

# *Swarm Cognition: an interdisciplinary approach to the study of self-organising biological collectives*

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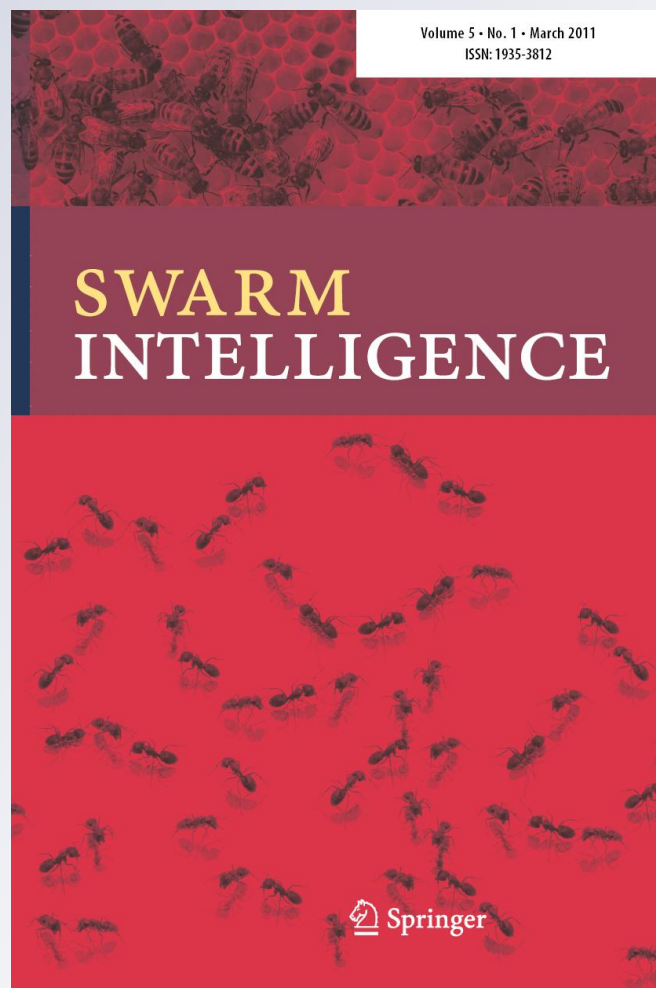
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# Swarm Cognition: an interdisciplinary approach to the study of self-organising biological collectives

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**Abstract** Basic elements of cognition have been identified in the behaviour displayed by animal collectives, ranging from honeybee swarms to human societies. For example, an insect swarm is often considered a “super-organism” that appears to exhibit cognitive behaviour as a result of the interactions among the individual insects and between the insects and the environment. Progress in disciplines such as neurosciences, cognitive psychology, social ethology and swarm intelligence has allowed researchers to recognise and model the distributed basis of cognition and to draw parallels between the behaviour of social insects and brain dynamics. In this paper, we discuss the theoretical premises and the biological basis of *Swarm Cognition*, a novel approach to the study of cognition as a distributed self-organising phenomenon, and we point to novel fascinating directions for future work.

**Keywords** Swarm Cognition · Social ethology · Cognitive neurosciences · Self-organisation · Artificial life

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## 1 Introduction

The term Swarm Cognition is the juxtaposition of two concepts that evoke, on the one hand, the power of collective behaviours displayed by natural swarms, and on the other hand the complexity of cognitive processes in the vertebrate brain. Behind the words, there is a relatively young and genuine interdisciplinary effort which aims at developing an alternative epistemological perspective on cognition that may help to bridge the still existing gap between behavioural and neuroscientific explanations of cognitive phenomena (Marshall and Franks 2009; Trianni and Tuci 2009). The aim of this paper is twofold: first, we intend to illustrate the theoretical premises and the empirical evidence underlying this relatively novel approach to the study of cognitive phenomena. Second, we aim at pointing the reader to those open challenges and interesting research questions that are specifically brought about by the Swarm Cognition perspective on cognition. We expect that, by reviewing theoretical and methodological bases as well as by pointing to fascinating directions for future work, we contribute to open a space in which scientists from different disciplines with a common interest in cognition can constructively interact and nurture this challenging idea with solid empirical data.

Recent findings suggest that at a certain level of description, operational principles used to account for the behaviour of natural swarms turn out to be powerful tools in identifying the neuroscientific basis of cognition. In other words, the massively parallel animal-to-animal interactions which operationally explain cognitive processes of natural swarms are functionally similar to neuron-to-neuron interactions which underlie the cognitive abilities of organisms, including humans (see Couzin 2009; Visscher and Camazine 1999). Starting from these observations, Swarm Cognition represents a novel interdisciplinary perspective that aims at unifying the study of cognitive abilities in biological collectives by looking at them as self-organising social entities. Self-organisation is considered to be the common mechanism that allows relatively simple units (e.g. ants, bees and neurons) to display complex spatio-temporal patterns. As a consequence, Swarm Cognition aims at explaining colony behaviour and cognition in terms of self-organising processes determined by the interaction among the low-level units and their environment. In other words, Swarm Cognition encourages scientists to look at the rules of interaction that describe the behaviour of natural swarms as effective operational principles which can be used to identify the neural basis of cognition in neural assemblies.

Within the Swarm Cognition framework, what counts as “cognitive” goes beyond the phenomena that can be ascribed to single biological individuals and extends to group-level behaviour (Goldstone and Gureckis 2009). Cognition can be recognised both in individuals and in groups because the properties of cognitive behaviour do not depend on the locus of the process. For example, it is possible to talk about cognitive behaviour in the context of decision-making performed by ant colonies, despite the fact that no individual ant is aware of the full range of possible alternatives or possesses an explicitly programmed solution (Franks et al. 2003). Moreover, cognition is at the same time characterised as information processing and adaptive behaviour. This “dual identity” goes beyond the common dichotomy in which cognition is either related to behavioural phenomena (Pfeifer and Scheier 1999), or to the neural mechanisms that support cognitive processes (Schartz 1990). Swarm Cognition postulates that these two aspects are deeply intertwined, and that a holistic approach is necessary to advance our current understanding. By studying cognition as a distributed phenomenon emerging from the self-organisation of simple units embodied and situated in their ecological niche, useful insights can be obtained into both the underlying mechanisms and behavioural manifestations of cognition.

