On optimal decision-making in brains and social insect colonies

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The problem of how to compromise between speed and accuracy in decision-making faces organisms at many levels of biological complexity. Striking parallels are evident between decision-making in primate brains and collective decision-making in social insect colonies: in both systems, separate populations accumulate evidence for alternative choices; when one population reaches a threshold, a decision is made for the corresponding alternative, and this threshold may be varied to compromise between the speed and the accuracy of decision-making. In primate decision-making, simple models of these processes have been shown, under certain parametrizations, to implement the statistically optimal procedure that minimizes decision time for any given error rate. In this paper, we adapt these same analysis techniques and apply them to new models of collective decision-making in social insect colonies. We show that social insect colonies may also be able to achieve statistically optimal collective decision-making in a very similar way to primate brains, via direct competition between evidence-accumulating populations. This optimality result makes testable predictions for how collective decision-making in social insects should be organized. Our approach also represents the first attempt to identify a common theoretical framework for the study of decision-making in diverse biological systems.

Keywords: decision-making; diffusion model; optimality; neurons; social insects; sequential probability ratio test

1. INTRODUCTION

Animals constantly make decisions. Habitat selection, mate selection and foraging require investigation of, and choice between, alternatives that may determine an animal’s reproductive success. For example, many animals invest considerable time and energy in finding a safe home (Hazlett 1981; Seeley 1982; Hansell 1984; Franks et al. 2002). Similarly, an animal may frequently have to deal with ambiguous sensory information in deciding whether a predator is present or not (Trimmer et al. 2008).

There has been ongoing speculation as to whether decision-making mechanisms in brains and in colonies of social insects might be closely related to each other, beginning at least with Hofstadter (1979) and generating continued interest (Seeley & Buhrman 2001; Visscher 2007; Passino et al. 2008). In this paper, we examine a model of decision-making in the primate brain (Usher & McClelland 2001) and compare it with three new models of collective decision-making during house-hunting by social insect colonies. These models are based on a proposed model for emigration in the rock ant Temnothorax albipennis (Pratt et al. 2002), and two models proposed for nest-site selection in the honeybee Apis mellifera (Britton et al. 2002). The similarities are striking: both systems are modelled with mutually interacting populations; in both systems, a decision is made when one population exceeds some threshold; and in both systems, this threshold can be varied to mediate between the speed and the accuracy of the decision-making process. As well as examining the structural similarities and differences between the neuron model and social insect models, we examine optimality criteria for decision-making in the social insect models. Bogacz et al. (2006) showed how the model of decision-making in the brain proposed by Usher & McClelland (2001) can be parametrized to implement the statistically optimal strategy for choosing between two alternatives. Here, we analyse to what extent each of the social insect models can implement or
approximate this statistically optimal strategy. This gives testable predictions for how social insects should behave when house-hunting in order to optimize their decision-making. The analysis we present represents the first step in establishing a common theoretical framework for the study of decision-making in biological systems, i.e. based on the interactions between their components rather than the details of the components themselves. Hence, this framework should prove applicable to diverse biological systems at many levels of biological complexity.

2. OPTIMAL DECISION-MAKING

Decision-making is a process in which uncertain information must be processed in order to make a choice between two or more alternatives. We can illustrate decision-making with a simple perceptual choice task, in which a primate subject is presented with a display filled with moving dots. The subject is required to decide whether the majority of dots move to the left or the right and to make an eye movement in the same direction. The proportion of the displayed dots that move in a coherent direction can be varied to make the decision task easier or harder, and the rewards for correct choices can be modified to vary the optimal compromise between the speed and the accuracy of the decision.

The above description is just one example of a decision-making problem, but diverse organisms face a wide variety of decision problems exhibiting the key features of variable difficulty, and a dynamic tension between the speed and the accuracy of the decision-making process (Edwards 1965; Chittka et al. 2003). Based on the analysis of human reaction-time distributions in decision tasks, psychologists proposed the ‘diffusion model’ of decision-making (Stone 1960; Ratcliff 1978), which represents the process abstractly as Brownian motion on a line representing relative distributions in decision tasks, psychologists proposed the ‘diffusion model’ of decision-making (Stone 1960; Ratcliff 1978), which represents the process abstractly as Brownian motion on a line representing relative evidence for the two alternatives, with constant drift towards the correct hypothesis (figure 1).

