# Emergence of Temporal and Spatial Synchronous Behaviors in a Foraging Swarm

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## Abstract

Biological populations often exhibit complex and efficient behaviors, where temporal and spatial couplings at the macro-scale population level emerge from interactions at the micro-scale individual level, without any centralized control. This paper specifically investigates the emergence of behavioral synchronization and the division of labor in a foraging swarm of robotic agents. A deterministic model is proposed and used by each agent to decide whether it goes foraging, based on local cues about its fellow ants' behavior. This individual model, based on the competition of two spiking neurons, results in a self-organized division of labor at the population level. Depending on the strength and occurrences of interactions among individuals, the population behavior displays either an asynchronous, or a synchronous aperiodic, or a synchronous periodic division of labor. Further, the benefits of synchronized individual behaviors in terms of overall foraging efficiency are highlighted in a 2D spatial simulation.

## Introduction

Nature displays fascinating examples of biological populations that achieve complex tasks without requiring any centralized control. How to efficiently achieve a distributed and decentralized control, a key issue for biological and artificial systems alike, is still far from being entirely elucidated (Camazine et al., 2001), although the interplay between the individual, micro-scale level and the population, macro-scale level has been extensively studied in the literature (see Beshers and Fewell (2001) for a survey).

This paper focuses on behavioral synchronization and the division of labor in a robotic swarm. On the biological and ethological side, behavioral synchronization and division of labor have been shown to enhance the adaptive value in various insect species such as spiders (Krafft and Pasquet, 1991), collembola (Leinaas, 1983), fireflies (Branham and Greenfield, 1996) and have also been observed in ants (Goss and Deneubourg, 1988; Cole, 1991). Experimental studies devoted to the foraging behavior in ant colonies suggest that synchrony might contribute to a better communication among agents (Bonabeau et al., 1998b), and significantly improves the foraging performance compared to asynchronous behaviors (Bonabeau et al., 1998a; Delgado

and Solé, 2000). The emergence of synchrony is explained from both individual factors, e.g. internal individual mechanisms, and local interactions among individuals.

On the artificial and robotic side, the self-organized division of labor in an ant colony is nothing like easily mastered by a robotic swarm. Notably, in many cases the micro-scale models proposed in the ethology literature might exceed the plausible physical or cognitive resources of most simple agents (e.g. due to the required resources or the presence of random generators supporting stochastic models). The swarm robotics framework involves specific limitations; while it considers a large population[1], power consumption remains a critical issue, entailing limited communication and computational abilities. Quite a few authors have been considering foraging robotic swarms in the last two decades (see Bayindir and Sahin (2007) for a survey), proposing hand-crafted architectures (be they bio-inspired (Labella et al., 2006; Panait and Luke, 2004) or not (Liu et al., 2007; Hauert et al., 2008)), or using evolutionary computation to optimize the individual decision model (Dorigo et al., 2005).

In the meanwhile, how to enforce the synchrony of individual behaviors has seldom be considered. Wischmann et al. (2006) and Hartbauer and Romer (2007) have investigated the use of coupled oscillator-based models, respectively considering an energy-foraging and a cleaning task. Taking inspiration from insect synchronous behavior such as chorusing male insects, both approaches illustrate how group synchronization can emerge from local communications. Trianni and Nolfi (2009) present a thorough study of swarm synchronization from the perspective of dynamic systems, notably using Evolutionary Computation to optimize efficient synchronization strategies.

Resuming an earlier work Chevallier et al. (2010), this paper presents a frugal model aimed at robotic swarm foraging, called *SpikeAnts*. This model, based on the coupling of two spiking neurons with different internal dynamics (Gerstner and Kistler, 2002), enables an individual

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[1]Contrasting with early work on multi-robot systems; see (Parker, 2008) and references therein.

agent to decide whether it must go foraging based on local cues from other agents. Spiking neurons, now a well-established formalism, are known to display rich temporal dynamics and synchronization patterns (Paugam-Moisy and Bohte, 2011). From the individual decisions and interactions within *SpikeAnts*, synchronous and asynchronous population behaviors are shown to emerge depending on the range of interactions among the individuals. This paper investigates the implications and merits of synchronous behaviors in terms of overall foraging efficiency, where spatial interactions are modelled through a collision avoidance mechanism. Synchronous population behavior, decreasing the chances of collisions, result in more fluid individual trajectories and better foraging returns.

This paper is organized as follows. First, the notion of "foraging swarm" is specified. For the sake of self-containedness, the next section sums up the *SpikeAnts* model, explaining the spiking neurons used and their coupling. Afterwards, the notions of temporal and spatial couplings of agents' behaviours in a swarm are discussed. Some conjectures on the benefits of synchrony are presented. The experimental setting proposed to study these conjectures is presented. The last section reports on the experimental results, discussing the trajectories of the robotic swarm in a simulated 2D environment. The paper concludes with a discussion and some perspectives for further research.