Research work in Swarm Cognition aims at providing a principled understanding of the mechanisms of cognition through the use of various existing methods in neuro- and cognitive sciences, as well as through the development of new methodologies based on the design of autonomous artificial swarm systems, that is, simulated or real autonomous agents capable of displaying cognitively rich behaviour (e.g. artificial agents that focus their attention on relevant features of the environment, categorise them and make decisions in multiple-choice conditions). The glue that holds diverse disciplines together has to be found in the theoretical perspective which advocates that cognition is the emergent result of the collective dynamics of either interacting autonomous agents or basic control units in a single agent, and in which the single interacting entities have no reference to the global pattern or cognitive phenomenon they are contributing to create.

Although Swarm Cognition is an interdisciplinary field that crosses traditional boundaries between classic disciplines in neuro- and cognitive sciences, the research activities carried out in different domains are meant to be highly integrated and fully complementary. Cooperation among different scientific disciplines is achieved through a comparative and a synthetic approach. The comparative approach calls for the recognition of the mechanisms underlying cognitive processes in both brains and swarms, and promises the identification of general rules that support the cognitive abilities of organisms at different levels of biological complexity. Such rules should therefore be general enough to provide a principled understanding of the cognitive process under study, so that they can be exploited and engineered within artificial swarm systems. The synthetic approach proceeds through the synthesis of the cognitive processes under study in artificial swarm systems, and aims at directly generating and understanding the mechanisms relevant for the cognitive processes, by employing stochastic models, dynamical systems theory, or network theory. This approach can lead to the identification of the rules that embrace the organisational principles of the system. Finally, by confronting artificial and natural systems, research work in Swarm Cognition should attempt a generalisation of the discovered principles. Clearly, different systems may be incompatible when observed at a microscopic/individual level. However, at a macroscopic/system level, it should be possible to identify common features that enable us to isolate the mechanisms exploited to bring forth cognitive processing. The identification of such mechanisms constitutes the main scientific output of the research work in Swarm Cognition.

The paper is organised as follows. In Sect. 2, we briefly introduce the concept of self-organisation and we illustrate what are the novelties in the Swarm Cognition approach, and how much it builds upon existing scientific disciplines. Sections 3 and 4 illustrate two different ways in which bridges across different disciplines can be built in search of the distributed, self-organised mechanisms that support cognition. In particular, in Sect. 3, we review research work in which cognitive processes are recognised in the self-organised behaviour of natural swarms. This work, described in Passino et al. (2008), models the nest site selection behaviour of honeybee swarms, and recognises processes that effectively correspond to attention and short-term memory. Such processes, however, are not observed at the level of the individual insect, but rather pertain the level of the swarm behaviour. In Sect. 4, we review the work described by Marshall et al. (2009), drawing a parallel between nest site selection behaviour in ants and honeybees and brain dynamics during decision-making in a perceptual choice task. The authors show that the swarm behaviour can be described by the same dynamical system that was proposed for decision-making by Ratcliff and Smith (2004). In Sect. 5, we argue that the Swarm Cognition approach can progress through the use of a particular type of simulation model, namely swarm robotics models, in which control systems are designed to guide a group of autonomous embodied agents required to cooperatively solve a specific task. Each section concludes with a discussion of open research questions and by offering some ideas for future work.

## 2 Self-organisation in natural swarms

Swarm Cognition has its foundations in the studies of self-organising systems, particularly biological systems that can display complex, adaptive behaviour. The notion of self-organisation started to be discussed in the mid-twentieth century by a multi-disciplinary group of scientists, such as the thermodynamicists Nicolis and Prigogine (1977) or the cyberneticians Ashby (1962) and von Foerster (1960). Self-organisation refers to a spatio-temporal pattern that can be observed in a system (e.g. a physical structure or a temporal organisation), which is not explicitly programmed in the individual components of the system, but emerges from the numerous interactions among them. Each component is subject to simple rules, which are dependent only on the local configuration of the system, without any reference to global properties. Early studies on self-organisation mainly focused on physical rather than biological systems. To date, it has been recognised that certain behaviours of insect populations can be considered self-organised (Camazine et al. 2001). This is not a trivial discovery, also considering that the complexity of the individual insects—with their sensing, motor and cognitive abilities—could allow for alternative explanations of the group's organisation. Instead, rather than being a limiting factor for self-organisation, the individual abilities enhance the number and the complexity of the self-organised patterns that can be observed in animal collectives, far beyond the possibilities of non-biological systems (Detrain and Deneubourg 2006). For instance, it has been shown that self-organised behaviours can find optimal solutions to complex problems, such as ants choosing the shortest path from the nest to a foraging location (Deneubourg et al. 1983, 1990). To date, self-organised behaviours have been demonstrated in real biological societies, especially in—but not limited to—social insects. Much work has been devoted to the study of collective motion in fish, birds and mammals, as well as to collective decisions, synchronisation and social differentiation (for some recent reviews, see Camazine et al. 2001; Couzin and Krause 2003; Couzin 2007; Sumpter 2010; Franks et al. 2002; Strogatz 2003).

The basic ingredients of self-organisation are often recognised in *multiple interactions*, which generate *positive* and *negative feedback* processes that allow the system to amplify certain *random fluctuations*, and to control the evolution of a coherent spatio-temporal pattern. A self-organising system is therefore able to achieve and sustain a certain spatio-temporal structure despite external influences (Camazine et al. 2001). In a biological system like an ant colony, however, the behaviour displayed by the single individuals can be modulated by some environmental factors, as well as by the needs of the colony. External and internal factors can therefore influence the system organisation, which adaptively responds to the newly encountered conditions (Garnier et al. 2007). In this case, the self-organising system can be considered a complex dynamical system close to a bifurcation point. This means that the system, upon variation of some control parameters—e.g. temperature or population density—rapidly changes, presenting new spatio-temporal patterns—e.g. a new type of collective behaviour or physical structure. The formation of these patterns is also dependent on random fluctuations, which play an important role in the organisation of the system: when at the bifurcation point, these fluctuations allow the system to “choose” among the new appearing solutions. Finally, self-organising systems are often distributed within their environment. As a consequence, positive feedback mechanisms allow the amplification of some information found by one or a few system components, enabling the system as a whole to promptly react to such local, weak environmental signals.