The diffusion model of decision-making is, in fact, a special case of the more general sequential probability ratio test (SPRT). The SPRT provably achieves a special case of the more general sequential probability ratio test, and by varying the decision threshold $z$ one can compromise between speed and accuracy of decision-making.

Figure 1. The diffusion model of decision-making can be thought of as a random walk with normally distributed step size (Wiener process or Brownian motion) along a line where the positive direction corresponds to increasing evidence for one of the available alternatives, and the negative direction to increasing evidence for the other alternative. The random walk is subject to a constant drift $A$, a tendency to move along the line towards the better alternative, whose strength is the difference between the expectations of the incoming data on the available alternatives. The variance in the random walk (proportional to $\sigma^2$) represents the uncertainty in these incoming data. The diffusion model of decision-making implements the statistically optimal sequential probability ratio test, and by varying the decision threshold $z$ can compromise between speed and accuracy of decision-making.

Inset. A sample trace of the diffusion model: at time $t=0$ when decision-making starts, there is no evidence in favour of either alternative. As time passes evidence accumulated so far varies stochastically, but consistently tends to increase in favour of one of the two alternatives. At approximately time $t=90$, the positive decision threshold is reached and the corresponding alternative is chosen.

The diffusion model of decision-making has recently been shown to fit reaction-time data better than the models that do not implement statistically optimal decision-making (Ratcliff & Smith 2004). Moreover, neural recordings from cortical regions in monkeys undertaking the moving-dots decision task are better described by the diffusion model than by other, non-optimal models (Ratcliff et al. 2003). This suggests that neural decision networks can be parametrized in a way that allows optimal decision-making, as we shall discuss in §§3 and 4.

3. DECISION-MAKING IN THE CORTEX

The neural bases of decision-making are typically studied in the context of the moving-dots experiment described in §2. Neuronal activity recordings from single cells in the monkey cortex suggest that decision-making during this task involves two main brain areas.

First, the neurons in the medial temporal (MT) area process the motion present in the visual field. Each of the MT neurons responds proportionally to the magnitude of motion in a particular direction (Britten et al. 1993). Hence, the neurons in the MT area that are selective for motion in different directions provide sensory evidence supporting the corresponding alternatives. However, this sensory evidence is uncertain owing to the noise present in the stimulus and the neural representation itself.

Second, the neurons in the lateral intraparietal (LIP) area and the frontal eye field are concerned with controlling eye movement. These neurons are selective for the direction of eye movement. During the motion discrimination task, it has been observed that the neurons corresponding to the correct alternative...
gradually increase their firing rate (Schall 2001; Shadlen & Newsome 2001; Roitman & Shadlen 2002). Detailed studies of their activity provide strong evidence that the LIP neurons integrate input from the corresponding MT neurons over time (Huk & Shadlen 2005; Hanks et al. 2006). Hence, as time progresses in the task, the sensory evidence accumulated in the LIP neurons becomes more and more accurate.

It has been observed that when the activity of the LIP neurons exceeds a certain threshold, the decision is made and an eye movement in the corresponding direction is initiated (Schall 2001; Shadlen & Newsome 2001; Roitman & Shadlen 2002). This arrangement of neural populations with decision thresholds lends itself to representation through a simple model, as described in §4.

4. THE USHER–MCCLELLAND MODEL

The Usher–McClelland model represents decision-making using neural populations that act as mutually inhibitory, leaky integrators of incoming evidence (figure 2). In the moving-dots decision task described above, these integrator populations would represent the LIP neural populations corresponding to the different possible eye movement decisions. Each population of integrator neurons receives a noisy input signal that it integrates, subject to some constant loss. Each population also inhibits the activation of the other to a degree proportional to its own activation. So, as one population becomes highly activated, the suppression it exerts on the activation of the other grows stronger. For a binary choice, the linearized version of the system is formally described as a pair of coupled stochastic ordinary differential equations

\[
\begin{align*}
\dot{y}_1 &= I_1 + c\eta_1 - y_1 k - y_2 w, \\
\dot{y}_2 &= I_2 + c\eta_2 - y_2 k - y_1 w,
\end{align*}
\]

