A global attractive controller for controlling a swarm of robots

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ABSTRACT—

A large number of robots especially in micro or nano-scale are difficult to control. This is because of the number of control inputs that have to be provided and the implementation of the necessary hardware in micro or nano-scale is a herculean task. Previously work has been done on using a global signal to control a swarm. The control inputs were mean, variance and covariance instead of the control space of the swarm, this drastically reduces the parameters used and with this under actuated system they were able to perform different tasks. Using the swarm's distribution the primitives of block pushing were achieved. Our goal is to create a global attractive controller to control the swarm instead of a global addressable controller and compare results.

I. PROBLEM

Micro- and nano-robotics have diverse potential applications in targeted material delivery, construction, assembly, and surgery. Constraints on computation prevent autonomous operation, and direct control over individual units' scales poorly with population size. Instead these systems often use global control signals broadcast to the entire robot population. Additionally, it is not always possible to gather pose information on each robot for feedback control. Robots might be difficult or impossible to sense individually due to their size and location. However, it is often possible to sense global properties of the group, such as mean position and variance.

Swarm robotics is an emergent field of collective robotics that studies robotic systems composed of swarms of robots tightly interacting and cooperating to reach their goal. Based on the social insect metaphor, swarm robotics emphasizes aspects such as decentralization of the control, limited communication abilities among robots, use of local information, emergence of global behavior and robustness. In a swarm robotic system, although each single robot of the swarm is a fully autonomous robot, the swarm as a whole can solve problems that the single robot cannot cope with because of physical constraints or limited capabilities. This paper addresses the use of a global attractive controller to move a swarm of robots in a maze. To make progress in automatic attractive control with global inputs, this paper presents a swarm manipulation controller requiring only mean and variance measurements of the robot's positions. This attractive controller is used as a primitive to perform a block-pushing task illustrated in Fig. 1. In particular, we report some of the results obtained with the implemented attractive controller, and then compare the results obtained with attractive controller with that of a global controller.

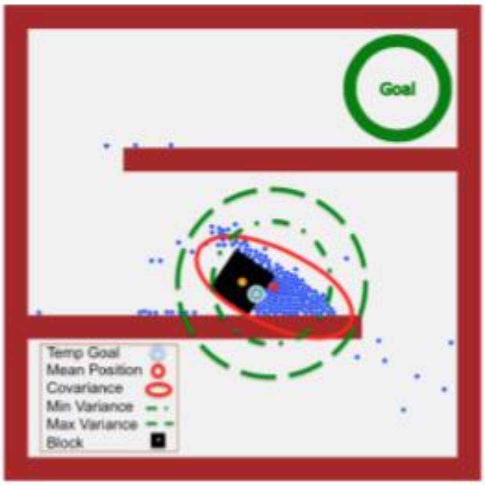


Fig. 1. A swarm of robots, all controlled by a uniform force field, can be effectively controlled by a hybrid controller that knows only the first and second moments of the robot distribution. Here a swarm of simple robots (blue discs) pushes a black block toward the goal.

Source: [1]

II. BACKGROUND

Swarm robotics is the study of how large number of relatively simple physically embodied agents can be designed such that a desired collective behavior emerges from the local interactions among agents and between the agents and the environment. The research of swarm robotics is to study the design of robots, their physical body and their controlling behaviors. It is inspired but not limited by the emergent behavior observed in social insects, called swarm intelligence. Relatively simple individual rules can produce a large set of complex swarm behaviors. A key component is the communication between members of the group that build a system of constant feedback. The swarm behavior involves constant change of individuals in cooperation with others, as well as the behavior of the whole group. Unlike distributed robotic systems in general, swarm robotics emphasizes a large number of robots and promotes scalability, for instance, by using only local communication. The local communication for example can be achieved by wireless transmission systems, like radio frequency or infrared. Generally, in multi-agent systems, the coordination of the agents is achieved by complex strategies, in a fixed topology. Often a central controller is used to determine the optimal action for each of the agents. Such methods, however, scale poorly with the number of agents. Swarm intelligence aims at controlling a large number of cooperative autonomous agents, in a varying topology, with simple, local rules. The analysis of a swarm intelligence system typically focuses on the dynamics of the swarm as a whole, rather than on the dynamics of the individual agents.