The latter remarks are particularly relevant for Swarm Cognition studies. Insects in a colony are capable of collectively retrieving, distributing and processing information, as a result of a sophisticated network of interactions among individuals (Detrain et al. 1999;



Detrain and Deneubourg 2006; Garnier et al. 2007). Based on this evidence, several scientists have recently suggested that it is possible to ascribe cognitive abilities to the insect colony, as emerging from a self-organising process. One important goal of Swarm Cognition is exactly the recognition and the study of the cognitive abilities that pertain to collective systems (see Passino et al. 2008 and Turner 2011 within this issue). Such cognitive abilities need to be precisely described and explained in terms of self-organising processes that involve multiple interactions among the individual units of the system. In this way, Swarm Cognition aims at uncovering the self-organising basis of the cognitive processes observed in collective systems. Collective mechanisms may prove to be functionally similar to the mechanisms observed in the vertebrate brain (Marshall et al. 2009), as we shall discuss in Sect. 4. In this respect, Swarm Cognition aims at building bridges between ethological studies of collective behaviours, and experimental/neuro-scientific studies of cognitive processes.

The above discussion suggests which are the peculiar features that characterise Swarm Cognition with respect to other disciplines. In our view, Swarm Cognition partly falls in the larger field of swarm intelligence, especially for those studies that focus on the recognition of the cognitive abilities of collective systems, be they natural or artificial. However, Swarm Cognition addresses fundamental questions that are normally ignored in swarm intelligence studies: (i) What are the cognitive processes brought forth by the colony while performing a given behaviour? (ii) What are the mechanisms that support the emergence of the observed cognitive abilities? (iii) Does the colony present cognitive abilities that are not commonly observed, and under what conditions does this happen? Experimental studies in natural and laboratory conditions should be performed to verify the claims about the cognitive abilities attributed to the collective system, and to uncover the dynamics of the system under study. On the other hand, Swarm Cognition extends beyond the boundaries of swarm intelligence by linking to studies in cognitive neurosciences. The novel contribution of Swarm Cognition to such fields consists in proposing a different epistemological perspective that puts together information processing and adaptive behaviour. The ultimate goal is to find general mechanisms supporting cognitive behaviour at different levels of biological complexity, and featuring universality and optimality properties. Finally, as we shall discuss in Sect. 5, Swarm Cognition can contribute to artificial intelligence and artificial life by exploiting the acquired knowledge to synthesise innovative artificial systems presenting cognitive abilities based on distributed, self-organising mechanisms.

### 3 Recognising cognition in natural swarms: honeybee swarm cognition during nest-site selection

In honeybee (*Apis mellifera*) nest-site selection, a cluster is formed by the colony splitting itself when the queen and about half of the old colony depart and assemble nearby, often on a tree branch (see Fig. 1(a)). To find a new home, “scout” bees from the swarm cluster begin to search a large area for a suitable new nest-site, typically in the hollow of a tree. Scouts assess the quality of sites based on cavity volume, entrance height, entrance area, and other attributes that are correlated with colony success. Bees that find good sites return to the cluster and their initial number of waggle runs or “dance strength” (with each run communicating the angle and radial distance to the nest-site via the angle the run makes relative to the sun and the length of the run) is in proportion to the quality of the nest-site. Such bees will revisit the site many times, but each time they return to the cluster their dance strength decreases until they no longer dance. The number of recruits to each nest-site is in



**Fig. 1** (a) Detail of the surface of a swarm of honeybees (*Apis mellifera*). When searching for a new home, honeybees form a dense cluster, or swarm, on a tree branch or other suitable structure. The swarm consists of several thousand bees, with the queen at their centre. Scout bees depart from the swarm, discover potential nest sites in hollow tree-trunks or similar cavities, and return. On returning, scout bees advertise the vector of their discovery by performing “waggle-dances” on the surface of the swarm (Von Frisch 1967), which are followed by other bees that may then fly off to find the advertised site themselves (photo: Thomas Schlegel). (b) Tandem-running rock ants (*Temnothorax albipennis*). During house-hunting, scouts of the genus *Temnothorax* discover potential nest sites in small cavities, then return to the old nest to recruit others to their discovery. Initially recruitment is by a slow-process known as “tandem-running”, where one ant physically leads another and thereby teaches them the route (Franks and Richardson 2006), so they can in turn recruit others (photo: Tom Richardson)

proportion to the number of dances for each site on the cluster. “Unemployed” scouts either rest or seek to observe dances. If they easily find a dancer, they get recruited to a relatively high quality site. If they must wait too long to find a dancer, this means that there are not many good nest-sites currently being assessed so they go explore the environment for more sites. There is a quorum-sensing process at each nest-site, where once there is a certain number of bees at the site, the bees from that site “choose it” by returning to the cluster to prompt lift-off and guide the swarm to its new home. There is significant time-pressure to complete the nest-site selection process as fast as possible since weather and predators pose significant threats to an exposed colony. However, enough time must be dedicated to ensure that many bees can conduct independent evaluations of the site and all agree that it is the best site found. Hence, during nest-site selection the swarm optimises a balance between time minimisation and site quality choice maximisation.

Elements of a honeybee swarm performing nest-site selection can be viewed as a physical basis for group cognition mechanisms (Passino et al. 2008, 2010). Individual bees are cognition units interconnected via dances and cues, and sensory units that are allocated to either search or nest-site assessment tasks. Nest-site quality evidence accumulates in parallel for each candidate site, is built on “early” sensory processing and bee-to-bee communications, and is held in a spatially distributed group-level memory. This “group memory” is encoded in multiple dancing bees on the cluster and aggregates of bees at candidate sites. The group memory at the cluster is a group-level estimate of the relative site qualities (proportionally more bees dancing for a site indicates it is of higher quality), while at the nest sites it represents the swarm’s current preferences (more bees at a site indicates that the swarm thinks the site is of higher quality and is hence preferred). A second layer of “late” processing is achieved at several locations in the swarm. For instance, at the cluster when recruits follow



randomly encountered dances, the number of recruits to each site is proportional to the total number of dancers for each site, which is a group memory. When it is difficult to locate a dancing bee, workers are allocated to search for potential nests rather than to nest-site assessment, and this is also a clear use of group memory. Layered processing occurs at the nest sites during quorum sensing which is a parallel self-referential check of swarm preference exceeding a threshold. To provide justification that this Swarm Cognition perspective is more than just an extended analogy, Passino et al. (2008, 2010) first conduct a series of simulated behavioural tests to evaluate the ability of the swarm to (i) discriminate between site qualities even in the presence of significant individual bee nest-site assessment noise, (ii) avoid being misled by multiple inferior distractor nest sites via parallel processing and simultaneously focus on the best sites, and (iii) order the percentage of choices for each site according to relative nest-site qualities and thereby avoid negative context-dependent effects on choice performance. Next, they show that Swarm Cognition mechanism parameters that represent both early and late processing have been tuned by natural selection to provide a balance between speed and accuracy of choice. Moreover, the key determinant of Swarm Cognition success, accurate group memory, is a result of this same balance. The analysis at multiple levels illustrated by Passino et al. (2008, 2010), spanning from mechanisms and behaviours to the adaptation level, serves to solidify connections between the biology of social insects, neuroscience, psychology, and cognitive ecology.