(4.1)

where \(y_i\) is the activity of population \(i\); \(y_1\) is the change in that activity over time; \(I_i\) is the strength of the input signal for alternative \(i\); \(c\eta_i\) is the noise in that input signal described as a Wiener process with mean zero and standard deviation proportional to \(c\); \(w\) is the rate at which one population inhibits the activation of the other; and \(k\) is the rate at which a population’s activation level decays. The decision is made by the model if the activity of either of the populations reaches a threshold value.

Choosing different coordinates, \(x_1 = (y_1 - y_2)/\sqrt{2}\) and \(x_2 = (y_1 + y_2)/\sqrt{2}\), the model can be decoupled into two independent random processes

\[
\begin{align*}
\dot{x}_1 &= (w - k)x_1 + I_1 - I_2 \sqrt{2} + c\eta_1', \\
\dot{x}_2 &= (-k - w)x_2 + I_2 + I_1 \sqrt{2} + c\eta_2',
\end{align*}
\]

(4.2)

where \(\eta_i' = (c\eta_1 - c\eta_2)/\sqrt{2}\), and similarly for \(c\eta_2'\). If \(w = k\), then \(x_1\) simply undergoes a biased random walk. Moreover, taking both these parameters to be large, \(x_2\) quickly converges to a limiting value (figure 3).

Since \(x_2\) quickly converges, the decision is made when the difference between integrated evidence, \(x_1\), exceeds a positive or negative threshold (Bogacz et al. 2006). This corresponds to the statistically optimal diffusion model of decision-making (figure 1). Thus, when \(w = k\) and both of these parameters are relatively high, the Usher–McClelland model approximates optimal decision-making.

5. DECISION-MAKING IN SOCIAL INSECT COLONIES

The rock ant T. albipennis lives in colonies of up to a few hundred individuals, inhabiting small enclosed cavities such as rock crevices, which break down over time. Colonies of the honeybee A. mellifera are substantially larger, often comprising more than 50 000 workers nesting in large cavities in hollow trees. For both species, the need to hunt for a new nest site arises when the nest degrades or is destroyed, or when the colony propagates. To minimize exposure, colonies must minimize the duration of the emigration, while still gathering substantial information about potential nest sites. ‘Scout’ individuals leave the old nests...
nest (or the bee swarm) to search for new suitable sites. When an individual has located a new site, this is thoroughly inspected according to multiple criteria (Mallon & Franks 2000; Franks et al. 2003b, 2005, 2006a, 2007a).

A unanimous decision among the discovered nest sites is required, and the highest quality site should be identified to maximize future success. To achieve all of this, both rock ants and honeybees use a process of quality-dependent recruitment to nest sites, causing positive feedback, coupled with quorum sensing, ultimately leading to a collective decision.

In T. albipennis, scouts recruit nest-mates to a site they have discovered by tandem running, teaching others the route (Möglicher & Hölldobler 1974; Möglich 1978; Franks & Richardson 2006; Richardson et al. 2007). The recruiters pause for longer before recruiting to poor nests than they do for good nests (Mallon et al. 2001). Recruits inspect the new nest and also start recruiting, leading to a positive feedback, with more ants arriving faster at higher quality nest sites. When a certain number of ants, a quorum, have accumulated in the new site, all ants that are committed to it switch from tandem running to carrying nest-mates. This represents a switch to decision implementation, as brood items and passive ants are carried to the chosen nest site. The colony’s collective decision for a new nest is thus usually for the site that first attracts the quorum number of ants. By adjusting this number, the ants opt for a quick but error-prone, or a slower but more accurate decision, depending on their group size and external conditions (Franks et al. 2003a; Dornhaus & Franks 2006).

