Macroscopic information processing in natural systems as an insight for swarm robotics

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I. Introduction

Robot systems have been modelled *on* animals, have been models *for* animals, and have served as models *of* animals [12]. Among the most notable examples, particularly in the third category, are robotic swarms consisting of several simple robots that exhibit complex collective behavior despite simple local interactions (e.g. Kube [5], Beckers et al. [2], Holland and Melhuish [4]). In such cases, robots are tools with which to explore the nontrivial relationship between behavior at the level of the individual (microscopic detail) and that produced through the aggregate actions of each robot within the group (macroscopic behavior). With increasing robot swarm size, the distinction between spatio-temporal behavior at these two levels becomes increasingly crisp and, consequently, such multi-scale descriptions are expected to grow in importance.

Robotic swarms are typically guided by biology in two specific ways: (1) at the microscopic level—hypothesized and well understood mechanisms provide constructive guidelines, design constraints, and sometimes interaction rules for robots; (2) at the macroscopic level—observations of natural collective behavior suggest potential tasks and problem domains as well as metrics for evaluation and comparison. Most often both micro- and macroscopic insights operate concomitantly, the two complementing each other, and providing the roboticist with a local method of achieving some global behavior.[1] When a well understood structure or process is implemented in simulation or physical hardware, that knowledge is used to guide the design of the resulting system in a constructive sense. To date the vast majority of constructive insights are the result of microscopic observation. This is likely a consequence of the dearth of methods for achieving predictable collective behavior during the design time.

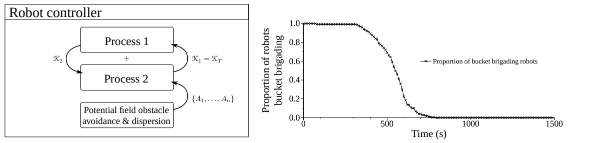
[1]However, this need not necessarily be the case as there are several researchers who perform tasks inspired by nature, e.g. foraging [10], without using biologically plausible methods.

This paper describes how taking a broad view of information processing within distributed biological systems results a set of design guidelines that have a very different flavor to those that result from microscopic examination of biological systems. The intention is to use macroscopic insights in a constructive sense rather than simply as loose inspiration. To do so one requires a method for synthesizing predictable behavior in swarm robot systems. The following section is an overview of the beginnings of one such method currently under development. The remainder of this paper shows that despite the method's limitations, it can reproduce a form of distributed computation found in nature.

II. Synthesis methodology

We propose a *compositional approach* in which the elementary components are simple distributed processes that use local communication. These processes are coupled together to produce robot controllers. The key idea is that macroscopic predictions of the elementary processes can be used guide controller design. The intention is produce controllers in an incremental fashion using macroscopic predictions at each step. The micro- to macro- predictions rely on the processes themselves having a mixing property (more formally ergodic dynamics) which permits construction of a time-independent or equilibrium characterization. This characterization is coarse-grained to give a macroscopic description. Processes are coupled at different time-scales in a manner that preserves equilibrium. These two assumptions, ergodicity and a "slow" coupling, limit the generality of the method but they also permit a degree of controller prediction. We view the predictions as primarily qualitative and are satisfied to the point of considering further modeling simplifications. As of now, the limits that the assumptions have on the generality of the approach is poorly understood.

Focusing only on processes for which analysis has successfully produced a suitable characterization limits the number of options available to the programmer, but



(a) Controller structure. (b) Example of swarm of 250 simulated robots switching foraging strategies.

Fig. 1. Symmetry-breaking by employing ergodic interaction rules.

the framework permits the sequential generate-and-test method widely used to be sped up or eliminated altogether. Current work has employed the analytical tools to study the computational aspects of the controller rather than spatial properties of the swarm itself. Particular random or dynamic spatial coverage behaviors could be analyzed in a similar manner. Also, the approach stresses a perspective in which complexity is achieved at the macro-level rather than through adding increasingly complex local rules. It remains an open question as to what levels of complexity can be achieved through a predominantly macroscopic viewpoint.

