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# What Could Models of Superorganismal Cognition Offer to Embodied AI?

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**Abstract.** Superorganisms such as ant or honeybee colonies exhibit extraordinary collective intelligence, such as an ability to identify and choose the best available nest site in an uncertain world. This collective cognition is inextricably reliant on the embodiment of individual agents, specifically their movement through space. We have recently developed models of superorganismal cognition based on a compelling analogy with techniques in Bayesian statistics, which are likewise aimed at grappling with the uncertainty and incompleteness of real data sources. These models foreground some potential lessons for the design of embodied artificial intelligences, such as robot swarms. For example, the spatial distribution of independently judging agents can convey valuable information, relaxing expectations that regular inter-agent ('inter-neuronal') communication is necessary for cognition, which points to the potential of minimal field swarm robotics. Meanwhile, the importance of individual heterogeneity to effective and resilient collective cognition in biology suggests great potential in this area for engineering.

## 1. Introduction

Many animals live in groups and make common actions together, such as choosing foraging patches or resettling to a new home. Such collective action has been described as 'collective cognition' [1], and the associated collective information processing is particularly remarkable in social insects such as ants or honeybees [2]. This is because their close-knit societies resemble single organisms, or 'superorganisms' [3], and their cognition in certain respects resembles a single brain [4, 5]. Such collective 'brains' have recently been described as 'liquid brains', where the individual 'neurons' have mobility and transient connections with each other, rather than the persistent architecture of interactions seen in 'solid brains' [6]. Indeed, the spatial movement of individuals within superorganisms is undoubtedly key to their cognition, and by association, so is their embodiment. This might be something of a statement of the obvious, but working in artificial intelligence, one may tend to under-appreciate the information that is intrinsically conveyed by an embodied agent's decision to be in one location rather than another. The field of 'movement ecology' has emerged in the scientific push to understand animal movement within the broader context of internal animal states, traits, constraints and interactions among themselves and with their environment [7]. In our own effort to make clear the inseparable relationship between movement, environment and superorganismal cognition, we have recently developed a new perspective that highlights the close analogy between colony behaviour and certain Bayesian statistical methods. These models may indicate some future directions for embodied artificial intelligence.