The characteristics of a swarm can be summarized as follows: (i) swarm consists of a set of cooperating autonomous individuals (ii) individuals have their own strategies they aim to satisfy and they are not aware of the global objective (iii) Each individual locally interacts with the environment and communicates with its neighbors (iv) There is neither a supervisor, nor a fixed and predefined hierarchical structure

A list of advantages of multi-robotic systems compared to single-robot systems approaches are the following: (i) Improved performance: if tasks can be decomposable then by using parallelism, groups can make tasks to be performed more efficiently (ii) Task enablement: groups of robots can do certain tasks that are impossible for a single robot (iii) Distributed sensing: the range of sensing of a group of robots is wider than the range of a single robot (iv) Distributed action: a group a robots can actuate in different places at the same time (v) Fault tolerance: under certain conditions, the failure of a single robot within a group does not imply that the given task cannot be accomplished, thanks to the redundancy of the system. Additionally, the most promising uses of swarm robotics is in disaster rescue missions. Swarm of robots of different sizes could be sent to places rescue workers can't reach safely to detect the presence of life via infra-red sensors. On the other hand, swarm robotics can be suited to tasks that demand cheap designs, for instance mining tasks or agricultural foraging tasks. Much more controversial that the above mentioned use of swarms, they can also be used in military to form an autonomous army of their own.

III. RELATED WORK

Recently, there has been a growing interest in the research community for the study of complex robotic systems that could present features like versatility, robustness or capacity to perform complex tasks in unknown environments [2, 6]. In this section, we overview some of the recent studies belonging to the areas of swarm robotics and collective robotics, which are closely related to the experiments presented in this paper.

The term swarm intelligence was coined by Beni and Wang [4] to describe a new approach to the control of distributed cellular robotic systems. Later, Bonabeau et al. [8] extended this definition to include "any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies" ([8], page 7). This new definition promoted swarm intelligence as a new computational paradigm for solving a large variety of problems. Swarm robotics consists in the application of swarm intelligence to the control of robotic swarms, emphasizing decentralization of the control, limited communication abilities among robots, use of local information, emergence of global behavior and robustness. Within swarm robotics research, to the best of our knowledge, there is very little work on self-organized aggregation. Most of the research about aggregation refers to tasks like foraging or object clustering, in which robots have to form clusters of some objects initially scattered in the arena. In foraging, objects must be collected and retrieved in a particular area (the home or the nest). In clustering, the focus is put on the dynamics of the process, no matter the place in which the cluster is formed. A number of papers study the self-organized clustering and sorting of objects in a closed arena, taking inspiration from the cemetery organization and brood sorting behaviors of ants. Gaussier and Zrehen [10] manually designed reactive behaviors for controlling a group of Khepera robots, in order to cluster objects in an arena. Beckers et al. [11] and Holland et al. studied the clustering and sorting of colored frisbees by a group of real robots. Frisbees were initially scattered on the ground, and the robots had to sort them in clusters of different colors. They designed a simple behavioral rule set for this purpose and concluded that the real-world physics was an essential component of the self-organization observed. Martinoli [12] studied the clustering of small cylinders by a group of real robots. In particular, he analyzed the interactions between the robots and the effect of the group size on the performance. Efficiency in the foraging task is the main focus of the study of Sugawara et al. [13]. They showed that the use of a simple form of communication among robots could increase the efficiency of the swarm, if the distribution of pucks to be retrieved is not uniform in the environment. In a more recent work [14], Sugawara et al. studied puck clustering. Also in this case, a set of simple behavioral rules was developed and a simple form of broadcast communication was used. Simulations showed that increasing the "interaction duration", that is, the duration of the communication signal, led first to an increase and then to decrease of the performance of the system. This indicates that there is an optimum interaction duration for the clustering process. Concerning the coordinated motion task, it is worth mentioning the work of Sugawara et al. [15]. They proposed a simple behavioral model that, by varying some parameters of the system, could let a swarm of robots generate four different types of collective motion. The robots could either (i) form a fixed lattice and move in a straight line; or (ii) remain in an almost fixed lattice and present a wavy movement; or (iii) constantly change their relative positions, with a resulting irregular movement; or (iv)not maintain any particular structure without moving much.

