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Synthetic collective intelligence

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ABSTRACT

Intelligent systems have emerged in our biosphere in different contexts and achieving different levels of complexity. The requirement of communication in a social context has been in all cases a determinant. The human brain, probably co-evolving with language, is an exceedingly successful example. Similarly, social insects complex collective decisions emerge from information exchanges between many agents. The difference is that such processing is obtained out of a limited individual cognitive power. Computational models and embodied versions using non-living systems, particularly involving robot swarms, have been used to explore the potentiality of collective intelligence. Here we suggest a novel approach to the problem grounded in the genetic engineering of unicellular systems, which can be modified in order to interact, store memories or adapt to external stimuli in collective ways. What we label as *Synthetic Swarm Intelligence* defines a parallel approach to the evolution of computation and swarm intelligence and allows to explore potential embodied scenarios for decision making at the microscale. Here, we consider several relevant examples of collective intelligence and their synthetic organism counterparts.

1. Introduction

Intelligent behaviour has been defined as the ability to successfully operate in uncertain environments by adaptations based on experience (Sternberg, 2000). To succeed, intelligent agents have to be able to measure information, sense their inner and environment states, and perform actions, receiving some kind of reward (Legg and Hutter, 2006). Additionally, agents have to be able to store these experiences and properly correlate experiences, becoming memory an additional item essential for systems adaptation and the development of an intelligent behavior. Our biosphere is currently populated by a plethora of information-processing entities. They are different instances of life forms. As pointed by John Hopfield, the ability to perform computations is a key feature of biological organisms (Hopfield, 1994). Such special feature also distinguishes biological phenomena from natural physical processes.

Among the major transitions that have punctuated the history of life on our planet, several great steps involved novel ways of manipulating information and adapting to the external world by means of non-genetic mechanisms. These cellular, physiological, anatomical and behavioral innovations became a key factor in dealing with complex environments. As organisms became capable of processing information in complex ways, they were able of dealing with uncertainty. Intelligent behaviour was largely responsible for the success of costly multicellular systems as a consequence of their potential for being autonomous agents capable of storing and processing epigenetic information. A milestone in this race towards increasingly complex ways to process information was, as Jablonka and Lamb (2006) pointed out, the emergence of the neural individual:

> "with a high level of internal integration and the ability to make rapid adaptive responses. However, the emergence of the neural individual meant more than a change in the nature and speed of adaptation. Neural processing led to behaviour based on sensory perception, and this in turn led to a form of communication between individuals that did not require contact or the transmission of physical material from one to the other. This mode of information transmission had interesting consequences, one of which was the ability of animals to learn from others through perceiving their behaviour or the outcomes of their behaviour, i.e. it led to social learning."

Different kinds of neural structures can be identified within the long road from cellular systems with simple sensors to full-fledged brains (Rose, 2005). After cell membranes became complex enough,

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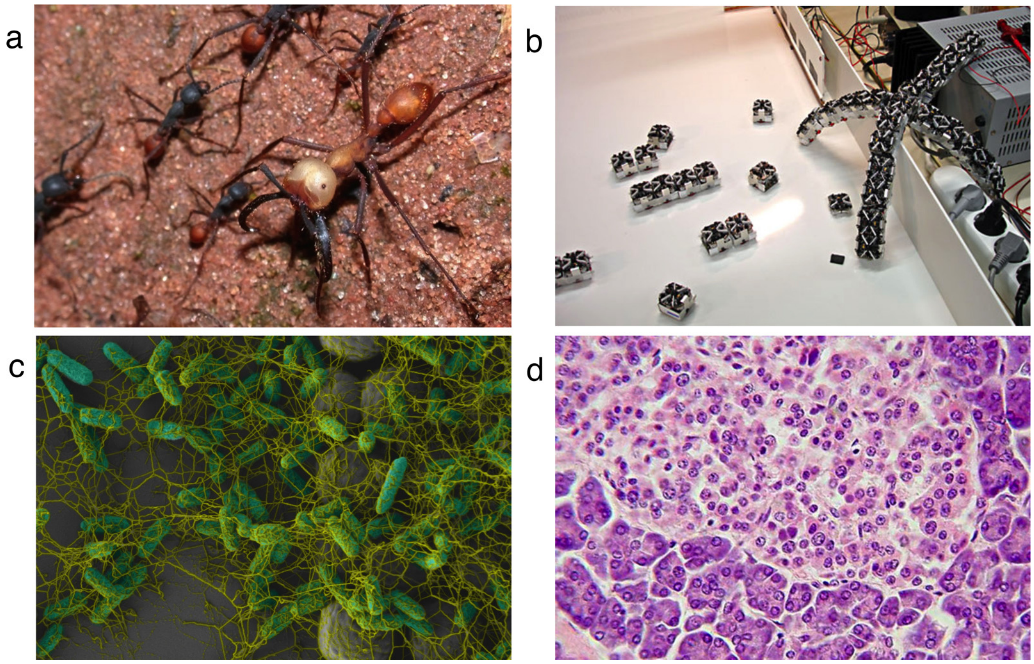