## 2. Models of Superorganismal Cognition

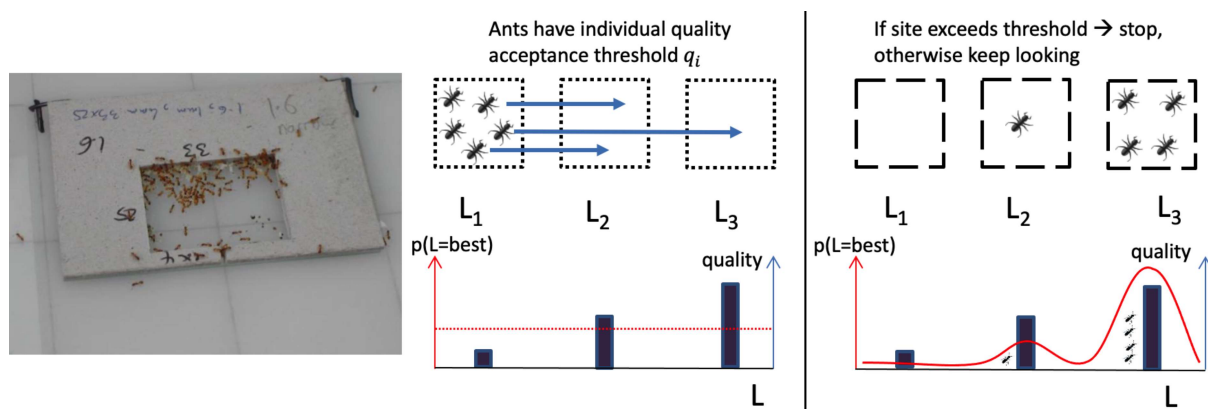
### 2.1. Movement for Foraging

The acquisition of food resources is a key problem for any living organism. For superorganisms like ant or honeybee colonies, there is the added challenge of acquiring food not only for oneself, but for the group. In this case, one would expect the evolution of a colony-level foraging strategy that maximizes colony fitness (i.e. long-term reproductive success). In the ‘ergonomic’ stage of a colony’s life cycle, the focus is on exponential growth, where workers collect food to be ‘reinvested’ by the egg-laying queen into more and more workers. This has parallels with betting, where one can reinvest one’s winnings into bigger bets. The optimal strategy there is a ‘Kelly’, or probability-matching, strategy whereby one makes bigger bets on more likely outcomes (e.g. to put a bigger bet on the favourite in the horse race). If one sees the environment as having a variety of probabilities of food payoff in different locations, then one would expect the colony to ‘allocate’ (via self-organization) a higher proportion of worker ants to food patches with more reliable yields (probability matching behaviour has recently been identified in honeybees [8]). In an unknown environment, an individual is initially unaware of the distribution of such probabilities, but the distribution can be estimated via Markov chain Monte Carlo (MCMC) methods such as the Metropolis-Hastings algorithm; in this case the ‘walker’ is the animal itself [9]. MCMC walking naturally results in an individual spending proportionally more time in regions of higher probability (probability matching), following a ‘burn in’ exploration period. Coordination via pheromones could speed up the dispersion of walkers across the space [10]. The colony’s performance is maximised when the distribution of ants across the environment, as represented by a probability distribution, best matches the patch payoff probability distribution, which can be quantified using the Kullback-Leibler divergence. Thus, we see the relevance of information theory measures in the evolution of (embodied) movement strategies, beyond the application of information theory to e.g. sensory-motor coordination [11], and could be seen a macro-level expression of the ‘principle of information self-structuring’ [12]. Such a MCMC movement strategy is inherently relevant to superorganisms because probability matching as a strategy is only realisable with a ‘bank’ of organisms, permitting bet-hedging; it would not be possible or desirable for a single organism.

### 2.2. Movement for Nest Site Selection

Apart from finding food, obtaining a good place to live is of fundamental importance to most animals, and this certainly the case for superorganisms like colonies of honeybees or ants. The ant *Temnothorax albipennis* is very good at choosing between different nest site options, a type of ‘best-of-n’ problem [13]. This is despite the fact that individual ants do not need to make direct comparison of the options in order for the colony as a whole to end up at the best available site [14, 15]. This is because if a number of ants simultaneously explore the options, and accept/reject depending on an individual quality threshold, a larger number will tend to accumulate at higher quality sites (Figure 1).

We have developed a model of this nest-finding process [16] as being analogous to Approximate Bayesian Computation (see Sunnåker et al. for an introduction to ABC [17]). One might call the ants’ behaviour *Spatial* Approximate Bayesian Computation (‘SABC’, see Algorithm 1.). Essentially, the individual acceptance or rejection of nest sites can be compared to the accept/reject of simulated parameter values in ABC, except in SABC the accept/reject is enacted by the physical (embodied) movement of an agent to a different location. Just as after the accept/reject of a large number of parameter samples, one obtains a posterior distribution for that parameter, here we argue that the distribution of ants over the environment can be seen as a posterior estimate of the probability that each location is likely to be the best available nest site. For the colony to make the best choice, then, it simply needs to identify the highest probability location: where most of its own worker scouts have decided to put themselves.



**Figure 1.** Simple model of superorganismal nest site selection. Left: real ants (size  $\sim 2\text{mm}$ ) leaving an artificial nest site that has been destroyed (roof removed). Right: Simulated non-interacting ants inspect nest sites and compare quality observations to an internal threshold. If this is exceeded, they stop searching, otherwise they keep looking for alternatives. Their macroscopic distribution approximates the posterior distribution of location qualities. Four out of five ants at location 3 corresponds to an 80% probability it is the best one.

Additional mechanisms to allow inter-agent interaction can be included, such as the one-to-one leading of naive workers to high quality sites (‘tandem running’), which we compare to particle filtering (preferentially sampling important parts of the distribution) [16].

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**Algorithm 1:** Pseudocode for simple SABC nest finding method.