IV. UNCERTAINITIES

In the research of controlling a swarm of robots, there is uncertainty concerning other robots' intentions: coordination requires to know what other robots are doing. If this is not clear robots can compete instead of cooperate. For the proposed idea in the problem that has been solved, uncertainities are in mean, variance and co-variance of the swarm of robots. Since the system is an under actuated system, the initial uncertatinity was in position of the robots. There is noise added in the measurements and this adds uncertainity to the system. Just by controlling the mean position of the robots one will not be able to achieve goals like block pushing and reaching a goal with maximum population. Hence variance as an input parameter was incorporated into the system. This helps in achieving goals like block pushing by controlling the 2sigma ellipse which will have 96% of the robot population inside the elipse. Changing the orientation of the swarm cannot be achieved just by controlling variance and hence covariance as an input parameter needs to be introduced for varing Ө on a 2-D map.

V. SIMULATION RESULTS

Inspired by large-scale human experiments with swarms of robots under global control, work has been done which investigated controllers that use only the mean and variance of a robot swarm. It was proved that the mean position is controllable, and provided conditions under which variance is controllable. Automatic controllers for each of the robots and a hybrid, hysteresis-based switching control has been derived to regulate the first two moment of the robot distribution and hence control the mean and variance of a robot swarm. An attractive controller was then employed as primitives for block-pushing task.

A brush-fire alogroithm was the path finding algortithm used to find the shortest distance that the robot need to travel to reach the destination. First, a discretized map with tiles are created and the empty spaces and the robot goal locations are marked. A het map is generarted which depicts the distance between goal anf evry tile on the map as shown in Figure 2. The last step is to generate a vector field, which gives the angle solution and the shows angle in which the robots should travel to reach the goal(Figure 3).

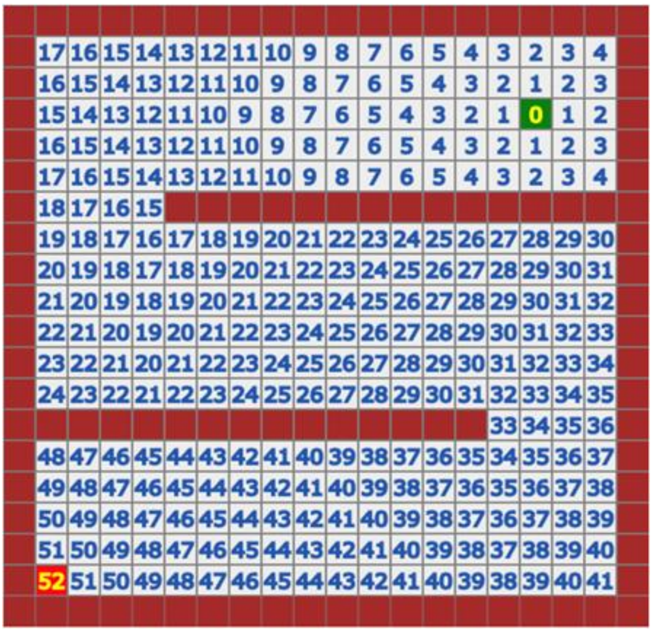


Figure 2 - heat map generated using brush fire algorithm [1]

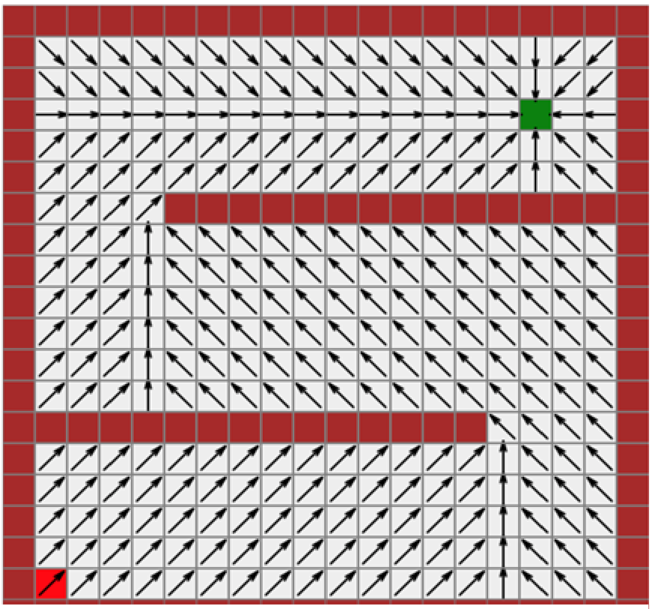


Figure 3 - Vector Field generation which gives the angle [1]

