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On the Problem of Representing and Characterizing the Dynamics of Multi-Robot Systems

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1. Introduction

In the recent years, there has been a growing interest in the design and programming of multi-robot systems. This is mainly due to the potential advantages of these systems, such as physical deployment, redundancy and parallelism in sensing and actuation.

The interest of the collective robotics community has focused on the development of technology to support the interaction among single robots to achieve common goals, such as methods for inter-robot communication, kin recognition, sensor fusion, and information sharing. The outcomes of this research are seen to be of direct relevance to other fields involving the inter-operation of various software and physical components, such as sensor networks and ubiquitous computing.

In spite of all the progress made in collective robotics in the last years, a lot of work remains to be done both in describing and understanding the behavior of multi-robot systems without regard to their internal mechanisms. However, theoretical descriptions of the dynamics of multi-robot systems pose a considerable challenge to robot designers because they do not rely on well-established and quantitative laws of behavior. As a matter of fact, collective robotics suffers from a lack of descriptive and analytical tools for estimating the tendencies and evolution of the dynamics of multi-robot systems under a variety of conditions.

Some efforts have been made towards the theoretical understanding of multi-robot systems, such as the introduction of metrics for measuring specific aspects of multi-robot systems, e.g. diversity (Balch, 2000) and fluctuations from a steady state (Lerman et al., 2006), as well as attempts to describe the dynamics of multi-robot systems by using formal and semi-formal methodologies, e.g. ergodic dynamics (Shell et al., 2005).

In this work, various attempts to describe the dynamics of multi-robot systems are presented and discussed. Two large-scale measures, average flow and average activity, are namely introduced and applied in experiments of simulated foraging robots, in order to characterize the systems limits. These measures are supported on parameters of crowd behavior applied in mechanical statistics. In addition, based on a set of selected case studies we provide experimental evidence about the quantification of the performance of multi-robot systems.

This research aims at contributing to understand and characterize multi-robot dynamics, in order to generate a favorable framework to detect strengths and weaknesses in current designs.

2. The dynamics of multi-robot systems

By the dynamics of a multi-robot system we mean the set of influencing factors that produce the system's activity. This in turn is relevant because its association with systems change. Note that the dynamics of the system may be useful for its understanding and characterization.

The dynamics of a multi-robot system should represent the activity of the members of the system, in terms of the evolution of their behavior and interactions over time, as a whole. By characterizing a multi-robot system its designers may determine what sort of influences can be traced from multiple experiments using the system under different environmental circumstances, they also can find bounds on the expected performance of the system, and they can also study the system's sensitivity to changes in the population size or the population diversity, to mention but few tasks to undertake to answer some of the challenging questions in collective robotics.

It is worth mentioning that we use the concept of multi-robot system in a very general sense, meaning a group of autonomous or semi-autonomous robots. Thus, the category of multi-robot systems is a broad family comprising teams of homogeneous and heterogenous robots, of collaborative and "individualist" robots; modular robots with static or dynamic reconfiguration capabilities, to mention some examples. For extensive surveys and taxonomies of multi-robot systems, see (Dudek et al., 1996; Cao et al., 1997; Iocchi et al., 2001; Farinelli et al., 2004; Bayinder & Sahin, 2007).

A problem faced by roboticists to characterize the dynamics of a multi-robot system is the *sui generis* nature of choices of the system parameters that are directly measurable, on the one hand; and the available tools to measure the system's activity on the other hand.

The parameters of multi-robot systems, for both physical and simulated robots, that can be directly measurable are, for instance, the goal achievement rate (Tang & Parker, 2007), the average time (Parker, 1993; Couture-Beil & Vaughan, 2009) or steps (Sgorbissa & Arkin, 2003; Mataric et al., 1995) needed to reach a goal, the work distribution (Wawerla & Vaughan, 2010), the cost and use of common resources, such as recharging time (Sempé et al., 2002; Wawerla & Vaughan, 2008) or spatial occupation (Goldberg & Mataric, 1997; Likhachev & Arkin, 2000; Balch et al., 2001). These parameters indicate important aspects of the behavior and interaction of a multi-robot system, as such they will keep being indicators of the performance of the system under varied circumstances. However, parameters indicating the "projection" of the system in a wide variety of circumstances have been rarely measured in the context of multi-robot systems. An exception to that is probably the characterization of the system in terms of fluctuations from a steady state introduced by Lerman et al. (2006) (see section 3 for a detailed description of this work).

Concerning the available tools to measure the system's activity, there is a lot of different numerical tools that can be used for analyzing and assessing robot behavior. However, when the analysis focuses on group behavior issues there is no evidence to justify the use of specific tools. Descriptive statistics are useful tools to describe and summarize properties of data concerning multi-robot systems in a simple and understandable manner.

We consider that descriptive statistic tools can capture significant parameters of the performance of a multi-robot system, such as the mentioned directly measurable parameters, provided that a variety of "projections" of the system can be sized. These "projections" can be generated by a gradual exposure of the system to the variation of scenarios, as we show at the end of this work. These projections should reflect a scale-dependent picture of the multi-robot system, in terms of the selected measurable parameters.

3. Related work

Below we review two works that are closely related to the nature of our research and that deal with the problem of capturing in some way the dynamics of a multi-robot system.