While the focus of Passino et al. (2008, 2010) was on honeybees, the *methodology* may represent a *generic* approach to the scientific investigation of group decision-making in Swarm Cognition. This methodology entails: (i) construction of a model that is validated with experiments, (ii) development of a deep understanding of the physics, elements, communications, and low/high level dynamics of the sociobiological process in order to identify the physical basis of cognition; (iii) execution of behavioural tests with both experimental and modelling approaches, and (iv) consideration of the robustness and adaptation of the decision-making via model-based simulations of how the perturbation of experimentally validated behavioural parameters affects group-level performance. This methodology demands attention to physics and biology, yet admits that models have value in conducting certain types of behavioural tests (ones that may be difficult to administer in experiments) and evaluations of adaptation (that are likely impossible to study experimentally).

There are a number of future directions that may be fruitful to investigate in the study of honeybee Swarm Cognition. First, there is a need to study cognition processes during other modes of hive operation (e.g. during social foraging). Second, it would be interesting to explore if higher-level cognition processes are using the group memory in the swarm. For instance, can a swarm exhibit classical conditioning? For this, we would need to find a stimulus that gives rise to some swarm response. Then, we would find a new stimulus that we can associate with the first stimulus (e.g. by presenting it before the first stimulus). Then, after repeated trials where we paired the two stimuli to get the response, we would determine if the new stimulus could give rise to the same response as the first stimulus, without presentation of the first stimulus. The swarm would have then learnt a new stimulus-response pair. At first glance, one would think that the swarm could exhibit classical conditioning since individual bees can do so. Yet, we would be seeking classical conditioning at the group, not individual level. Evidence that classical conditioning occurred at the group and not individual level would be present if no individual learnt the new stimulus-response pairing during the swarm (group) training process.

#### 4 Drawing parallels between mechanisms in swarms and brains

As the previous section showed, there are potential qualitative parallels between neural-based cognition, and group cognition in colonies of social insects, such as honeybees. It is interesting to examine how far the analogies between neural and swarm cognition can be taken. In particular, can more rigorous and quantitative analogies be made, and is there any benefit from doing so? Just as the mechanism of decision-making in a social insect colony can be understood through observation of the individual behaviours of its components, so modern neuroscientific techniques such as single-neuron recording allow the neural mechanisms behind individual decision-making to be discovered. The neural basis of decision-making in vertebrate brains has now been extensively studied through well-established perceptual decision-tasks, combining neural recordings with manipulation of decisions through varying task difficulty (e.g. Roitman and Shadlen 2002).

Various “competing accumulator” models exist to describe decision-making by neural populations. As shown by Bogacz et al. (2006), under appropriate parameterisations several of these apparently distinct models can be shown to be equivalent to each other. A particularly influential model is known as the “leaky competing accumulator”, or Usher–McClelland model (Usher and McClelland 2001). This model represents a decision-making process implemented by populations of sensory neurons subject to noise, and exciting accumulator (or integrator) populations. The decision problem is to select the stronger signal from the sensory populations. The accumulator populations in their turn suppress each other’s activation, so that the larger the activation of one accumulator the greater the strength of inhibition it exerts on the other. These populations also leak accumulated evidence at some rate. When one of the accumulator populations reaches a pre-specified activation threshold, a decision is made for the corresponding alternative. The populations thus modelled and their behaviour match the neural recording data taken during perceptual decision-making tasks (e.g. Roitman and Shadlen 2002). A simplified linear version of the Usher–McClelland model for choice between two alternatives can be expressed as a pair of coupled stochastic ordinary differential equations (ODEs), as described by Bogacz et al. (2006):

$$\begin{aligned}\dot{y}_1 &= I_1 + c\eta_1 - y_1k - y_2w, \\ \dot{y}_2 &= I_2 + c\eta_2 - y_2k - y_1w.\end{aligned}\tag{1}$$

In (1),  $y_1$  and  $y_2$  are the activation levels of the two accumulator populations. These receive input from the sensory neurons corresponding to each alternative, with signal strengths  $I_1$  and  $I_2$ . The signals are subject to Gaussian white noise with mean zero (i.e. a Wiener process  $\eta_i$ ) with standard deviation  $c$  (noise is described as equal for both signals above, but this is not necessary). The accumulators’ activation ‘leaks’ at rate  $k$ , and the accumulators inhibit each other with strength  $w$ . When one of the accumulators reaches a threshold,  $z$ , a decision for the corresponding alternative is implemented.

As noted by several authors (e.g. Visscher 2007; Passino et al. 2008), there are striking parallels between the neural architecture just described, and the decision-processes of social insect colonies searching for a new home, such as described in the previous section for honeybees. To summarise, colonies of ants (genus *Temnothorax*) and honeybees (*Apis mellifera*) periodically search for new nest sites, either due to destruction of the home site, in order to find a superior nearby alternative, or to form a daughter colony through fission (e.g. see Fig. 1(a)). In both ants and honeybees, scouts search for and discover potentially suitable sites, make a noisy assessment of site quality, and then recruit nestmates to evaluate their discovery, via tandem-running in ants (see Fig. 1(b)) or, as described in the previous

section, the waggle-dance in honeybees. The strength of this recruitment is proportional to the perceived quality of the site. When one of the decision populations reaches a threshold, known as a quorum, the colony begins emigrating to the corresponding nest site. One potential model of collective decision-making in social insect colonies describes recruiters committed to each alternative attempting to influence others to switch their commitment directly, again using a pair of stochastic ODEs (Marshall et al. 2009):

$$\begin{cases} \dot{y}_1 = (n - y_1 - y_2)(q_1 + c\eta_{q1}) + y_1(n - y_1 - y_2)(r_1 + c\eta_{r1}) \\ \quad - y_1k + y_1y_2(r_1 - r_2 + c\eta_{r1} - c\eta_{r2}), \\ \dot{y}_2 = (n - y_1 - y_2)(q_2 + c\eta_{q2}) + y_2(n - y_1 - y_2)(r_2 + c\eta_{r2}) \\ \quad - y_2k - y_1y_2(r_1 - r_2 + c\eta_{r1} - c\eta_{r2}). \end{cases} \quad (2)$$

In (2), the  $y_i$  now correspond to the number of scouts voting (i.e. waggle-dancing or tandem-running) for a potential nest site  $i$ ,  $n$  is the total size of the scout population,  $q_i$  and  $r_i$  are respectively the rates of independently discovering and becoming committed to site  $i$ , and of recruiting uncommitted scouts to site  $i$ . Rates  $r_i$  are the rates of recruitment of scouts to alternative  $i$ , that are already committed to the other alternative. A number of independent Wiener processes model noise in each of these rates.

