collapsed environments today becomes in a real alternative solution to support rescue efforts in landslide and other disasters. However, these environments have special features (unknown and dynamic) under which rapid responses are required (little processing time) with a major limitation of sensors (problems for the use of cameras and

GPS's for example) and communication. In this paper, we analyze an alternative of navigation for swarm robots with very limited capabilities (very limited processing power, communication and sensing). Our minimalist approach seeks to solve the problem without requiring system identification, geometric map building, localization, or state estimation. Instead, we propose a strategy based on Brownian motion, in which each robot is modeled as a particle whose motion is influenced by landmarks installed in the environment. The degree of influence on the robot corresponds to the design of the navigation route. Under this scheme, the robots

perform minimal processing, and the parallel navigation increases confidence in the search process. The proposed navigation scheme is analyzed and then evaluated by simulation.

RESUMEN

Los robots se han convertido hoy en día en una herramienta muy poderosa que apoya muchas de las tareas humanas. Sin embargo, las tendencias de desarrollo han estado en muchos casos separadas de su aplicación. El uso de enjambres de robots para la búsqueda en ambientes colapsados se convierte en una alternativa real de solución para apoyar los esfuerzos de rescate en deslizamientos y otros desastres. Ahora bien, estos ambientes tienen características especiales (desconocidos y dinámicos) bajo las cuales se requiere de una rápida respuesta (poco tiempo de procesamiento) con una gran limitación en el uso de sensores (problemas para el

1. INTRODUCTION

The search in collapsed environment is a complex problem with a possible use of huge digital systems to create or calculate the best rescue route. The complex of these systems depends on the number and kinds of sensors used. For example, the navigation systems require a camera to see its environment. In its management, the amount of memory increases exponentially according to the resolution of the image; the memory management becomes in the maximal task in number of memory access and quantity of MIPS (million instructions per second). Besides, the necessary number of matrix operation to calculate an optimal route using image processing has a logarithmic complexity. As expected, this also complicates other agent systems, in particular the communication system.

In addition to these hardware requirements, this kind of collapsed environment has conditions that make it more difficult the coordination of movement of robots. A camera, for example, may be blind due to the lack of light and dust. This bac-

ground has led us to analyze the problem from a minimalist point of view, reducing the hardware design (sensors, CPU and communication) and dealing navigation strategies that are successful in dynamic and complex environments.

usage of cameras and GPS, for example) and communication. In this article, we analyze an alternative of navigation for a swarm of robots with very limited capacities (very limited capacity of processing, communication and sensing). This minimalist approach seeks to solve the problem without the use of the identification of the system, the construction of geometric map, the localization or the estimation of states. In its place, we propose a strategy based on the Brownian movement, in which each robot is modeled as a particle whose movement is influenced by marks in the environment (landmarks). The degree of influence on the robot corresponds to the design of the navigation route. Under this scheme, the robots perform a minimum processing, and the navigation parallelly increases the confidence in the search process. The proposed navigation scheme is analyzed and evaluated by simulation.

The proposed navigation strategy aims to ensure that the swarm robots to travel a route established according to the projection of the expected behavior of the robots on a speed field designed on the environment. Navigation is done according to Brownian motion [1], but with the particles of the environment fixed as landmarks, and whose pushing force (signal strength) is designed according to the desired behavior.

This first part of the research focuses on analyzing the navigation algorithm, the movement policies of the robots and the design of the speed field on the environment, maintaining the premises of minimalism, autonomy, and scalability. One question that guided us throughout the entire design process was: ¿Can the robot navigate the environment without collecting information?

Our ideas are also closely linked to research in behavior-based control systems for autonomous robots [2, 3, 4, 5 and 6]. In this control scheme, the designer works the group of robots as a system, where each node corresponds to a robot, and to solve the task, each node has a different behavior. This structure is called a hybrid automaton, and allows use in the system design the capacity for abstraction of hybrid systems [7, 8, 9, 10]. We hope that our control ideas may be used as an alternative to the use of state-feedback control laws within continuous regions.