In A. mellifera, scouts similarly start recruiting to discovered nest sites, here using the honeybee waggle dance (Lindauer 1955; von Frisch 1967; Seeley 1982). The probability of performing waggle dances, as well as their duration, depends on the quality of the discovered site. Positive feedback thus arises only if recruits become recruiters, which happens only for superior sites (Seeley & Buhrman 1999, 2001). Eventually all recruitment is for a single site, which is then chosen by the honeybee swarm (Seeley 2003). Honeybees may also use a quorum at the new site to determine whether this decision has been made (Seeley & Visscher 2004b).

Both of these decision-making mechanisms operate without central control, and individuals use only local information (Mallon et al. 2001). Both species can select the best nest site even if news of it arrives late in the decision-making process (Britton et al. 2002; Franks et al. 2007b). However, there are some differences between the two collective decision-making systems. In the bees, the decision-making process is separated from the execution of the decision: the flight of the swarm to the new site occurs after the decision has been made, and is guided by a small number of informed individuals (Beekman et al. 2006; see also Couzin et al. 2005). In the ants, these processes are integrated, introducing a logistics problem into the decision problem (Planqué et al. 2007). Note that the decision problem solved by colonies during emigration is one of optimal consensus decision-making, and thus differs from the problem of distributed resource intake maximization that colonies tackle during foraging (e.g. Seeley 1995).

6. MODELS OF HOUSE-HUNTING BY SOCIAL INSECT COLONIES

In this section and 7, we will examine how social insect colonies might implement optimal decision-making, through formal analysis and numerical simulations of mathematical models. We propose three new models based on one published model of house-hunting by T. albipennis (Pratt et al. 2002) and two published models of house-hunting by A. mellifera (Britton et al. 2002). Our aim is to examine which model or models can implement optimal decision-making, and use this to generate testable hypotheses about how social insects should behave if they are to decide optimally.

To understand how collective decision-making may be optimized in situations characterized by uncertainty, our models are stochastic differential equations, as in the neural case. This departs from previous modelling efforts using deterministic differential equations (Britton et al. 2002; Pratt et al. 2002), population matrix models (Myerscough 2003) or individual-based models (Pratt et al. 2005; Marshall et al. 2006). All the models represent flows between populations of individuals having different behavioural states. The structure of all of these models is very similar, and one such model is presented by way of illustration in figure 4; the models differ however in the details of the rates at which individuals flow between these populations.

6.1. House-hunting in T. albipennis

We begin with the model of emigration by T. albipennis (Pratt et al. 2002). The full model considers the complete emigration process both before and after the quorum threshold is satisfied at a potential site: thus the model includes both tandem-running behaviour and carrying. In accordance with current biological understanding, we model only the decision-making process up to quorum satisfaction, considering that after this
point a collective decision has been made and all that remains is its implementation (Pratt et al. 2002). This view is not without its problems (Franks et al. 2007b; Planqué et al. 2007), but is an acceptable simplification for our purposes. We further simplify the original model by removing the intermediate class of assessor ants: ants thus switch directly from uncommitted to committed.

Our simplified version of the Pratt et al. (2002) model thus considers only ants discovering nest sites and recruiting to them through tandem running. Ants leave the class of uncommitted scouting ants, s, discover and become recruiters y, for nest site i at rate qi; this rate is proportional to the nest site’s quality and ease of discovery, and is subject to noise cni. Recruiters for a site recruit uncommitted scouts in class s at noisy, quality-dependent rate r′(s) where

\[ r′(s) = \begin{cases} r_i + cni, & \text{if } s > 0, \\ 0, & \text{otherwise.} \end{cases} \]

Finally, recruiters for a site spontaneously switch to recruiting for the other site at rate ri or switch to being uncommitted to any site at rate ki. These rates are subject to noise cni and cni, respectively. In this model, as in the other stochastic models below, we consider only stochasticity in any process related to quality assessment of the available alternatives. This enables our analysis to concentrate on how this relevant noise is processed by the system. This strategy has already been used implicitly in the Usher–McClelland model: there decay and inhibition are modelled deterministically, yet corresponding neural processes in the real world will of course be noisy.