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**Result:** probabilities  $p_L$  each location is best

initialize:  $N$  ants, true location  $L$  qualities  $Q_L$ , individual ant priors re. location

qualities  $\mu_{iL}, \sigma_{iL}$ , collective decision threshold  $p_{quorum}$

**while**  $\forall p_L < p_{quorum}$  **do**

**for**  $ant\ i=1:N$  **do**

    rand. draw from  $L$  priors  $q_{iL} \sim \mathcal{N}(\mu_{iL}, \sigma_{iL}^2)$

    move to  $L$  with highest draw

    make quality observation

    update  $q_{iL}$  for chosen  $L$  using Kalman filter

**end**

  calculate each  $p_L = \Sigma_L(\text{ants at location } L)/N$

**end**

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### 3. Relevance to Embodied Artificial Intelligence

The models of foraging [9, 10] and nest site selection [16] foreground some interesting insights into the nature of embodied intelligence, which are also relevant to the design of embodied artificial intelligences, especially robot swarms. Here are three ideas.

First, at least in the *Temnothorax* ant system we have examined, the spatial distribution of individuals conveys valuable information, beyond the knowledge of any single agent. This information is emergent from the independent action of many individuals across the environment, and is exploited in nature via a quorum-sensing mechanism, where agents judge the local agent density to estimate the number of nestmates in the same place [18]. In an artificial system, a user

could exploit a similar self-organized approach, or would also have the option of simply observing the distribution of agents from the ‘top down’, assuming some kind of tracking or ‘bird’s-eye view’ is possible. That is to say, the  $p_L$  in Algorithm 1 can be estimated/calculated by the agents within the system, or by an onlooker. As we develop cyber-physical systems, we should not lose sight of what the overall physical view of system components is telling us. The MCMC-based models of movement also point toward the applicability of information-theory-based insights at higher levels of (biological) self-organisation, at the interaction between colony movement strategies and their ecology. In the swarm robotics context, one indeed will be aware that that movement strategies for individual robots must be optimised for group-level performance. This is because swarm performance is emergent from individual interactions, sometimes purposeful cooperation. To develop individual controllers via artificial evolution, information-theory-based metrics comparing the swarm’s spatial distribution to various user-defined targets could be employed as objective functions, in an exploratory fashion. This holistic focus on finding the ‘shape’ of high-performance swarms goes beyond thinking about information theory descriptions at the individual level, for instance in sensory-motor coordination.

Second, interaction between agents can be rather limited, or not needed at all, to nevertheless obtain useful information from their macroscopic distribution. Pointing in this direction, a recent study has confirmed the value of less intensive interactions in robot swarm decision-making [19]. For a user deploying truly minimal field swarm systems, for example biodegradable floating balls that change colour when in a pollution patch [20], the probability distribution of the most polluted patches could still become evident even if the ‘robots’ do not communicate. Nevertheless, one might still venture to describe this as some form of cognition, emergent from the encounter with the environment.

Third, biological research points toward the value of heterogeneity in behavioural thresholds for more accurate and resilient collective decisions [21, 22]. For instance, a small proportion (3-12%) of *Temnothorax* workers are persistent in exploring during a nest-site decision [23], which may correspond to high acceptance threshold ‘picky’ ants who keep looking for the very highest quality nest sites. This may ensure that the best option (global maximum) is usually discovered eventually. A distribution of behavioural traits in robot swarms could likewise be key to unlocking higher performance in tasks such as exploration and decision-making. Obtaining a suitable trait distribution is likely to rely on a mixture of pre-deployment (offline) optimisation in artificial evolution and laboratory trials, and also online flexibility to adapt to the actual environment. I have suggested that this flexibility can be understood as part of a general ‘phenotypic plasticity’ needed for successful embodied intelligence [24]. Neurons in a brain are not homogeneous, neither in their morphology nor their connectivity, and likewise to realise embodied artificial intelligence we should be more willing to experiment with agent heterogeneity, either by design or accident. This suggests that traditional engineering paradigms that seek to control variation and noise will need to be somewhat inverted. There is some growing awareness in e.g. the field of cyber security that deliberately engineered differences in components can make systems more resilient [25], but such insights have yet to permeate more broadly. Although these three ideas arise from trying to model the statistical computation of superorganismal cognition, they are not dependent on specific model details, and could be among general features of distributed embodied cognition.

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