The paper is organized as follows. Section 2 presents preliminary concepts and problem formulation. Section 3 shows the sensor-based planning algorithm, definition, formulation and structure. Section 4 we present the simulation results. And finally, in Section 5, we present our conclusions.

2. PROBLEM FORMULATION

Let $W \subset \mathbf{R}^2$ be the closure of a contractible open set in the plane that has a connected open interior with obstacles that represent inaccessible regions. Let \mathcal{O} be a set of obstacles, in which each $O \subset \mathcal{O}$ is closed with a connected piecewise-analytic boundary that is finite in length. Furthermore, the obstacles in \mathcal{O} are pairwise-disjoint and countably finite in number. Let $E \subset W$ be the free space in the environment, which is the open subset of W with the obstacles removed.

Let us assume a set of n agents in this free space. The agents know the environment E in which they move from observations, using sensors. These observations allow them to build an information space I . An information mapping is of the form:

$$q : E \rightarrow S \quad (1)$$

where S denote an *observation space*, constructed from sensor readings over time, i.e., through an observation history of the form:

$$\bar{o} : [o, t] \rightarrow S \quad (2)$$

The interpretation of this information space, i.e., $I \times S \rightarrow I$ is that which allows the agent to make decisions [11].

We consider a group of n agents, differential robots, whose kinematics is defined by:

$$\begin{aligned} \dot{\mathbf{z}}_i &= \mathbf{u}_i \\ \mathbf{z}_i &= (x_i, y_i, \theta_i) \end{aligned} \quad (3)$$

With:

$$\begin{aligned} \dot{x}_i &= v_i \cos \theta_i \\ \dot{y}_i &= v_i \sin \theta_i \\ \dot{\theta}_i & \end{aligned} \quad (4)$$

Where $(x_i, y_i) \in \mathbf{R}^2$ is the position of the i th robot, θ_i is its heading, and v_i and $\dot{\theta}_i$ are the controlled translational and rotational velocities, respectively. \mathbf{u}_i denote the agent's control input.

We assume the agents are able to sense the proximity of their teammates and/or obstacles within the environment, using minimal information. Therefore, the neighborhood of \mathbf{z}_i is given by the range and field of view of the sensing hardware.

For navigation, the environment has a total of k landmarks. All landmarks broadcast a signal. However, the value of the signal for each landmark is dependent on the navigational path designed for robots. The signal is modeled as an intensity function over \mathbf{R}^2 . Let m denote the signal mapping $m : \mathbf{R}^2 \rightarrow [0, 0.2]$, in which $m(p)$ yields the intensity at $p \in E$. We assume that the robot's sensing range is a small circle in \mathbf{R}^2 whose radius r is on the order of the robot's typical displacement.

The environment E and even the signal mapping m are unknown to the robot. Furthermore, the robot does not even know its own position and orientation.

Our goal is to design the control rules for the n robots in order to independently solve navigation

tasks in a dynamic and unknown environment.

3. NAVIGATION ALGORITHM

This section presents an algorithm for each one of the robots that guarantees that they reach the goal, i.e., regardless of their initial position in the environment, size, shape, or obstacles in it, they sail through it by following a set path with the help of the landmarks.

3.1. Robot movement strategy

Our control strategy is supported by the intention to develop the simplest possible system, but able to collectively solve complex navigation tasks. The main feature we want is robustness in real applications.

With this approach, we developed a strategy that not requires determining the coordinates of the robots, their mathematical models or a central control unit. Furthermore, it is expected that environmental conditions limit the use of sensors, so that our minimalist approach also seeks to examine architectures that robots take the minimum necessary amount of information from the environment, and therefore they have low processing and communication requirements.

The navigation strategy that we propose intended to duplicate the movement of particles suspended in a fluid, due to the continuous bombardment of atoms and molecules. This phenomenon is known as *Brownian Motion*, a name also given to the mathematical models used to describe it [12, 13].