The informal description of neural decision-making and swarm decision-making above yields some apparent similarities, namely populations integrating noisy evidence and competing to reach a decision threshold. Yet, on a more formal level, comparison of (1) and (2) seems to present as many differences as similarities. In particular, (1) is a system of linear equations, whereas (2) is non-linear. On what basis could one hope to find common organisational principles in these decision-making systems at these very different levels of biological complexity, which simultaneously seem to be similar but different? One very compelling idea is to apply optimality theory to analysing the behaviour of these different systems. In other words, the proposal is to take a *functional* approach to comparing the behaviour of these different *mechanisms*. For decision-making, it is reasonable to assume that the speed and accuracy of decision-making constitute a universal currency to be optimised. Organisms should behave so as to increase decision speed while reducing decision accuracy, or vice-versa, according to need. This idea has already been applied to the Usher–McClelland model of neural decision-making by Bogacz et al. (2006). The Neymann–Pearson lemma, familiar to many scientists concerned with data analysis, states that the optimal compromise between speed and accuracy of decision-making over two alternatives is achieved by computing a function of the *difference* in the integrated evidence for each alternative. Bogacz and colleagues showed how the Usher–McClelland model, and the other competing accumulator models that can be reduced to it, can be parameterised to approximate optimal decision-making (Bogacz et al. 2006). By setting the decay and inhibition rates to be equivalent, the Usher–McClelland model can be simplified to a one-dimensional stochastic process known as the drift-diffusion model (Ratcliff 1978), in which the difference between accumulated evidence is integrated to a decision threshold. This procedure of integrating the difference corresponds to the application of the Neymann–Pearson lemma just mentioned, and hence implements optimal decision-making, with the integration threshold being varied to compromise optimally between speed and accuracy of decision-making. Formally, the drift-diffusion model is the continuous-time limit of the sequential application of the Neymann–Pearson lemma (i.e. the ‘sequential probability ratio test’, for which data are assumed to be discrete), and can be characterised as a Brownian-motion process with a constant drift:

$$\dot{x} = A + c\eta. \quad (3)$$

In (3),  $x$  is proportional to the difference in size of the two accumulator populations ( $x \propto y_1 - y_2$ ),  $A$  is the strength of drift and captures the signal in the decision problem, and  $c$  is the standard deviation of the noise in the decision problem. When  $x = 0$  there is no accumulated evidence, and the process continues until either a positive or negative decision threshold is reached. Hence, there is a tendency to move towards the correct decision boundary due to the signal ( $A$ ), but noise ( $c$ ) can push the decision process in the wrong direction, and the decision thresholds can be varied to compromise between speed and accuracy of decisions.

Attempting a similar optimality analysis with the collective decision-making model of (2) gives, in the limit of all scouts being committed to some potential site, a rather more complicated decision process (Marshall et al. 2009)

$$\dot{x} = \frac{n^2}{2} - x^2 - \frac{r_1 - r_2}{\sqrt{2}} + c\eta_r \quad (4)$$

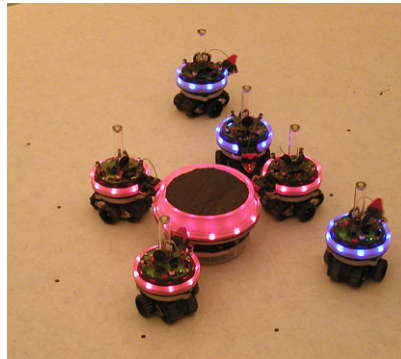
As before,  $x \propto y_1 - y_2$ ; however, now the equation is quadratic rather than linear as in (3). Yet both the signal and the noise in the decision process are scaled by the same factor, so in fact a simple non-linear transformation allows (4) to be expressed in terms of the optimal drift-diffusion model (3) (Marshall et al. 2009).

The analysis just outlined demonstrates how optimality theory can be applied to collective decision-making, and how analytic techniques developed in theoretical neuroscience can be applied to understand social insect colonies. The analysis also shows how social insect colonies may be able to approximate statistically optimal decision-making. Much further work remains, for example in testing the predictions from this optimality analysis with emigrating ant and honeybee colonies. However, work also remains to be done in considering refinements of the decision-making analysis, such as incorporating prior information, but also in considering the optimality criteria used themselves. When importing optimality criteria from the theoretical literature and from other disciplines, it is important to remember that the real maximand for organisms is *fitness*, and the means to maximise this may not be the same in different biological systems, despite apparent similarities between them.

## 5 Swarm cognition and artificial life

As discussed in Sect. 1, the Swarm Cognition epistemological perspective aims at overcoming any body-brain dualism by recognising the significance of bodily, environmental, and neural factors as causal elements of cognition. However, as recently mentioned in Barsalou (2010), neurophysiological and behavioural accounts of cognitive phenomena have not always been converging in the last 30 years of cognitive science research. That is, it has been difficult to unveil causal relationships between neurophysiological and behavioural/environmental variables, without reducing cognition to either the neural or the behavioural domain. This is often due to the characteristics of classic methodological tools in neuro- and cognitive sciences, which restrict the observational domain to either the neurons or the behaviour of an organism. In order to encourage the development of a holistic explanation of cognition, Swarm Cognition is relying on research methods which are complementary to those already used by neuro- and cognitive sciences. In particular, Swarm Cognition intends to exploit artificial life (hereafter, ALife) models as a methodological tool in which neural, behavioural, and environmental factors can be concurrently observed and manipulated. As suggested by Langton (1988), ALife is life made by man rather than by nature. The goal of ALife is to re-create in an artificial world instances of biological phenomena in order to derive general theories about life. There are several different types of

**Fig. 2** Swarm of *s-bots* (see Dorigo et al. 2004, and <http://www.swarm-bots.org>) that cooperate in order to transport an heavy object that cannot be moved by a single *s-bot* (Tuci et al. 2006)



ALife models. Multi-robot or swarm robotics systems are interesting ALife methods that we think can be very helpful to strengthen the Swarm Cognition methodological toolkit. Generally speaking, physical or simulated robots are excellent tools to study brain–body–environment dynamics and their bearing on the emergence of cognitive abilities such as categorisation, decision-making, attention and learning (Harvey et al. 2005).