Tucker Balch has been tackling the problem of defining quantitative metrics for multi-robot systems. He introduced a metric inspired by Shannon's information theory that he called "social entropy" that is applied to correlate how group member diversity affects learning in multi-robot systems (Balch, 1997). This metric is subsequently extended to a continuous measurement of diversity in robot groups by combining the previous social entropy with a measure of behavioral difference between individual robots. The extended metric, that is called the "hierarchic social entropy", is applied to investigate a more general question concerning how group member diversity impacts the whole system performance (Balch, 2000).

Diversity is measured by Balch from a behavioral perspective in such a way that perceptual states associated to robot behaviors are represented as binary patterns. These associations are then compared in order to quantify a behavioral difference between two robots. Social entropy and hierarchic social entropy look forward to the improvement of coarse-grain taxonomies that represent multi-robot systems as extreme points in a linear dimension. Balch reviews the flat taxonomy of multi-robot systems that considers two unique classes, homogeneous versus heterogeneous robots. And he proposes instead a more comprehensive taxonomy that holds various degrees of heterogeneity in multi-robot systems, represented as numerical values. An interesting finding regarding Balch's work is that diversity is not desirable *per se*, and that, for some tasks such as foraging, homogeneous robot teams perform better than diverse robot teams. Balch suggests that inherently cooperative tasks, such as robot soccer, are better performed by diverse teams than by homogeneous teams, whereas for more individualistic tasks such as foraging, the opposite performance is observed.

The measures proposed by Balch capture the composition of multi-robot systems in a precise way. At the same time these measures provide evidence that the performance of multi-robot systems is certainly related to their composition, and more precisely that this performance is affected by small differences in the behavioral profile of the members of the system. However we do not know in detail the evolution of the activity of a multi-robot system over time by applying these measures.

The research of Lerman et al. (2006) aims at representing and studying the dynamics of multi-robot systems. This work is closely related to our research in the sense that a global measure of the performance of a multi-robot system is calculated in spite of having incomplete information about that system and its environment. This measure is calculated from the observations of the environment made locally by each robot of the system and recorded onto its own memory. Memory is described by the authors as a rolling history window of finite length.

In the work of Lerman and her colleagues the performance of a multi-robot system is not only measured for characterization purposes. They also investigate how the number of observations, from the local perspective of each robot of the system, and the decisions made by robots from these observations affect the performance of the whole system. For that, transition probabilities between states are calculated by each robot from its individual history. The authors focus their analysis on a scenario of dynamic task allocation, a class of the general problem of task-allocation. The latter is described as the process of assigning individual robots to sub-tasks of a given system level task, whereas dynamic task allocation is the process of assigning robots to subtasks that may need to be continuously adjusted in response to

changes in the task environment or group performance. In this scenario, robots decide their task allocation.

A mathematical model of a group of robots that apply previous mechanisms is also introduced, and theoretical predictions made by this model are compared with experimental results of a group of simulated foraging robots. By applying this mechanism, a steady state of the multi-robot system, as well as fluctuations or variations of the steady state are identified, in terms of the number of tasks or foraging objects, and the length of the history of robot observations. Simulated results fit very well with the theoretical results given by the model, which means that the dynamics of the system is well understood and can be captured in the proposed performance measure.

In this research we share the interest of Lerman and her colleagues in macroscopic approaches to study collective behavior in large systems. Our research focuses on homogeneous multi-robot systems.

4. Hands-on practice in representing the dynamics of multi-robot systems

In this section we summarize some efforts of our research group to describe the dynamics of multi-robot and multi-agent systems at various levels. It is worth mentioning that representing and characterizing the dynamics of both, simulated and physical multi-robot systems is far from being obvious. First, we present some examples that illustrate the representation of microscopic robot interactions using a case study approach. And second, we introduce a measure of global multi-robot performance based on ideas of crowd behavior applied in the field of mechanical statistics.

4.1 Microscopic interactions in small group size

The microscopic measurement of interaction among the members of a multi-robot system can be monitored directly throughout one or various experiments. These measurements are basically recordings of detailed observations of robots. These observations are important since based on them, robots are able to make decisions on how to behave. Microscopic measurements are adequate for small groups of robots, where interactions and their effect on robot decisions can be readily captured and traced. We present two cases of microscopic interaction recordings.

Case study 1- The representation of the dynamics is delimited by the nature of the task

The nature of the problem can give some indication of the system dynamics, and this is the case of multi-robot resource sharing applications. We have conducted an experimental study to investigate mechanisms for ensuring some degree of self-sufficiency (McFarland, 1995) in a small group of autonomous robots. The goal of this research was to enable three Pioneer mobile robots from ActivMedia© to remain in operation and efficiently share a charging station using simple mechanisms. A plot of the autonomy of robots during a period of one hour using different sharing strategies gives us a good idea about the interactions of the system, see Figure 1. It can be noticed in the plots that, even though robots manage and allocate a common resource, they might experience delays when accessing the charging station. This information was in fact very useful for defining better sharing strategies. For a detailed description of this work see Sempé et al. (2002).