In the mathematical description of Brownian motion developed by Albert Einstein [1], Einstein made a diffusion equation for Brownian particles in which the diffusion coefficient, or mass diffusivity D , is related to the mean square displacement of the particle. If $\rho(\mathbf{z}, t)$ is the Brownian particle density in the point \mathbf{z} at time t , then ρ satisfies the diffusion equation:

$$\frac{\partial \rho}{\partial t} = D \frac{\partial^2 \rho}{\partial \mathbf{z}^2} \quad (5)$$

Following the moments given by the solution of equation (5), and assuming this behavior model for our robots, the movement of our robots in small time intervals Δt , defined by its own dynamics (response speed), can be determined as:

$$\mathbf{z}_i(t + \Delta t) = \mathbf{z}_i(t) + \mathbf{v}(\mathbf{z}_i)\Delta t + \sqrt{2D\Delta t} \quad (6)$$

where \mathbf{z}_i is the kinematics of robot i , and $\mathbf{v}(\mathbf{z}_i)$ is the value of the speed field sensed by the robot i at position \mathbf{z}_i . As shown in equation (6), the displacement of the robot is determined by two terms, one which depends on the intensity of the speed field in the environment, and another which depends on the diffusion coefficient.

The robots are basically event-driven agents. They move continuously changing direction randomly when hitting an obstacle. Their forward direction is adjusted according to the speed field, which is indicated by specially designed landmarks. These landmarks in our model emulate the behavior of the molecules in the fluid, but unlike many real systems, we do not want to fill the environment with them; the installation of a few is enough to coordinate the movement of the robots.

We consider two kinds of sensors. A first contact sensor, which reports when the robot is in contact with the environment boundary ∂E :

$$h_{\sigma_i}(x_i, y_i) = \begin{cases} 1 & (x_i, y_i) \in \partial E \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

And the intensity sensor, which indicates the strength of the signal in the landmark:

$$h_{\mathcal{E}_i}(x_i, y_i) = h(x_i, y_i, E, m) \quad (8)$$

The intensity values are normalized in the interval $[0, 0.2]$, where 0.2 m/s corresponds to the maximum speed value in the environment. We chose the maximum value of 0.2 m/s for convenience, since this is the speed at which move our laboratory prototypes.

The robots do not require other types of sensors, such as global positioning, odometry, or a compass. Therefore, it is unable to obtain precise position or angular coordinates.

Our robots have no differential speed control on its wheels; this reduces the possible actions or motion primitives that are given to move the robot, simplifying the control and modeling. Furthermore, this allows some slack in the design of the robots; i.e., the scheme is robust regardless of variations in implementation (it is very difficult to build identical robots, and always keep them in that way). The robots are allowed only four motion primitives (figural1):

- $u_{fwd} \rightarrow$ The robot goes straight forward in the direction it is facing; both wheels rotate at their rated positive speed.
- $u_{bwd} \rightarrow$ The robot goes backward in the opposite direction it is facing. Both wheels rotate at their rated negative speed.
- $u_{rgt} \rightarrow$ The robot rotates clockwise, turns right. The left wheel runs at rated positive speed, and the right wheel runs at rated negative speed.
- $u_{lft} \rightarrow$ The robot rotates counterclockwise, turns left. The left wheel runs at rated negative speed, and the right wheel runs at rated positive speed.

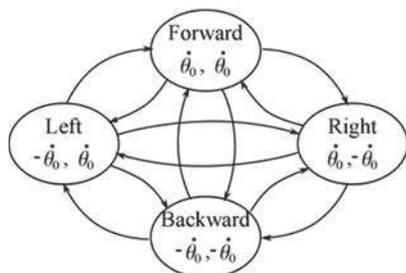


Figure 1. State diagram corresponding to the robot's behavior from the point of view of movement of the motors.

Let us consider our testing task: We want a group of robots to navigate the environment along a rou-

te, from some arbitrary point in E , according to the speed field in the environment. This speed field is specifically designed for the desired route, but for now is considered that exists in the environment, and is indicated to the robots through landmarks. The intensity sensor on the robot allows knowing the value of the speed field indicated by the landmark, but only when the robot locates the landmark. This feature reflects the robot's limited sensing capacity. The impact sensor completes the motion structure of the robot. Every time the robot detects an environmental limit or an obstacle on the way, the robot rotates on its axis a random angle, and advances again at constant speed. This random movement is what guarantees that the robot eventually finds the landmarks in the environment [14]. Applying the primitives for forward, backward and rotation, the robot can follow the behavior described above. A possible navigation plan that solves this task is shown in table 1.