Swarm robotics is an emergent field of collective robotics that studies robotic systems composed of numerous robots tightly interacting and cooperating to reach a common goal (see Fig. 2). The robots in a swarm are characterised by limited communication abilities, local sensing, and autonomous control. However, they are potentially capable of performing complex tasks by coordinating in a group. Indeed, a peculiar feature of swarm robotics systems is the transfer of behavioural complexity from the individual to the interactions among individuals. Viewed from a Swarm Cognition perspective, robots of a swarm can be considered cognitive units playing either the role of the individual insect in a swarm, or the role of neurons or of an assembly of neurons in the brain. Within the Swarm Cognition framework, this transfer of complexity from the individual behaviour to the interactions among individuals is fundamental to understand how cognitive processes can be supported by distributed systems. Swarm robotics is therefore a valuable means to study self-organisation in embodied and situated models.

It is important to make clear that not all swarm robotics models meet the requirements of Swarm Cognition. There are several swarm robotics models in which the behavioural repertoire of single agents have been explicitly designed by drawing inspiration from the behaviour observed in natural swarms. From our point of view, being loosely or strongly inspired by the behaviour of natural swarms is not sufficient to make a swarm robotic model relevant to Swarm Cognition. Robotics models that “serve the cause” of Swarm Cognition should be designed in order to contribute to the identification of common working principles that underlay the targeted cognitive phenomena. For this, it is important that, whatever is the nature of the scientific contribution of the robotic model, this contribution must be developed within a comparative framework in which what the model delivers in term of scientific knowledge is confronted to existing neuroscientific or ethological knowledge of the modelled cognitive phenomenon. This confrontation can be accomplished in various ways. The model can either be used as an “intuition pump” to develop hypotheses concerning the mechanisms underlying certain cognitive phenomena (see also Dennett 1995), or as a proof-of-concept to show that indeed the considered cognitive phenomenon can be explained by the supposed mechanisms captured by the model.

At present, there are only few robotics models that specifically target issues of relevance in Swarm Cognition. Santana and Correia (2010) describe a study in which a robot is re-

quired to perform a navigation task, including obstacles avoidance, by exploiting a particular visual attention system, which relies on the behaviour of a group of autonomous agents that inhabit its sensory input. These agents search in a collectively coordinated way for obstacles exploiting the ant foraging metaphor. The results show that parsimonious and accurate visual attention, operating on a by-need basis, is attained by making the activity of the visual attention agents modulated by the robot's action selection process. A by-product of the system is the maintenance of active, parallel and sparse spatial working memories. In short, the model exhibits the self-organisation of a relevant set of features composing a cognitive system. This visual attention model has been further extended and validated on physical autonomous robots in a paper published in this special issue (see Santana and Correia 2011).

Morlino et al. (2010) describe a simulation model which aims at studying collective perception in a robotic swarm. The goal of this study is to understand which are the self-organising processes underlying the collective perception of a macroscopic environmental feature, which is not accessible to the individual robots due to their limited perceptual abilities and to the nature of their individual exploration strategies. Therefore, multiple robots need to interact in order to give a collective response that correlates with the macroscopic variable. The results show that the agents rely on two different visual communication strategies which tend either to inhibit or to excite the signalling behaviour of neighbouring robots. The authors conclude their work by pointing to the fact that the presence of two counter-acting mechanisms that regulate the activity of the group is common to systems as diverse as brains and swarms. A positive feedback loop allows to amplify small perturbations and quickly spread information in a system, while a negative feedback loop controls the competition between different options and modulates the information spreading.

Decision-making as well as collective attention and categorisation are definitely cognitive phenomena that may be targeted by swarm robotics models in search for a holistic explanation of cognition. For example, the N-choice problem (i.e. a decision-making problem where the number of alternatives N is a priori unknown) can be instantiated in many interesting robotics scenarios, in which the robots cooperate in order to make the best choice among N available alternatives. The N-choice problem captures the challenges that honeybee are facing when searching for a new nest-site, as illustrated in Sect. 3. A potential robotic scenario, in which the robots are required to solve a N-choice problem, could be one in which environmental features have to be categorised and a selection among multiple possibilities has to be performed. In this scenario, each individual robot does not know how many potential alternatives will be discovered, neither what is their relative quality. Nevertheless, the swarm as a whole has to be able to make good decisions, exploiting a collective process that also accounts for speed-accuracy trade-offs. In the context of decision-making, it is also important to assess the ability of a system to discriminate between comparable options. Many different organisms are recognised to follow the Weber's law in decision-making, which describes the relationship between the magnitude of a stimulus and the intensity perceived (Deco et al. 2007). It is therefore important to study the basic mechanisms behind decision-making in collectives, and to test the adherence with the Weber's law, in order to find comparable dynamics between brains and swarms.

Another research topic is distributed estimation of numerosness. Numbers are entities that, in spite of the efforts of neuroscientific investigations, remain allegedly associated to the domain of logic reasoning. That is, entities that seem to evade any operational definition grounded on the current scientific understanding of the neural basis of cognition. Although recent studies show that numbers and animals' judgements concerning the relative locations of objects into their perceivable surroundings may emerge from similar brain structures and



functions, our explanatory paradigms appear too weak to house logical entities into biologically plausible determinants. This may be due to the limitations of current neuroscientific methods in providing empirical evidence for holistic explanations of brain functioning. Swarm robotics models may be a powerful methodological tool to generate insights on how a group of functionally independent entities may produce phenomena that can be considered embodied instances of logical entities. For example, consider a swarm of robots that must decide whether they are more or less than a given number. In order for the swarm to be able to self-estimate its cardinality, the individuals of the swarm have to be equipped with underlying mechanisms that translate into the language of physical interactions properties such as number and quantities. If it is possible to find the required (cognitive) ingredients to allow the robots to count themselves, we generate powerful hypothesis-testing machines that will hopefully help us to shed light on the neuro-biological basis of numbers and other elements of logic reasoning. Experimentation on human subjects could verify the validity of the proposed models.