Thus the ants’ decision-making process is described by the following equations:

\[ \begin{align*}
\dot{y}_1 &= (n - y_1 - y_2)(q_1 + c_{n1}) + y_1 r′(s) \\
&\quad + y_2(r_1 + c_{r1} - y_1(r_1 + c_{n1}) - y_1 k_1 + c_{h1}), \\
\dot{y}_2 &= (n - y_1 - y_2)(q_2 + c_{n2}) + y_2 r′(s) + y_1(r_1 + c_{n1}) \\
&\quad - y_2(r_2 + c_{n2}) - y_2(k_2 + c_{h2}).
\end{align*} \]

(6.2)

where as population size is constant s = n – y1 – y2, and hence the equation for s is redundant.

In the (x1, x2) variables, we seek to parametrize the model so that the random process x1 is independent of the random process x2, and is identical to the diffusion model of decision-making. It can easily be shown that this parametrisation requires the decay parameters and switching rate parameters to be set according to the qualities of both the alternative nest sites under consideration (see the electronic supplementary material). In other words, optimal decision-making can only be achieved under this model if individuals have global knowledge about the alternatives available. Given our understanding of social insects' house-hunting mechanisms, we do not expect all committed individuals to have quantitative knowledge of the qualities of both alternatives. Hence, optimal parametrisation of our model of house-hunting in T. albipennis seems biologically unrealistic.

6.2. House-hunting with indirect switching in A. mellifera

In this section and §6.3, we now consider two models of house-hunting in A. mellifera due to Britton et al. (2002). These models differ only in whether or not they allow scouts committed to one site to switch directly to the alternative site. First, we consider the case in which scouts cannot directly switch: that is, they can only change their commitment by first becoming completely uncommitted.

We adapt the model of Britton et al. (2002) so that, as in the Pratt et al. model, we have one population of uncommitted scouts, s, and two populations of recruiters, y1 and y2, for the two alternative sites under consideration. This is a simplification of the full Britton et al. model, in that we dispense with their populations of committed but inactive recruiters. We make a further small modification to the Britton et al. model by adding spontaneous discovery of alternative sites by uncommitted scouts at rates q1 and q2. We make these rates independent of site quality, to agree with the modelling approach of Britton et al. and with the current biological understanding of A. mellifera (Seeley 2003); however, they may vary according to how distant, or how hard to discover, a potential nest site is.

Using the same notation as in equations (6.2), our indirect-switching model of house-hunting by A. mellifera is described by the following equations:

\[ \begin{align*}
\dot{y}_1 &= (n - y_1 - y_2)(q_1 + c_{n1}) - y_1(k_1 + c_{h1}) \\
&\quad + y_1(n - y_1 - y_2)(r_1′ + c_{r1}), \\
\dot{y}_2 &= (n - y_1 - y_2)(q_2 + c_{n2}) - y_2(k_2 + c_{h2}) \\
&\quad + y_2(n - y_1 - y_2)(r_2′ + c_{r2}).
\end{align*} \]

(6.3)

It is easy to show that the indirect-switching model can neither be reduced to two independent random processes, nor does it asymptotically converge to the diffusion model of decision-making (see the electronic supplementary material). Thus, the indirect-switching model of decision-making in A. mellifera cannot be (asymptotically) reduced to one dimension and therefore cannot be made exactly or approximately equivalent to the diffusion model of decision-making. This does not rule out the possibility that indirect switching may be an effective decision-making strategy, but it does rule out it being a statistically optimal decision-making strategy.

6.3. House-hunting with direct switching in A. mellifera

We now consider the Britton et al. model in which the scouts can directly switch their commitment between alternative sites (figure 4). The equations for this decision-making system are

\[ \begin{align*}
\dot{y}_1 &= (n - y_1 - y_2)(q_1 + c_{n1}) + y_1(n - y_1 - y_2) \\
&\quad \times (r_i′ + c_{r_i}) - y_1 k_1 + y_1 y_2(r_1 - r_2 + c_{n1} - c_{r_1}), \\
\dot{y}_2 &= (n - y_1 - y_2)(q_2 + c_{n2}) + y_2(n - y_1 - y_2) \\
&\quad \times (r_2′ + c_{r_2}) - y_2 k_2 - y_1 y_2(r_1 - r_2 + c_{n1} - c_{r_2}).
\end{align*} \]

(6.4)
The key differences between the model described above for *A. mellifera* and the *T. albipennis* model of equations (6.2) are in the nature of the recruitment mechanism. In the *T. albipennis* model of §6.1, the number of ants recruited per unit time is a linear function of the number of recruiters (as long as recruits are still available). In the honeybee, recruitment occurs through waggle dancing, which is a process in which both parties meet (von Frisch 1967); thus in the *A. mellifera* model, the number of bees recruited per unit time depends on the numbers of both recruiters and potential uninformed recruits. If either is small, the growth of new recruiter numbers is limited.