Table 1. Plan for the navigation task

1.	If $h_{sc}=1, \Rightarrow$ apply u_{bwd} , and then apply u_{lft} or u_{rgt} (random selection) a random angle. Go to step 1.
2.	If $h_{sc}=0, \Rightarrow$ apply .
3.	If $h_S(x, y) \neq 0, \Rightarrow$ calculate the movement of the robot according to equation 6 and the value of $h_{IS}(x,y)$. Apply $u_{fwd}, u_{bwd}, u_{rgt}$ or u_{lft} as required by the new position. Go to step 1.

In order to evaluate the behavior of this strategy, we performed a first simulation of motion of a robot, under the following parameters:

1. A single robot in the environment. Constant robot speed of 0.2m/s.
2. Environment of unlimited size and without obstacles.
3. Environment full of Brownian particles (landmarks), with random value of speed field. The

range of values was taken between 0 and 0.2 m/s.

4. Robot's mass of 0.530 kg, according to real prototype. Mass assumed for Brownian particles of 0.1 kg.
5. Diffusion coefficient of the environment of $30 \times 10^{-6} \text{ m}^2/\text{s}$.
6. Simulation time of one minute.

Starting from the position (0,0), and following the behavior policy described in table 1, the robot navigated in the environment duplicating the behavior of a Brownian particle as shown in figure 2.

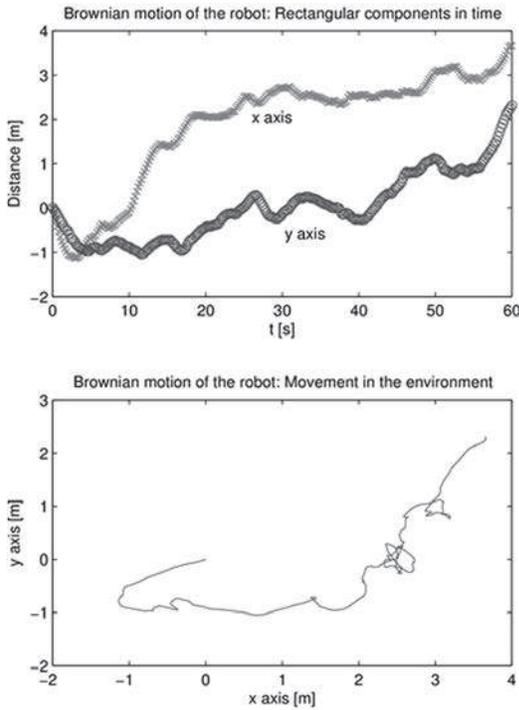


Figure 2. Brownian motion of a robot in an environment full of particles with random field intensity. (a) Evolution of the rectangular components of the displacement of the robot along the time. (b) Movement of the robot in the environment, starting from the position (0,0).

3.2. Route planning

This section presents a possible strategy for the design of the speed field in the environment of the robot, according to a desired path. Using this speed field to define the intensity of the signal in the landmarks, and according to the robot motion strategy proposed in the previous section, we hope that the robots to achieve the goal, i.e., they will navigate the environment to their destination, avoiding obstacles, and no matter what were their starting point, after a finite number of motion primitives.

Let the function $p(x,y)|_{p_o \rightarrow p_1}$ be the route designed for the robots in the environment E (figure 3). Let $v(x,y)$ be the speed field on E which guides the movement of robots. Let D be the diffusion coefficient, that in the model is related to the concentration in the environment, and is therefore proportional to the mobility of the robots (constant value, all the robots are identical and with fixed structure).

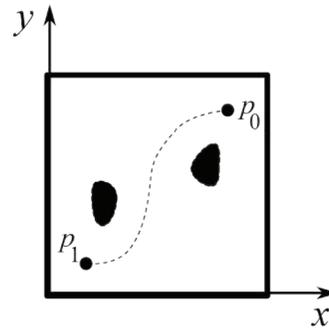


Figure 3. Planned route from p_0 to p_1 in two-dimensional environment with two obstacles.