A second example of representing the dynamics of systems in a multi-robot resource sharing scenario concerns the sharing of the environment. The problem of multi-robot exploration and mapping has been investigated under different approaches, such as multi-robot exploration with unknown start locations (Fox et al., 2006), or multi-robot localization
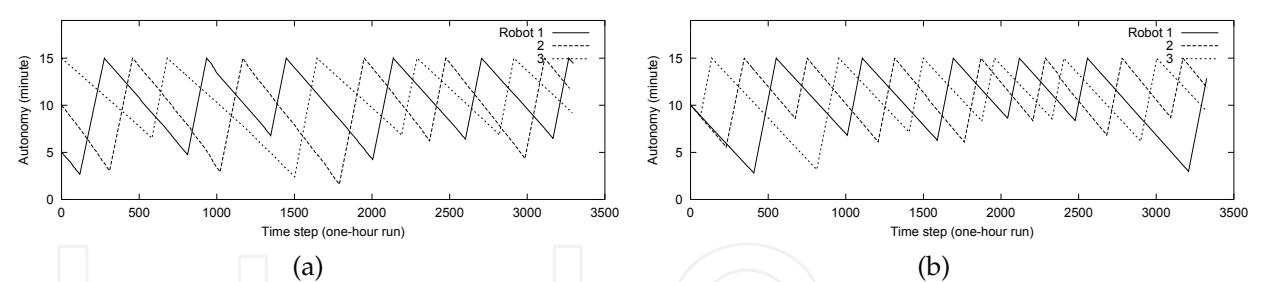
| (a) | (b) |

Fig. 1. Autonomy of three mobile robots sharing a charging station using a basic strategy with a 7.5-minute recharge threshold (a), and using an opportunistic strategy with a flexible recharge threshold (b) (Sempé et al., 2002).

based on encounters of pairs of robots (Roy & Dudek, 2000; Howard et al., 2006). We have conducted experiments of multi-robot exploration and mapping of known environments for map updating purposes. For that, a scheme for collective exploration was defined. This scheme enables robots to navigate and self-locate within an indoor environment, communicate to each other and with an external server, provide information to create local maps of their environment to be merged into a global map, and coordinate individual actions in order to explore autonomously the environment. A multi-robot system consisting of three micro mobile robots with very limited equipment was used in these experiments. The testing environment, and the local and global maps acquired by the robots are shown in Figures 2 and 3. Original and updated maps of the environment were also correlated in our work, in order to identify significant changes of the environment. These maps reflect properties of the environment as perceived by the robots, as well as a trace of their actions. Therefore, maps capture the dynamics of the system from the robot's perspective. For a detailed description of this work see (Méndez-Polanco, 2007; Méndez-Polanco & Muñoz-Meléndez, 2008).

Case study 2 - The representation of the dynamics is based on the system's behavior
Now we want to focus on the problem of representing the dynamics of a group of robots that require the performance of accurate physical maneuvers to operate, as it is the case of modular and self-assembling multi-robot systems (Mondada et al., 2003; Murata et al., 2002; Yim, 1994). In contrast to other applications of collective robotics in which isolated, even individualist autonomous robots can contribute to the successful operation of the whole system, a modular multi-robot system relies on the establishment and execution of agreements among its members. Therefore, a key aspect to trace in the dynamics of these systems is the way as their members reach agreements and coordinate their actions as a result, and that usually happens in very short periods of time. As we need a different approach to this problem we represent the dynamics of a modular system from a behavioral perspective.
The Mini-trans system is a home-made multi-robot system prototype consisting of three

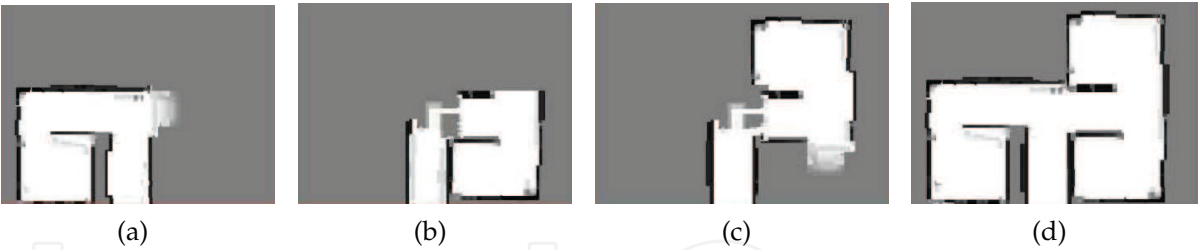Fig. 2. Environment used for the experiments of multi-robot exploration.

Fig. 3. Local maps acquired by individual robots (a-c) and global map merged by the server (d) from data of the environment illustrated in Figure 2.

mobile autonomous robots. It was developed in our laboratory of robotics as part of a master thesis (Jiménez-Velasco, 2006). The members of the Mini-trans system have very limited communication capabilities, based on simple devices such as near-IR photo-reflectors, photosensors, and LEDS. The whole system moves sequentially since a single robot is unable to pull or drag a motionless robot. For that, robots transmit messages to each other constantly in order to move collectively. Figure 4 shows a sequence of snapshots acquired during an experiment of collective exploration where various agreements were achieved by the robots. When there was enough space to go ahead, the supervisor stepped forward and a request to copy this movement was progressively propagated and executed from the head towards the tail of the formation. When an obstacle was perceived, a request to go backward was first propagated, followed by its execution from the tail towards the head of the formation. Figure 5 plots the behaviors executed by the robots during this experiment. The plot of behaviors captures the dynamics of the Mini-trans system. For a detailed description of this work see (Jiménez-Velasco, 2006; Jiménez-Velasco & Muñoz-Meléndez, 2006).