Unlike the *T. albipennis* model, it is not possible to make the random process \( \hat{x}_1 \) independent of the random process \( \hat{x}_2 \). However, we can analyse how \( \hat{x}_1 \) behaves in the limit when \( \hat{x}_2 \) converges. By setting the decay rate \( k = 0 \), all scouts will become recruiters over time so \( \hat{x}_2 \) approaches \( n/\sqrt{2} \). In this limit, the dynamics of \( \hat{x}_1 \) are described as

\[
\dot{x}_1 = \left( \frac{n^2}{2} - x_1^2 \right) \left( \frac{r_1 - r_2}{2} + c \eta \right). \tag{6.5}
\]

In this random process, both noise and strength of drift vary quadratically with \( x_1 \). Choosing an appropriate nonlinear coordinate transformation to \( x \) (see the electronic supplementary material), we find by the chain rule that the random process can be expressed as

\[
\dot{x} = \frac{dx}{dx_1} \frac{dx_1}{dt} = A + cn\eta, \tag{6.6}
\]

where \( A = (r_1 - r_2)/\sqrt{2} \).

Thus when \( k = 0 \), decision-making asymptotically converges to the diffusion model (figure 1), a decision-making process that is exactly equivalent to the statistically optimal strategy. We therefore describe the direct-switching model without decay as asymptotically optimal.

Optimal decision-making in the model occurs when no uncommitted scouts remain in the colony. For honeybees, we presume that this usually occurs, as swarms typically take hours or days to reach a decision. As the emigration progresses more and more honeybees enter the decision-making process, and the number of sites considered by the colony reduces as known alternatives are eliminated and new alternatives are discovered less and less frequently (Seeley & Bulrnan 1999; Visscher & Camazine 1998). Before this full-commitment stage is reached, decision-making will be governed by differences in discovery (\( q \)) and recruitment rates (\( r'_2 \)) for the available alternatives, and by the availability of information on the alternatives. These rates can depend not only on the quality of the available sites, but also on their distance, or the difficulty of their discovery. Thus an easy to discover, close but inferior site may attract more recruitment effort early on owing to positive feedback than a more distant, hard to discover but superior site. Once all scouts are committed, however, no new information on other alternatives can arrive (as there are no scouts searching), and decision-making between the available alternatives is made optimally, solely on the basis of their relative quality. The only deviation from purely optimal diffusion decision-making will be

**Figure 5.** Results from numerical simulation of the *A. mellifera* direct-switching model. When decay \( k > 0 \), decision-making is more strongly affected by the difference in discovery rates and recruitment rates from the home nest \( (q_1 - q_2) \) and \( (r'_1 - r'_2) \); if these differences are in favour of the superior alternative site (site 1), then decision time (DT) can be reduced by increasing \( k \). However, if the differences favour the inferior alternative, then increasing \( k \) increases decision time. Inset. If all differences are equally likely, then mean decision time (y-axis) is minimized when \( k \) (x-axis) equals zero.

**7. NUMERICAL SIMULATION**

To test whether decision-making in the *A. mellifera* direct-switching model is optimized by setting decay \( k = 0 \), we conducted a numerical sensitivity test of the model (see the electronic supplementary material): we simultaneously varied the differences in the initial discovery and recruitment rates, \( q_1 - q_2 \) and \( r'_1 - r'_2 \), respectively, so that they either favoured or disfavoured the selection of the superior nest site (site 1). The difference in the recruitment rates between the two populations of committed scouts, \( r_1 - r_2 = 2 \), reflects the true relative qualities of the two alternatives. We then simulated the model with decay \( k \) varying between 0 and 1. The results (figure 5) show that, although the benefit or cost of increasing \( k \) for decision time varies according to whether the superior site is easier or harder to find than its inferior alternative, setting \( k = 0 \) is robustly optimal as it minimizes expected decision time across all scenarios considered.