In order that the robots are oriented along $p(x,y)|_{p_o \rightarrow p_1}$, the intensity of the speed field should be minimal for the points belonging to $p(x,y)|_{p_o \rightarrow p_1}$. In addition, the field intensity should increase as the points away from the route. This increase can be calculated along a normal line to the path traced. For any point $P(x,y)$ which does not belong to the path $p(x,y)|_{p_o \rightarrow p_1}$, the value of the intensity of the speed field $p_o \rightarrow p_1$ should be proportional to the perpendicular distance from the point to the path.

Finally, as the path has a direction, the intensity of the speed field must also decrease along the path towards the destination. As an example, consider again a without obstacles two-dimensional environment for our robot in figure 2. Let us think now that we want to design a path to guide our robot to a certain position, for example, the position (5, 4). The initial position of the robot is unknown, it can begin anywhere. For convenience of design, we selected as the starting point of the route an opposite extreme, for example the position (1, 1). Following the given design parameters, we can construct a map of speed field as shown in figure 4 (the maximum speed is adjusted according to the speed of the robot).

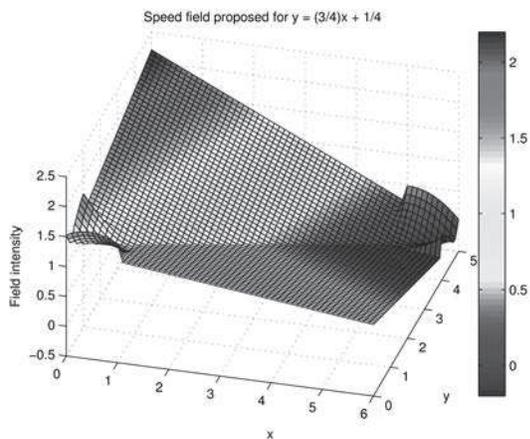


Figure 4. Speed field designed for the navigation path $y = \frac{3}{4}x + \frac{1}{4}$ between points (1, 1) and (5, 4).

This speed field does work as an attractive field for our particle, the robot. No matter what the initial position of the robot, the robot eventually will navigate guided by the path to its destination. To see this effect, we apply this speed field to the simulation case shown in figure 2, and we obtained a predictable behavior of the robot as shown in figure 5. All other parameters remained unchanged.

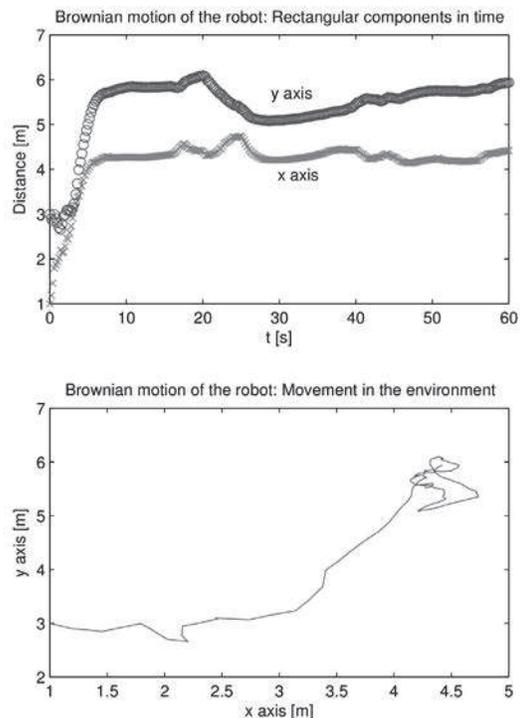


Figure 5. Brownian motion of a robot in an environment full of particles with designed field intensity for the navigation path $y = \frac{3}{4}x + \frac{1}{4}$ between points (1, 1) and (5, 4). (a) Evolution of the rectangular components of the displacement of the robot along the time. (b) Movement of the robot in the environment, starting from the position (1, 3).

We select the initial position of the robot arbitrarily in (1, 3). Unlike the random behavior shown in figure 2, this time the robot turned to the path designed, and followed it as a reference until it reaches its destination, where it stayed around. However, the expected behavior in the prototypes is significantly different. We want to install only a few landmarks in the environment, which will make the robot explore the area before reaching its destination.