4.2 Global interactions

In this part we review some cases where the group size of multi-robot systems is greater than that presented in previous section. For groups of 20 or more robots, as well as for large-scale repeated experiments it becomes necessary to provide a unique value that quantifies the
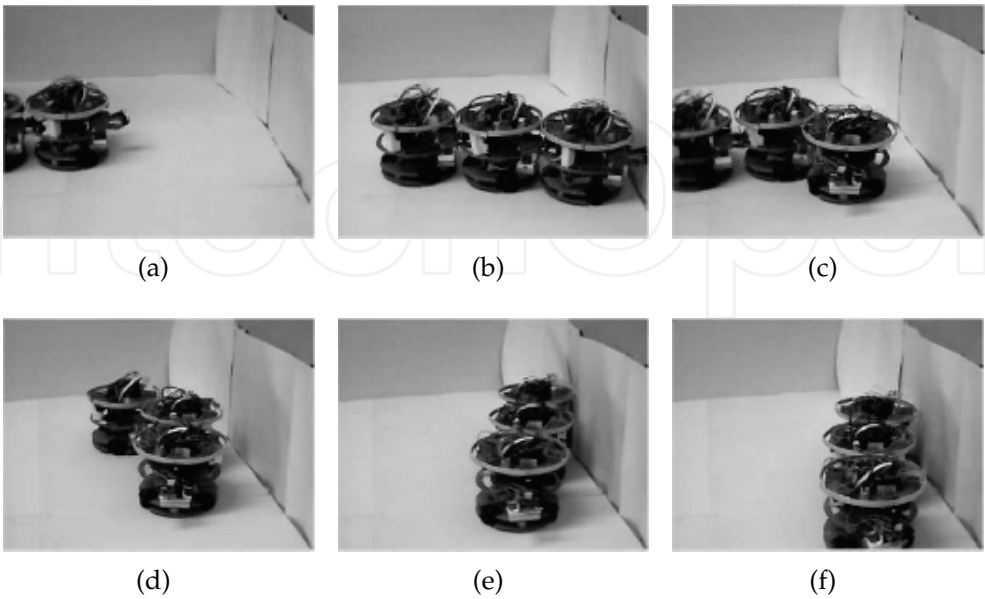

Fig. 4. The Mini-trans system during an experiment of collective exploration where avoidance maneuvers where conducted (Jiménez-Velasco & Muñoz-Meléndez, 2006).
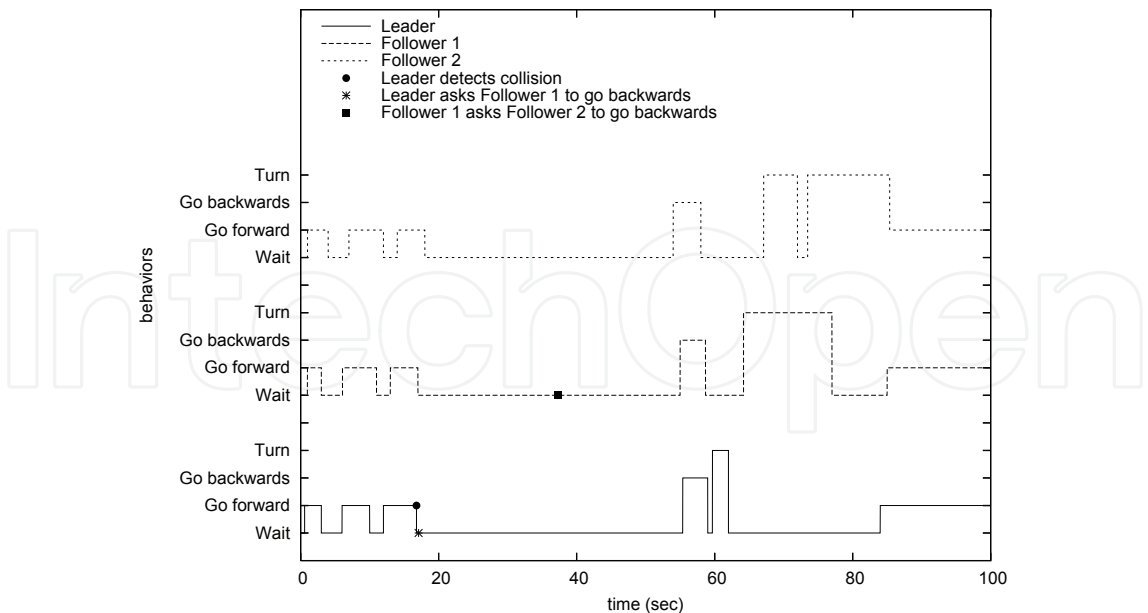
Fig. 5. Behaviors executed and time in which robots of the Mini-trans system send messages during the experiment illustrated in Figure 4 (Jiménez-Velasco & Muñoz-Meléndez, 2006).

global state of the system. We first represent the dynamics of a multi-robot system by summarizing the states of its members, then we represent the dynamics by considering flow aspects based on measures of crowd behavior applied in the field of mechanical statistics. As this section concerns extensive experiments, the selected case studies involve simulated multi-robot systems.