**8. DISCUSSION**

We have presented the first optimality hypothesis for collective decision-making during emigration for social insect colonies. We have also presented the first formal...
investigation of similarities between certain neural decision-making processes, and collective decision-making in social insect colonies, similarities which others have previously discussed (Hofstadter 1979; Seeley & Buhrman 2001; Visscher 2007; Passino et al. 2008). In both brains and social insect colonies, mutually interacting populations must reach an activation threshold to precipitate a decision. We argue that the interaction patterns between populations are the crucial part of the decision-making process at both these levels of biological complexity, organismal and super-organismal. Notwithstanding their impressive these levels of biological complexity, organismal and super-organismal interactions between populations are mutually interacting populations must reach an acti-

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(Bogacz et al. 2007), a scenario that may be common in nature, and under which both T. albipennis (Franks et al. 2003b, 2006a) and A. mellifera (Seeley & Buhman 2001) colonies have been experimentally demonstrated to perform well.

One complicating factor for our analysis is that in social insect colonies, decision-making is conflated with decision implementation. In T. albipennis colonies, once the quorum is satisfied, only those scouts that know the location of the new site will be able to undertake the transportation of the remainder of the colony: ants transported by carrying are carried in a pose unsuitable for learning the route. Hence, the quorum threshold must be optimized not just for optimality of decision-making, but for the efficiency of decision implementation (Planqué et al. 2007). This may account for other authors’ observations of a reduced effect of quorum threshold on emigration time during computer simulations of Temnothorax emigrations (Pratt & Sumpter 2006). A similar, but arguably less acute, situation occurs in A. mellifera colonies, where a sufficiently large minority of informed scouts must guide the entire swarm to the new nest site (Couzin et al. 2005). To increase confidence in the theoretical predictions from our models, which are necessarily simplified for analytical tractability, it could be interesting to attempt to validate these predictions using more biologically plausible individual-based models, such as those of Pratt et al. (2005), Marshall et al. (2006) and Passino & Seeley (2006).

An additional complication arises because, in real emigrations, news about all the alternatives is not available to the colony from the beginning: discovery of potential nest sites by scouts is a stochastic process, and the best available alternative may not be discovered until quite late in the decision-making process. Experimental (Franks et al. 2007b) and theoretical (Britton et al. 2002) work has examined the robustness of social insects’ collective decision-making to this kind of late information. Our analysis shows how such robustness might be understood because under the direct-switching model, once all scouts are committed and no further information on new alternatives can arrive, decision-making proceeds optimally between the available alternatives based on their quality: the only departure from optimality is the bias in the starting point of the decision process based on the relative discovery times of the alternatives.

The previous point brings us to one final observation, that social insect colonies may face a subtly different decision problem to neural circuits in the vertebrate brain. A social insect colony must actively acquire information from its environment, whereas in the visual decision-making task considered in this paper information on both alternatives arrives at an equal and unvarying rate. Scouts stochastically discover alternative sites, but once some potential sites are known the colony is faced with the traditional explore/exploit dilemma: should the colony send more scouts to assess the known alternatives and gain a better estimate of their quality, or should it allocate scouts to attempt the discovery of unknown, potentially better, alternatives? As previously noted (Marshall et al. 2006), the colony is thus faced with a decision problem that is a hybrid of the ‘bandit’ problem, in which trials must be allocated across noisy alternatives of unknown quality in order to maximize long-term gain, and the minimal decision time problem that the SPRT addresses. To our knowledge, no attempt has previously been made to formalize or analyse such a problem. We believe that analysis of the social insects’ behaviour, and models thereof, could provide a fruitful avenue for tackling this new decision problem. We expect that this problem will also reveal further similarities between collective and neural decision-making processes, leading to further extension of the general decision-making framework outlined here.

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REFERENCES


On optimal decision-making