4. PROTOTYPE AND SIMULATIONS

In this section, we use simulations to illustrate the results stated in the previous sections.

We perform the initial evaluation of the navigation strategy by simulation. However, the configuration of our simulator fully respects the criteria of our current laboratory tests. The simulations consider not only the functionality of the algorithm, we also have taken great care of the physical characteristics of the robot, i.e. size (0.20 m x 0.22 m), weight (0.530 kg) and speed (0.2 m/s). For our experiments, we use the Oomlout Company's open-source design SERB Robot. This is a differential robot constructed of acrylic, and equipped with two continuous rotation servomotors.

In relation to the diffusion model, we have assumed as mass of the particles of the environment a value of 0.1 kg, this in order that this mass be comparable with the mass of the robot, and generates the desired motion effects.

Our simulator allows the use of any graphic image as environment design. From it, the program creates a fictional scenario according to the image dimensions and characteristics of the real environment. Although the ideal is to work with black and white images, the program is capable of performing image processing (filtering and binarization). This feature allows us to use real photos of the environment.

The navigation task that we show below is to guide a group of five robots to your destination in the top right of the environment. The environment does not is full of landmarks, so we hope that the robots explore the environment before reaching their destination. The robots are placed randomly in the environment, and they move independently according to their own evaluation of the model. The landmark has been installed around the obstacles in the environment. This facilitated the characterization and implementation of the movement of the robots. We show the result observed in this simulation in figure 6.

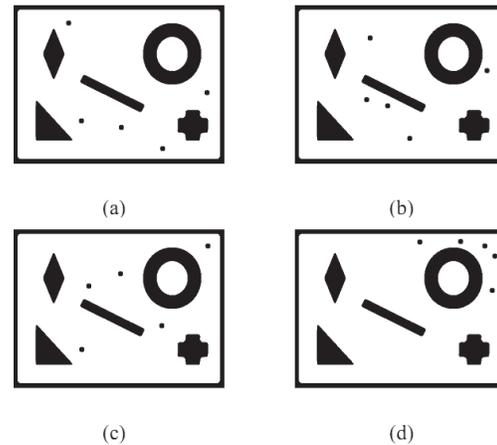


Figure 6. Simulation of five robots navigating from random positions. (a) Initial time of simulation ($t = 0$). The five robots start from random positions. (b) Sixteen seconds of simulation. The robots explore the environment and begin to proceed to their destination. (c) Thirty-five seconds of simulation. One robot has reached its destination. (d) Fifty-eight seconds of simulation. All robots have reached their destination.

After about a minute, all the robots managed to reach the target area. The first one arrived in 35 s. As we expected, the robots explored most of the environment during the navigation. When they reached the top right of the environment, the robots remained in that area navigating around it, this due to the design of the speed field in this area and the proximity of the landmarks.

5. CONCLUSIONS

Under the assumption that the dynamic equilibrium of a group of agents is reached, this paper proposes an algorithm to coordinate the movement of a swarm robots along an unknown dynamic environment. We have shown that a group of robots can be used to solve a navigation task and exploration using a single minimalist design in hardware, software and algorithm operation. The system dynamics (interaction between the robots and the environment) responds to the simplified algorithm of Brownian motion. The capabilities and system

functions can be scaled without problems changing the number of robots. The navigation task is performed by robots regardless if one or more of the agents are damaged. The robustness of the system, characterized by the multitude of agents developing the task, greatly increases the performance in real environments, unknown and dynamic.

The research developed to this stage leaves some important questions that we intend to attack. For example, how many landmarks set in the environment? And more importantly, what are the optimal locations? Since the landmarks can become simple color marks on the environment (with a color

code), one of the strategies under investigation involves analysis of graph coloring techniques.

6. ACKNOWLEDGEMENT

This work was supported by the Distrital University Francisco José de Caldas, in part through CIDC, and partly by the Faculty of Technology. The Distrital University does not necessarily endorse the views expressed in this paper. The authors thank the research group ARMOS for the evaluation carried out on prototypes of ideas and strategies.

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