Case study 3 - The representation of the dynamics is based on the states of the system
We have studied the problem of collective coordinated motion that is required in applications of flocking (Reynolds, 1987), and generation and maintenance of spatial formations (Unsal & Bay, 1994; Belta & Kumar, 2001; Jakob Fredslund, 2002). In these applications, a group of autonomous robots or agents have to move while keeping a spatial arrangement. Since the acquisition of complete and accurate information about mobile robots in a formation, such as their pose or their speed, is too expensive or inaccesible, local perception based methods are well suited for applications involving multi-robot systems capable of collective coordinated motion.
We proposed and evaluated several robot classes with different capabilities of perception and action, and then we defined a set of organization principles for robots capable of collective coordinated motion using "communicative" robots, a class of robots able to transmit their orientation using color signals on their bodies. For evaluation purposes we recorded the states of the robots which can be in one of two possible states, follower or leader, according to their perception. When they are isolated, robots are in the state of leader, and when they have joined a formation they are in the state of follower. We plotted the number of robots in these states along an experiment in order to verify if the system converges into a single stable formation. Figure 6 shows a sequence of snapshots acquired during an experiment using 25 simulated robots, and Figure 7 plots the states of the robots during this experiment, where robots succeed to generate a formation. For a detailed description of this work see (León-Fernández, 2005; León-Fernández & Muñoz-Meléndez, 2007).
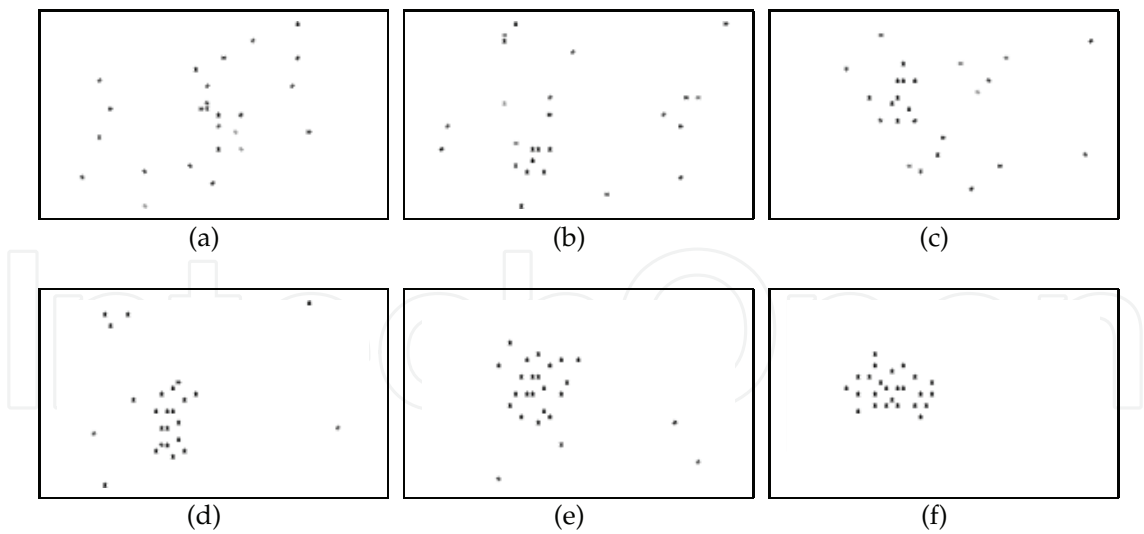
Fig. 6. Simulated robots while trying to gather together
(León-Fernández & Muñoz-Meléndez, 2007).

Case study 4 - The representation of the dynamics based on mechanical statistics metrics
In the previous cases we have succeeded in summarizing the state of a multi-robot system in such a way that its dynamics, in terms of its evolution towards the achievement of a goal, can be followed. Now we are interested in the large-scale replication of these experiments and measurements. We would like to investigate how scalable are the rules and the organizational principles underlying the previous applications, and if certain properties of the system can be characterized from a global measure of its dynamics.

We conducted a set of experiments of foraging robots increasing the population size from 2 robots (that occupy 0.1% of the size of the environment) up to 506 robots (that occupy 25% of the size of the environment), whose goal was to search and retrieve 1,012 pucks (that occupy 50% of the size of the environment) randomly distributed. The robots apply a reactive strategy to solve this problem, they search pucks randomly and carry them towards the center of the environment. Robots can perceive other robots and modify their speed when these encounters are detected, in order to avoid a collision.

Given the large number of experiments and robots, we applied metrics commonly used in the field of mechanical statistics to characterize the dynamics of crowds. The average
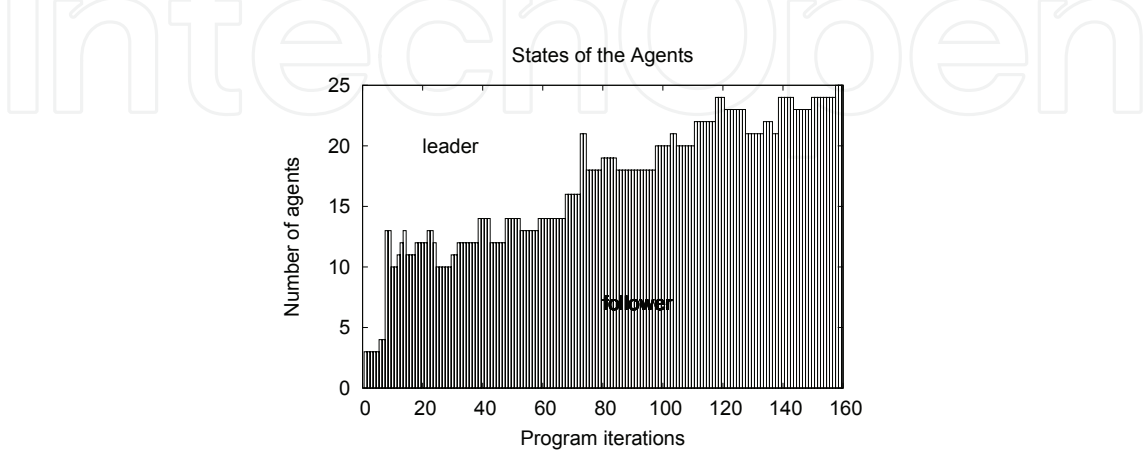