Fig. 1. Collective decision making in natural and artificial systems. Many different systems are capable of making decisions that are based on detecting and processing information in ways that require population responses. In social insects, such as the army ants in (a), very large swarms emerge out from local interactions (Image by Alex Wild, distributed under a CC0 1.0 license). Swarm robotics (b) has taken some advantage of these collective patterns. In microbial systems collective responses are often associated to the formation of so called biofilms (c) where spatially structured organisations emerge (image by Ronn Friedlander and Michael Bucaro). In physiology too organ-level functions, such as glucose regulation by the pancreas (d), result from sensing and responding to external signals (image by H.E. Färbung, distributed under a CC 2.5 license).

it became possible to process information in terms of chemical signals and internal metabolic responses. Later on, movement, coupled to these signalling phenomena, allowed autonomy to develop beyond simple changes of metabolite concentrations. The rise of multicellularity added a new potential for using specific types of cells facing the external world, whereas the rest could be freed from a direct interaction with the environment. As multicellular life forms further evolved, something close to "behaviour" could be defined.

Along with this neural individual, another major transition of evolution led to the emergence of societies formed by relatively simpler agents (such as ants, termites or bees) capable of performing complex cognitive actions at the collective level. Social insects belong, at the individual level, to the ganglion-based organisation of neural processing. But they reach a higher level of complexity by making these already sophisticated systems to interact within a much more complex, parallel and spatially distributed entity: the super organism (Hölldobler and Wilson, 2008). By means of their potential for gathering and storing information, systems displaying collective intelligence are capable of making decisions about their internal states, environmental resources, protection against damage or foraging strategies (Deneubourg and Goss, 1989; Camazine et al., 2003). An example of these systems is given by army ants (Fig. 1a) which are blind and communicate mostly by means of pheromones, and yet involve millions of individuals that are capable of coherently exploring vast areas in the rain forests.

In some ways, collective intelligent systems, particularly ant colonies, reminds us the way brains work (Hofstadter, 1979; Gordon et al., 1991; Solé and Goodwin, 2001). However, in such comparison ants must be seen as a fluid neural network (Solé et al., 1993) since no stable connections between pairs of ants exist. To a large extent, the cognitive potential associated to social insect behaviour is tied to both individual and collective responses to stimuli. On the one hand, ants and other social insects are capable of responding in sharp, almost digital ways to external inputs (Millonas, 1993; Gordon, 1999; Gordon, 2010; Camazine et al., 2003; Detrain and Deneubourg, 2006; Sumpter, 2006), often by exploiting bifurcations and nonlinearities as their source of internal structuring and decision making (Deneubourg et al., 1989; Bonabeau et al., 1996a; Bonabeau et al., 1999). Such features have been successfully implemented using swarms of robots (Fig. 1b).

The emergent field of synthetic biology gives us a novel way of exploring collective intelligence. It provides the adequate tools to modify and redesign living systems, instead of building artificial agents or making mathematical models. We could properly claim that we can create living micro-robots by modifying the behavioural repertoire of existing cells. In this paper we outline this synthetic biology path, using microbial engineered designs. Microbes are capable of integrating sensory information, store memories and display behavioural control (Ben-Jacob, 2009; Lambert and Kussell, 2014; Vladimirov and Sourjik, 2009). They thus incorporate several relevant components required to build or design complex decision making systems. However, the types of computations and information processing systems exhibited by microorganisms, are in many cases different from those displayed by ant colonies. Is it possible to engineer bacteria or other single-celled species in such a way that they behave as a collective intelligence? We label this field as *synthetic collective intelligence* (SCI). Such type of collective response can be found in biofilms (Fig. 1c) and some general principles are common to tissues (Fig. 1d).

Microbial systems are composed by non-neural agents (Reid et al., 2015). Their potential for performing computations in a collective fashion is determined by their self-organisation properties (2001). These include nonlinear dynamics, emergent behaviour and multistability. In this paper we aim to present several well defined examples of how to design a synthetic living system that is capable of capturing the key features of collective intelligence.