III. Example: Symmetry-breaking

Pheromone trail laying and following by ants is the single entomological phenomena that most stimulated computer science and robotic research in recent years. Research ranges from robots that lay physical chemical trails [9], to those that share trails in a shared virtual space [11], to placement of computational devices within the environment and generalization to "pheromone robotics" [7]. Each of these examples involves extracting an aspect of the microscopic mechanism employed by real ants, but various authors choose to consider these aspects increasing levels of abstraction.

In the case of pheromone trails, early observations suggested that the dynamics of trails themselves serve to optimize the route length. Dorigo et al. [3] generalized the procedure in order to perform distributed optimization of problems beyond spatial routing. The essential computational aspects at the macroscopic level were successfully isolated and reproduced. The preceding robotic examples show biological insight at the algorithmic and implementation levels [6], but ultimately the entire process is driven by insight at the computational level.

Trail laying results in distributed optimization because positive feedback is able to pick one route from several candidates. Elimination is achieved through a mechanism that performs biased symmetry breaking. This is the elementary information processing procedure that the pheromone trials enable. In physical pheromones there remain other aspects such as a spatial indexing mechanism (the position of the pheromone directly rather than symbolically represents a path choice), or the effects of diffusion (to propagate and smooth the route voting represented by the pheromone markers). Whereas symmetry breaking is an atomic operation, these aspects are features and convenient but are not essential from a computational point of view.

Thus, at a high level of abstraction, the biological system suggests that a multi-robot system should have a symmetry breaking procedure, and that this procedure can be used for collective decision making. We have set out to demonstrate this capability from within the synthesis methodology described above. The robots execute two processes, each of which is analyzed independently but coupled to achieve a symmetry-breaking phase-transition. The resultant behavior is then used to switch tasks during a simulation in which 250 robots are foraging. See the figure 1.

The view that symmetry-breaking is a fundamental coordination primitive is also supported by the fact that ants make use of operation for other tasks too, e.g., in colony relocation [8].

IV. Example: Division of labor

The same synthesis method can be used to reproduce another form of collective decision making: ant-inspired proportional division of labor. Task allocation is possible through reuse of one of the processes developed for symmetry breaking. The process requires that each robot pass some portion of its observations to a random neighbor. Executing the process on each robot results in the diffusion of information through the system.

This was used in a multi-robot foraging scenario in which robots forage one of two types puck. Each robot could occasionally switch foraging type but at some cost. Robots randomly encounter either type puck, making observations of each type in proportion with the puck distribution. These observations are smoothed by the dynamics of the two processes. Low probability observations (e.g., observing ten types of minority puck) are averaged out over the entire group of robots. Each robot makes a local decision as to which type of puck to forage. The result is a group of robots that adapts the division of labor in proportion to the distribution of tasks. Figure 2 shows the result of simulations with 100 robots.

Further examples of macroscopic information processing that are exhibited by natural systems include metastable states, hysteresis and transitions between stable equilibria in relatively rapid phase-transitions. Each of these has potential for robot swarms.

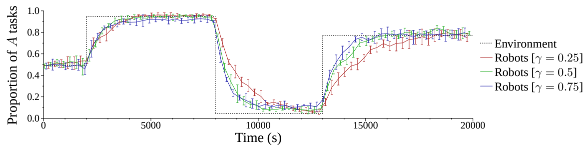


Fig. 2. Performance of task allocation processes. The vertical axis gives the proportion of tasks (for the broken line), and the division of robots among tasks (the solid lines).

V. Conclusion

Although the synthesis methodology employed is not biologically inspired (there is similarity with Ashby's notions of equilibrium [1]), we believe that high-level information processing descriptions of the computational capabilities of natural systems can inform swarm design within the methodology. Specifically, nature provides examples of capabilities that agents ought collectively to have. It suggests essential problems in which to test the limitations of a synthesis method. It is also conceivable that, with enough biological study, one could argue a sense of (non-formal) completeness of a particular synthesis method if it is sufficiently general to produce known biological distributed information processing.

By emphasizing macroscopic structures instead of the details pertaining to implementation, we hope that nature can provide insight for robot system programming in the form of general computational primitives.

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