Fig. 7. States of flocking robots during the experiment illustrated in Figure 6
(León-Fernández & Muñoz-Meléndez, 2007).

speed for all crossing robots is calculated, as well as a measure concerning the individual activity of robots. Activity is a value between 0 and 1 that is calculated from the local perception of each robot, where 0 means no activity in the perceptual field of the robot, and 1 means that a partner or a puck was perceived by the robot. Figure 8 plots the average speed and average activity recorded during 252 experiments where the population size was varied. From these measures we can conclude that this particular system behave as expected when the population size is increased up to 20% of the size of the environment (around 200 robots), for larger groups the activity remains stalled that is also reflected as an increase in the average speed of the robots that result from their useless wandering of the environment looking for pucks. Previous measures have exponential distributions, the average speed of robots exhibits an exponential growth whereas their average activity exhibits an exponential decay. Average speed summarizes the effect of robot decisions on their environment, and average activity summarizes the internal robot perception. Both measures change in proportion to the density of multi-robot groups. The task of foraging a number of pucks is quite beyond the capabilities of small groups consisting of less than 100 robots, as can be noticed in their slow speed and high level of activity. Mid-sized groups of around 200 robots and bigger groups retrieve pucks and move faster as a result of the "cleaning" of their environment. Note that the activity of groups consisting of more than 200 robots remains constant, since activity captures the permanent interaction among the robots. Activity and speed measured during large-scale repeated experiments provide a general idea of the performance of multi-robot systems, their evolution and the way as these systems are degraded. Specific design aspects such as the impact in robot dynamics of different robot controllers can also be analyzed by applying these metrics. The field of mechanical statistics has a well-trodden path to the understanding and characterization of crowd dynamics and the research on multi-robot systems can take advantage of its progress. A kinetic model of a multi-agent system for an application of pedestrian crowd simulation, as well as measures of speed and activity with inverse tendencies to those observed previously can be consulted in Rangel-Huerta & Muñoz-Meléndez (2010).

5. Conclusions

We described some efforts of our research group towards the theoretical understanding and characterization of homogeneous multi-robot systems. Event though collective robotics comprises a large diversity of applications, we analyzed a set of case studies and provided experimental results that illustrate that the dynamics of multi-robot systems can be represented in various applications. A lot of work remains to be done in order to represent and quantify the behavior, evolution and convergence of multi-robot systems in an effective and accurate manner. The experience gained in other fields such as, for instance, mechanical statistics should be considered in this effort. Representation and characterization of the dynamics and performance of multi-robot systems will certainly benefit the field of collective robots by providing design guidelines, good practices for roboticists, and standards of validation.