A proportional-derivative (PD) controller was used to control the mean of the robots. It was found that, proportional gain Kp increases the response, but also increases the overshoot, and derivative gains, Kd, reduced the overshoot, but slows the response. As you can see in figure 4, the graph on top with constant Kd and different

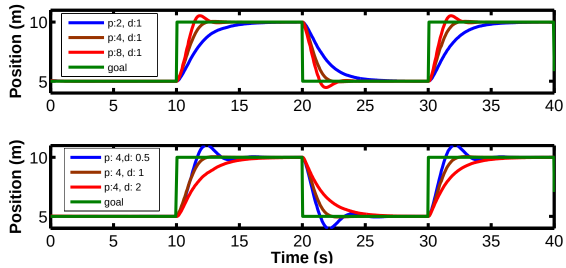


Figure 4: A PD controller position wrt time plot with different gain settings. [1]

Kp, shows that as Kp increases overshoot increases, and the graph on the bottom shows that with Kp constant, as Kd is increases, overshoot decreases but the response gets slower.

Our problem was to give a global attractive inputs to all these robots, and in this way, make the robots push the block to the goal location. Global attractive inputs in the sense that, all the robots receive one input and all the robots get attracted to that point, but the level or rather the force of attraction will be different for the robots i.e the one closer might get attracted faster than the one farther from it.

So the idea or rather the algorithm we used to solve this problem, was to calculate the center of mass (COM) of the block and assign the robots to get attracted to a point behind the BlockCOM, and then we pushed the block from the behind in the direction of the angle and path solution of the brushfire algorithm which enabled us in reason the goal as shown in the following figure. (Figure5)

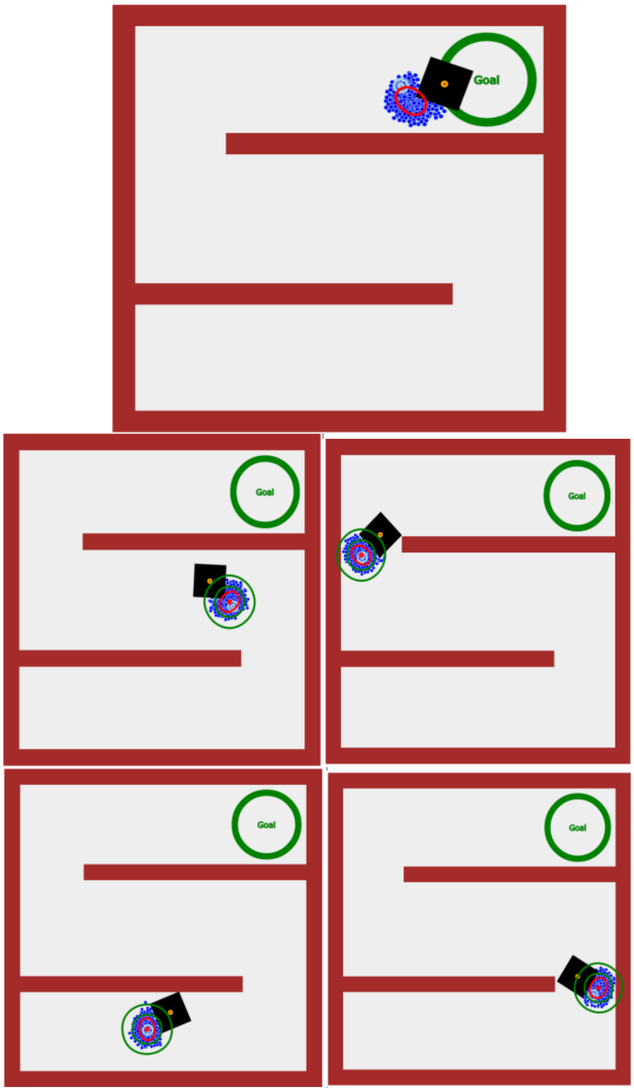


Figure 6: Snapshots showing the use of attractive controller to push a block to the desired location.