## 6 Conclusions

The discussions we have presented in the previous sections depict Swarm Cognition as an intriguing framework for future investigation on cognitive systems. We started from the observation that cognitive processes can be supported by distributed systems, be they composed of a multitude of insects or a population of neurons. In this respect, self-organisation is a key process, which leads the system to adaptively react to external disturbances displaying a coherent response as a result of a sophisticated network of interactions among the individual units of the system. Swarm Cognition therefore promotes the study of cognition as an emergent collective phenomenon. This can be done in multiple ways. On the one hand, it is suggested to recognise cognition in the behaviour of collectives, ranging from insect swarms to human societies. To do so, it is necessary to recognise the relevant interactions among individuals in the collectives that implement the information pathways necessary for the cognitive process. Going beyond a mere analogy, experimental work must be performed to verify the way in which information is retrieved, stored and processed, in order to recognise the abilities and the limits of the collective system under study. On the other hand, comparisons must be performed between swarm and neuro-computational models. In this case, it is often difficult to make comparisons on microscopic, structural terms, as the systems under study can significantly differ. However, it could be possible to identify functional correlations, borrowing analytic techniques from one field to better understand the other, and building solid bridges for cross-fertilisation among different disciplines. Finally, we have argued that a synthetic approach to Swarm Cognition can provide further instruments for an holistic approach to cognitive sciences. By synthesising cognition in distributed artificial systems, it is possible to concurrently study the environmental, behavioural and neural basis of cognition. As an interesting side effect, this synthetic approach can produce a new generation of artifacts, able to behave autonomously and display cognitive abilities beyond the current state-of-the-art.

Swarm Cognition is still in its infancy. Although the initial developments are quite promising, there are several open questions that need to be addressed in order to strengthen the scientific significance of the Swarm Cognition perspective. First of all, it is still an open question the extent to which hypotheses developed by studying the cognitive responses of biological and artificial collectives such as bees and robots can be effectively compared to the activities of neural assemblies. In this respect, we believe that it is necessary to carefully

select the methodological tools that can allow a comparison of the mechanisms observed in such different systems. As we have shown in Sect. 4, even if it is not possible to directly compare the dynamics of neural and swarm models, it is still possible to draw a parallel between the two processes at a *functional* level. Therefore, a grand challenge for Swarm Cognition is the development of novel methodologies to recognise and compare, through the lenses of self-organisation, phenomena in brains and swarms.

Moreover, by having a strong reference to Swarm Intelligence research, Swarm Cognition models may encounter difficulties in capturing one of the fundamental properties of the brain, which is its structural organisation in more or less functionally separated although interacting and cooperating modules. It is actually an open empirical problem to identify distributed models capable of capturing similar structural properties of biological brains. This potential limit can be ascribed to the lack of systematic studies in Swarm Intelligence research addressing structured, hierarchical and heterogeneous systems. In fact, much work is devoted to the understanding of the dynamics of specific behaviours (e.g. flocking or nest-site selection), without accounting for the relations that these behaviours have with other possibly concurrent tasks in which the swarm may be engaged. The goals of Swarm Cognition research should therefore extend beyond the boundaries given by specific self-organising behaviours, and account for more complex networks of interactions within structured, hierarchical systems.

A possible criticism to the Swarm Cognition approach concerns the metaphor that considers embodied agents as neuron-like cognitive units: to what extent a reasonable comparison can be made following this metaphor? What is the relevance of embodiment in these models? This is a very important issue that can be broadly linked to the debate about embodiment and its role in cognition (Pfeifer and Scheier 1999; Anderson 2003). In this respect, we champion the idea that embodiment has a fundamental role in cognition, as it determines and constraints the ability of organisms to adaptively interact with their physical and social environment. This is particularly relevant within the Swarm Cognition framework. In order to recognise the role of embodiment in the emergence of collective cognition, it is necessary to identify within collective systems which are the relevant interactions supported by the system embodiment that contribute to the production of cognitive phenomena, and which are the modulation mechanisms that reinforce or suppress such interactions.<sup>1</sup> Within this epistemological perspective, swarms of robots can be definitely considered cognitive units, with a clear potential to contribute to the development of the Swarm Cognition perspective. Nevertheless, we believe that Swarm Cognition will come to a scientific maturity as soon as a significant corpus of research work will prove that fruitful comparisons can be drawn between morphologically different or differently-embodied interacting units, as well as between functional descriptions and embodied instantiations of cognition.

In conclusion, we hope that this paper will help in gathering around this innovative perspective an increasing number of scientists interested in cognition. Future work should strengthen the theoretical and methodological bases of this approach, and increase the significance of the collective explanation of cognitive processes within the cognitive science community.

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<sup>1</sup>Note that this can equally well include neural assemblies and their embodiment in a bio-chemical substrate.