6. References

Balch, T. (1997). Social entropy: a new metric for learning multi-robot teams, *Proceedings of the 10th International Florida Artificial Intelligence Research Society Conference (FLAIRS-97,* pp. 272–277.
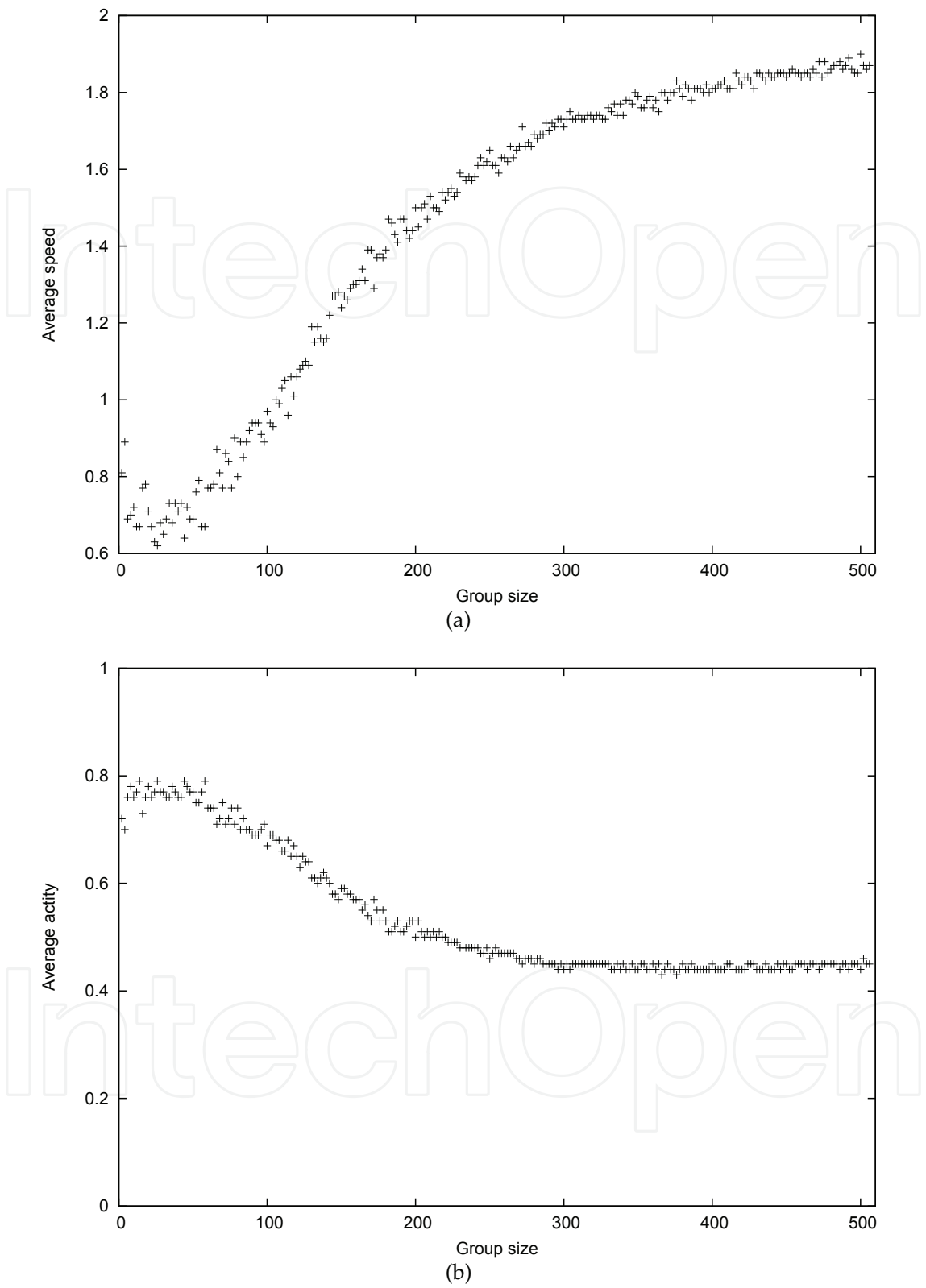
Fig. 8. Average speed (a) and average activity (b) of a foraging multi-robot system under different conditions of group size. The average speed is given in units of the simulation environment, where 1 unit is around 1m. The activity is a value between 0 and 1. All the experiments lasted 350 iterations of the program.

Balch, T. (2000). Hierarchic social entropy: an information theoretic measure of robot group diversity, *Autonomous Robots* 8(3): 209–237.

Balch, T., Khan, Z. & Veloso, M. (2001). Automatically tracking and analyzing the behavior of live insect colonies, *Proceedings of the 5th International Conference on Autonomous Agents*, pp. 521–528.

Bayinder, L. & Sahin, E. (2007). A review of studies in swarm robotics, *Turk Journal of Electronics and Engineering* 15(2): 115–147.

Belta, C. & Kumar, V. (2001). Motion generation for formations of robots: a geometric approach, *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, pp. 1245–1250.

Cao, Y. U., Fukunaga, A. S. & Kahng, A. B. (1997). Cooperative mobile robotics: antecedents and directions, *Autonomous Robots* 4: 226–234.

Couture-Beil, A. & Vaughan, R. T. (2009). Adaptive mobile charging stations for multi-robot systems, *Proceedings of the IEEE International Conference on Intelligent Robots and Systems (IROS'09)*, pp. 1363–1368.

Dudek, G., Jenkin, M. R. M., Milios, E. & Wilkes, D. (1996). A taxonomy for multi-agent robotics, *Autonomous Robots* 3.

Farinelli, A., Iocchi, L. & Nardi, D. (2004). Multi-robot systems: a classification focused on coordination, *IEEE Transactions on Systems, Man and Cybernetics - Part B* 34(5): 2015–2018.

Fox, D., andKurt Konolige, J. K., Limketkai, B., Schulz, D. & Stewart, B. (2006). Distributed multi-robot exploration and mapping, *Proceedings of the IEEE*, pp. 1325–1339.

Goldberg, D. & Mataric, M. (1997). Interference as a tool for designing and evaluating multi-robot controllers, *Proceedings of the 14th National Conference on Artificial Intelligence (AAAI-97)*, AAAI Press, pp. 637–642.

Howard, A., Parker, L. E. & Sukhatme, G. S. (2006). Experiments with a large heterogeneous mobile robot team: Exploration, mapping, deployment and detection, *The International Journal of Robotics Research* 25(5-6): 431–447.

Iocchi, L., Nardi, D. & Salerno, M. (2001). Reactivity and deliberation; a survey on multi-robot systems., *Balancing Reactivity and Social Deliberation in Multi-Agent Systems, From RoboCup to Real-World Applications*, Springer, pp. 9–34.

Jakob Fredslund, M. J. M. (2002). A general, local algorithm for robot formations, *IEEE Transactions on Robotics and Automation, special issue on Multi Robot Systems* 18(5): 837–846.

Jiménez-Velasco, M. G. (2006). *Design and implementation of a multi-robot system capable of self-assembling*, Master's thesis, Computer Science Department, INAOE. In Spanish.

Jiménez-Velasco, M. G. & Muñoz-Meléndez, A. (2006). Multi-robot motion coordination based on swing propagation, *Proceedings of the 7th International Conference on Computer Science (ENC'06)*, pp. 44–51.