The attractive controller thus implemented was found to be easier than the global and repulsive controller, as the robots never got spread out and always lied within the variance limits, since they all got attracted to a point unlike the repulsive and global controller where all the robots had to go to the corners control the variance of the robots. Thus on the basis of implementation attractive controller is much easier to implement with a simple algorithm. On the basis of performance, to compare the attractive and global controller, we came up with data logging plots (Figure 7) which shows the range of time taken by different robot cases (50, 100, 150 and 200). The experiments were conducted for 10-15 times.

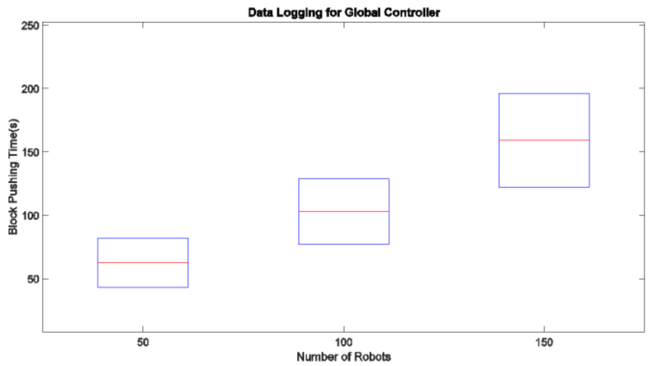


Figure 7a: Data logging plot of a global controller

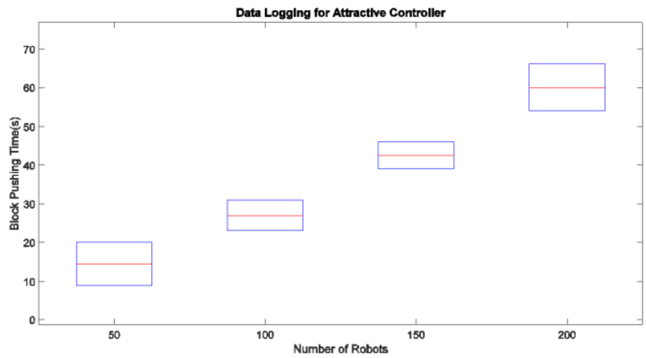
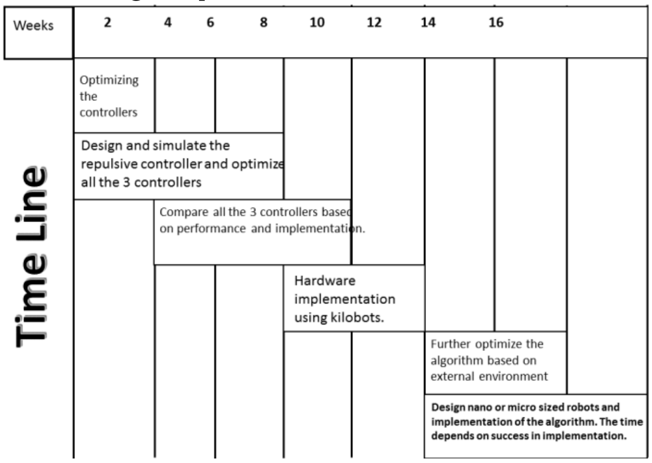


Figure 7b: Data logging plot of attractive controller implemented

As the number of robots increases, the time taken increases, this is because controlling becomes difficult and the computational time of mean and variance will increase as they are directly proportional to the number of robots. There were cases when global input controller failed when 96% of the robots did not and could not fall into the variance ellipse, but the attractive controller never failed as the robots never got spread and variance was always within the limits. As you can see in the data logging plots, attractive controllers are much faster. For example, 150 robots take approximately 130-200 seconds to push the block in the case of global controller, but even 200 robots take only approximately 55-65 sec to push the block in case of attractive controller. Thus, both performance wise and implementation wise, attractive controller seems to be better.