## References

- Anderson, M. L. (2003). Embodied Cognition: A field guide. *Artificial Intelligence*, 149, 91–130.
- Ashby, W. R. (1962). Principles of self-organizing systems. In H. von Foerster & G. W. Zopf Jr. (Eds.), *Principles of self-organization* (pp. 255–278). New York: Pergamon Press.
- Barsalou, L. W. (2010). Introduction to 30th anniversary perspectives on cognitive science: Past, present, and future. *Topics in Cognitive Science*, 2(3), 322–327.
- Bogacz, R., Brown, E., Moehlis, J., Holmes, P., & Cohen, J. D. (2006). The physics of optimal decision making: a formal analysis of models of performance in two-alternative forced-choice tasks. *Psychological Review*, 113(4), 700–765.
- Camazine, S., Deneubourg, J.-L., Franks, N., Sneyd, J., Theraulaz, G., & Bonabeau, E. (2001). *Self-organization in biological systems*. Princeton: Princeton University Press.
- Couzin, I. D. (2007). Collective minds. *Nature*, 455, 715.
- Couzin, I. D. (2009). Collective cognition in animal groups. *Trends in Cognitive Sciences*, 13(1), 36–43.
- Couzin, I. D., & Krause, J. (2003). Self-organization and collective behavior of vertebrates. *Advances in the Study of Behavior*, 32, 1–75.
- Deco, G., Scarano, L., & Soto-Faraco, S. (2007). Weber's law in decision making: integrating behavioral data in humans with a neurophysiological model. *The Journal of Neuroscience*, 27(42), 11192–11200.
- Deneubourg, J.-L., Pasteels, J. M., & Verhaeghe, J. C. (1983). Probabilistic behaviour in ants: a strategy of errors? *Journal of Theoretical Biology*, 105(259–271).
- Deneubourg, J.-L., Aron, S., Goss, S., & Pasteels, J. M. (1990). The self-organizing exploratory patterns of the Argentine ant. *Journal of Insect Behavior*, 3, 159–168.
- Dennett, D. C. (1995). Intuition pumps. In J. Brockman (Ed.), *The third culture: beyond the scientific revolution* (pp. 180–197). New York: Simon & Schuster.
- Detrain, C., & Deneubourg, J.-L. (2006). Self-organized structures in a superorganism: do ants “behave” like molecules? *Physics of Life Reviews*, 3, 162–187.
- Detrain, C., Deneubourg, J.-L., & Pasteels, J. M. (Eds.) (1999). *Information processing in social insects*. Basel: Birkhäuser.
- Dorigo, M., Trianni, V., Şahin, E., Groß, R., Labella, T. H., Baldassarre, G., Nolfi, S., Deneubourg, J.-L., Mondada, F., Floreano, D., & Gambardella, L. M. (2004). Evolving self-organizing behaviors for a swarm-bot. *Autonomous Robots*, 17(2–3), 223–245.
- Franks, N. R., & Richardson, T. (2006). Teaching in tandem-running ants. *Nature*, 439(7073), 153.
- Franks, N. R., Pratt, S. C., Mallon, E. B., Britton, N. F., & Sumpter, D. J. T. (2002). Information flow, opinion-polling and collective intelligence in house-hunting social insects. *Philosophical Transactions of the Royal Society of London: Series B*, 357(1427), 1567–1583.
- Franks, N. R., Dornhaus, A., Fitzsimmons, J. P., & Stevens, M. (2003). Speed versus accuracy in collective decision-making. *Proceedings of the Royal Society B: Biological Sciences*, 270(1532), 2457–2463.
- Garnier, S., Gautrais, J., & Theraulaz, G. (2007). The biological principles of swarm intelligence. *Swarm Intelligence*, 1, 3–31.
- Goldstone, R. L., & Gureckis, T. M. (2009). Collective behaviour. *Trends in Cognitive Science*, 1(3), 412–438.
- Harvey, I., Di Paolo, E. A., Wood, R., Quinn, M., & Tuci, E. (2005). Evolutionary robotics: A new scientific tool for studying cognition. *Artificial life*, 11(1–2), 79–98.
- Langton, C. G. (1988). Artificial life. In C. G. Langton (Ed.), *Artificial life* (pp. 1–47). Reading: Addison-Wesley.
- Marshall, J. A. R., & Franks, N. R. (2009). Colony-level cognition. *Current Biology*, 19(10), 395–396.
- Marshall, J. A. R., Bogacz, R., Dornhaus, A., Planqué, R., Kovacs, T., & Franks, N. R. (2009). On optimal decision-making in brains and social insect colonies. *Journal of the Royal Society Interface*, 6, 1065–1074.
- Morlino, G., Trianni, V., & Tuci, E. (2010). Collective perception in a swarm of autonomous robots. In J. Filipe & J. Kacprzyk (Eds.), *Proceedings of the international conference on evolutionary computation (ICEC 2010)* (pp. 51–59). Setubal: SciTePress.
- Nicolis, G., & Prigogine, I. (1977). *Self-organization in nonequilibrium systems*. New York: Wiley.
- Passino, K. M., Seeley, T. D., & Visscher, P. K. (2008). Swarm cognition in honey bees. *Behavioral Ecology and Sociobiology*, 62(3), 401–414.
- Passino, K. M., Seeley, T. D., & Visscher, P. K. (2010). Honey bee swarm cognition: Decision-making performance and adaptation. *International Journal of Swarm Intelligence Research*, 1(2), 80–97.
- Pfeifer, R., & Scheier, C. (1999). *Understanding intelligence*. Cambridge: MIT Press.
- Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, 85(2), 59–108.
- Ratcliff, R., & Smith, P. L. (2004). A comparison of sequential sampling models for two-choice reaction time. *Psychological Review*, 111, 333–367.

- Roitman, J. D., & Shadlen, M. N. (2002). Response of neurons in the lateral intraparietal area during a combined visual discrimination reaction time task. *Journal of Neuroscience*, 22(21), 9475.
- Santana, P., & Correia, L. (2010). A swarm cognition realization of attention, action selection and spatial memory. *Adaptive Behavior*, 18(5), 428–447.
- Santana, P., & Correia, L. (2011, this issue). Swarm cognition on off-road autonomous robots. *Swarm Intelligence*.
- Schartz, E. (1990). *Computational neuroscience*. Cambridge: MIT Press.
- Strogatz, S. H. (2003). *Sync: The emerging science of spontaneous order*. New York: Hyperion Press.
- Sumpter, D. J. T. (2010). *Collective animal behaviour*. Princeton: Princeton University Press.
- Trianni, V., & Tuci, E. (2009). Swarm cognition and artificial life. In *LNCS/LNAI: Vol. 5777–5778. Advances in artificial life*. Proceedings of the 10th european conference on artificial life (ECAL 2009).
- Tuci, E., Gross, R., Trianni, V., Mondada, F., Bonani, M., & Dorigo, M. (2006). Cooperation through self-assembly in multi-robot systems. *ACM Transactions on Autonomous and Adaptive Systems*, 1(2), 115–150.
- Turner, S. (2011, this issue). Termites as models of swarm cognition. *Swarm Intelligence*.
- Usher, M., & McClelland, J. L. (2001). The time course of perceptual choice: The leaky, competing accumulator model. *Psychological Review*, 108(3), 550–592.
- Visscher, P. K. (2007). Group decision making in nest-site selection among social insects. *Annual Review of Entomology*, 52, 255–275.
- Visscher, P. K., & Camazine, S. (1999). Collective decision and cognition in bees. *Nature*, 397, 400.
- von Foerster, H. (1960). On self-organizing systems and their environments. In M. C. Yovits & S. Cameron (Eds.), *Self-organizing systems* (pp. 31–50). London: Pergamon Press.
- Von Frisch, K. (1967). *The dance language and orientation of bees*. Cambridge: Harvard University Press.