León-Fernández, Y. (2005). *Generation and maintenance of spatial formations for collective robotics*, Master's thesis, Computer Science Department, INAOE. In Spanish.

León-Fernández, Y. & Muñoz-Meléndez, A. (2007). Investigación sobre los requisitos del movimiento colectivo coordinado en un sistema multi-agente, *Inteligencia Artificial. Revista Iberoamericana de Inteligencia Artificial* 11(34): 83–103.

Lerman, K., Jones, C., Galstyan, A. & Mataric, M. J. (2006). Analysis of dynamic task allocation in multi-robot systems, *International Journal of Robotics Research* 3(25): 225–242.

Likhachev, M. & Arkin, R. C. (2000). Robotic comfort zones, *Proceedings of SPIE Sensor Fusion*

andDecentralized Control in Robotic Systems III, Vol. 4196, pp. 27–41.

Mataric, M. J., Nilsson, M. & Simsarin, K. T. (1995). Cooperative multi-robot box-pushing, *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems 95 (IROS'95)*, Vol. 3, pp. 556–561.

McFarland, D. (1995). *The artificial life route to artificial intelligence: building embodied, situated agents*, Lawrence Erlbaum Ass., chapter Autonomy and self-sufficiency in robots, pp. 187–213.

Méndez-Polanco, J. A. (2007). *Local map fusion from the distributed perception of a robot team*, Master's thesis, Computer Science Department, INAOE. In Spanish.

Méndez-Polanco, J. A. & Muñoz-Meléndez, A. (2008). Collaborative robots for indoor environment exploration, *Proceedings of the 10th International Conference on Control, Automation, Robotics and Vision (ICARCV 2008)*.

Mondada, F., Guignard, A., Bonani, M., Bar, D., Lauria, M. & Floreano, D. (2003). Swarm-bot: from concept to implementation, *Proceedings of the 2003 IEEE/RSJ International Conference on Intelligent Robot and Systems (IROS 203)*, pp. 1626–1631.

Murata, S., Yoshida, E., Kamimura, A., Kurokawa, H., Tomita, K. & Kokaji, S. (2002). Mtran: A self-reconfigurable modular robot, *IEEE/ASME Transactions on Mechatronics* 7(4).

Parker, L. E. (1993). Designing control laws for cooperative agent teams, *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, Vol. 3, pp. 582–587.

Rangel-Huerta, A. & Muñoz-Meléndez, A. (2010). Kinetic theory of situated agents applied to pedestrian flow in a corridor, *Physica A: A Statistical Mechanics and its Applications* (389): 1077–1086.

Reynolds, C. (1987). Flocks, herds, and schools: A distributed behavioral model, *Computer Graphics* 21(4): 25–34.

Roy, N. & Dudek, G. (2000). Collaborative robot exploration and rendezvous. algorithms, performance bounds and observations, *Autonomous Robots* 11: 117–136.

Sempé, F., Muñoz, A. & Drogoul, A. (2002). Autonomous robots sharing a charging station with no communication: a case study, *in* A. H. et al. (ed.), *Distributed Autonomous Robotic Systems 5*, Springer-Verlag, pp. 91–100.

Sgorbissa, A. & Arkin, R. C. (2003). Local navigation strategies for a team of robots, *Robotica* 21(5): 461–473.

Shell, D. A., Jones, C. V. & Mataric, M. J. (2005). Ergodic dynamics by design: A route to predictable multi-robot systems, *Multi-robot systems: From swarms to intelligent automata*, pp. 291–297.

Tang, F. & Parker, L. E. (2007). A complete methodology for generating multi-robot task solutions using asymtre-d and market-based task allocation, *Proceedings of IEEE International Conference on Robotics and Automation (ICRA07)*, pp. 3351–3358.

Unsal, C. & Bay, J. S. (1994). Spatial self-organization in large populations of mobile robots, *IEEE International Symposium on Intelligent Control*, pp. 249–254.

Wawerla, J. & Vaughan, R. T. (2008). Optimal robot recharging strategies for time discounted labour, *Proceedings of the 11th International Conference on on the Simulation and Synthesis of Living Systems (Artificial Life XII)*, MIT Press, pp. 670–677.

Wawerla, J. & Vaughan, R. T. (2010). A fast and frugal method for team-task allocation in a multi-robot transportation system, *Proceedings of the IEEE International Conference on Robotics and Automation*.

Yim, M. (1994). *Locomotion with a unit modular reconfigurable robot*, PhD thesis, Deptartment of Mechanical Engineering, Stanford University.
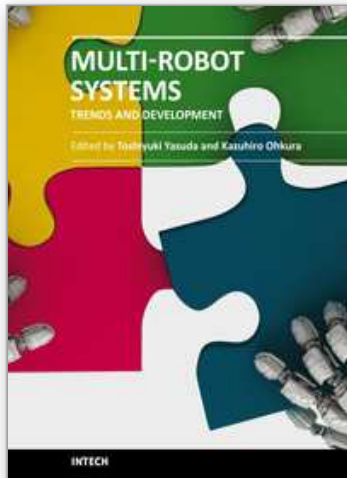
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This book is a collection of 29 excellent works and comprised of three sections: task oriented approach, bio inspired approach, and modeling/design. In the first section, applications on formation, localization/mapping, and planning are introduced. The second section is on behavior-based approach by means of artificial intelligence techniques. The last section includes research articles on development of architectures and control systems.

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