VI. TIMELINE AND FUTURE SCOPE

Future opportunities in the same lines as this project could be to find an ideal obstacle shape for a swarm of robots, and to find maybe better optimization and control techniques. This problem had a known environment, the goal, position and the obstacles were known. Future investigation can be done in an unknown environment. Investigation on heterogeneity can also be done i.e if it is advantageous to have a leader robot and make the others listen to them and if this will make things simpler.



This project can be made more interesting by optimizing all the three controllers, attractive, repulsive and global and comparing them based on implementation and performance for tasks like (i) box pushing in a maze, (ii) box pushing in open workspace, (iii) foraging in open workspace, (iv) foraging in maze, etc. Simple controllers can be implemented for each and their speed and implementation could be tested. Hardware implementation of these controllers can also be done using kilobots to check the effectiveness of the solution.

CONFERENCES FOR PAPER SUBMISSION:

1. ICRA, International Conference of Robotics and Automation.
2. IROS, Intelligent Robots and Systems, IEEE

VII. REFERNCES

[1] Siva Shahrokhi and Aaron T. Becker, Stochastic Swarm Control with Global Inputs.

[2] Y. U. Cao, A. S. Fukunaga, and A. B. Kahng. Cooperative mobile robotics: Antecedents and directions. Autonomous Robots, 4:1–23, 1997.

[3] Marco Dorigo, Vito Trianni, Erol Sahin, Roderich Groß, Thomas H. Labella, Gianluca Baldassarre, Stefano Nolfi, Jean-Louis Deneubourg, Francesco Mondada, Dario Floreano, Luca M. Gambardella, Evolving Self-Organinizing Behaviors for a Swarm-bot.

[4] G. Beni and J. Wang. Swarm intelligence. In Proceedings of the Seventh Annual Meeting of the Robotics Society of Japan, pages 425–428, Tokio, Japan, 1989. RSJ press.

[5] C. Ertel and A. Becker. (2013, Sep.) Swarmcontrol git repository.[Online]. Available: https://github.com/crertel/swarmmanipulate.git

[6] J. Liu and J. Wu. Multiagent Robotic Systems, volume 21 of International Series on Computational Intelligence. CRC Press, Boca Raton, FL, 2001.

[7] A. Becker, C. Onyuksel, T. Bretl, and J. McLurkin, "Controlling many differential-drive robots with uniform control inputs," The international journal of Robotics Research, vol. 33, no. 13, pp. 1626–1644, 2014.

[8] E. Bonabeau, M. Dorigo, and G. Theraulaz. Swarm Intelligence: From Natural to Artificial Systems. Oxford University Press, New York, NY, 1999.

[9] A. Becker, C. Ertel, and J. McLurkin, "Crowdsourcing swarm manipulation experiments: A massive online user study with large swarms of simple robots," in IEEE International Conference on Robotics and Automation (ICRA), 2014. [Online].Available:https://arxiv.org/submit/913241/view.

[10] P. Gaussier and S. Zrehen. A constructivist approach for autonomous agents. In N. Thalmann and D. Thalmann, editors, Artificial Life and Virtual Reality, pages 97–113. John Wiley & Sons, Chichester, UK, 1994.

[11] R. Beckers, O.E. Holland, and J.-L. Deneubourg. From local actions to global tasks: Stigmergy and collective robotics. In R. Brooks and P. Maes, editors, Proceedings of the Fourth Workshop on Artificial Life, pages 181– 189. MIT Press, Cambridge, MA, 1994.

[12] A. Martinoli and F. Mondada. Collective and cooperative group behaviours: Biologically inspired experiments in robotics. In Proceedings of the Fourth International Symposium on Experimental Robotics, pages 3–10. SpringerVerlag, Berlin, Germany, 1995.

[13] K. Sugawara and M. Sano. Cooperative acceleration of task performance: Foraging behavior of interacting multi-robots system. Physica D: Nonlinear Phenomena, 100(3/4):343–354, 1997.

[14] K. Sugawara and T. Watanabe. Swarming robots – Foraging behavior of simple multirobot system. In Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2002), pages 2702– 2707. IEEE Press, Piscataway, NJ, 2002.

[15] K. Sugawara, T. Arai, M. Sano, Y. Hayakawa, T. Mizuguchi, and T. Watanabe. Collective motion of interacting simple robots. In Proceedings of the 27th Annual Conference of the Industrial Electronics Society (IECON'01), pages 428–432.