## Foraging swarm

Basically, the foraging task aims at securing a sufficient amount of food for the (ant) colony at any time. The foraging activity however is itself energy consuming. Therefore it would be inappropriate that all individuals in the colony devote themselves to foraging. Hence the dilemma is: On the one hand, sufficiently many individuals should devote themselves to foraging, but no more; On the other hand, the division of labor between the foraging individuals and the others has to be enforced without any centralized control. Although the division of labor might be resolved by task assignment at the individual level (deciding once for all whether a given individual is a foraging one), such a fixed mechanism would hardly account for the famed flexibility of ant colonies, where the division of labor smoothly adapts to emergencies.

The approach proposed by Liu et al. (2007) involves a probabilistic finite state automaton, where each individual obeys a Markov decision process involving a few states (e.g., resting, foraging, grooming). The probabilities of transitions among states are optimized using evolutionary computation in order to maximize the overall performance of the swarm. The efficiency of this approach thus relies on the size of the swarm, enforcing that the number of individuals in a given state at any point is close to the desired one due to the law of large numbers. Notably, it also requires any individual agent to embed a random generator. Displaying a "truly random" decision making process is by no way a basic ability (human beings, for instance, are known to be poor random generators).

## The SpikeAnts model

The proposed individual model is inspired from both Goss and Deneubourg (1988) and Huang and Robinson (1999), where the agent decision results from internal and external factors, and the external factors reflect the other agents' behavior (social inhibitions).

### Foraging and Social Inhibitions in *SpikeAnts*

Formally, the *SpikeAnts* model involves three states, respectively called *foraging* (active), *sleeping* (inactive) and *observing* (activable), with deterministic transitions (Fig. 1). When in sleeping state, the agent switches to the observing state after some time $t_s$; when in foraging state, the agent switches to the sleeping state after some time $t_f$. The agent decision takes place in observing state, taking some cues from the agent' relatives: essentially, if it sees many other foraging agents (in a sense made precise below) the foraging incentive is low and the agent switches to the sleeping state[2]; otherwise, it switches to the foraging state. This mechanism thus implements social inhibitions, as opposed to e.g. threshold models where the agent decision is based on internal thresholds only (Bonabeau et al., 1998a).
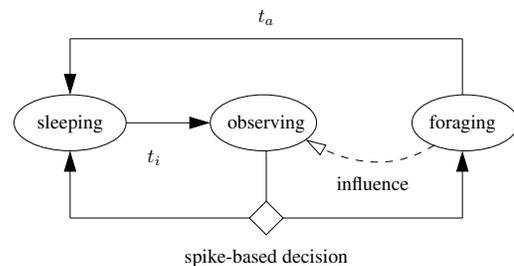


Figure 1: An agent is described by three states and the state transitions are indicated with black arrows. An observing agent decides to forage or not based on local information sent by neighboring active agents (white arrow).

### The competition of two spiking neurons

The agent decision in observing state is made through the competition of two spiking neurons. A model of spiking neuron describes the evolution of an internal variable, the membrane potential; the neuron fires an electrical pulse, called spike, when this membrane potential reaches a given threshold. By connecting spiking neurons to each other and

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[2]Note that agents in sleeping state are not necessarily resting but might achieve other tasks as well; the extension of the current model to multi-task settings is a research perspective (see Discussion and Conclusions).
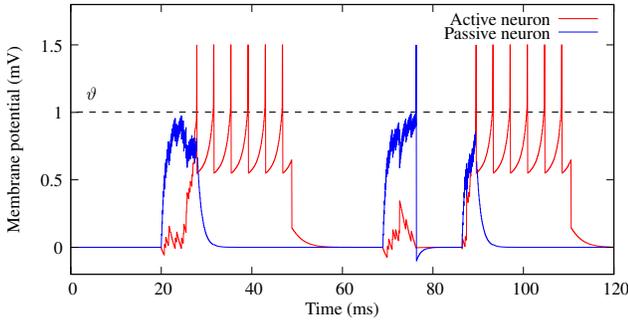
Figure 2: Membrane potentials of active (in dark/red) and passive (in gray/blue) neurons. The dashed line indicates the threshold $\vartheta$. Initially sleeping, the agent goes observing at time 20ms. As the active neuron fires before the passive one, the agent goes foraging and the active neuron sends spikes during the whole foraging period, signalling its activity to other agents. It then switches to sleeping state (from circa 50 to 70ms). A second observing period starts thereafter; this time the passive neuron fires before the active one. The agent then switches to sleeping state. At circa 90ms, a third observing period starts, and the agent switches to foraging almost immediately.

having them exchange information through spikes, a rich variety of dynamic activation and synchronization patterns can be obtained.

Formally, an agent is modelled as two spiking neurons, an active one and a passive one. The agent decision (foraging or sleeping) depends on whether the active or the passive neuron fires first. Both neurons are respectively inhibited and activated by the spikes coming from other agents, emitted when these are foraging.

The passive neuron is implemented as a Leaky Integrate-and-Fire (LIF) neuron (Gerstner and Kistler, 2002); the active one is implemented as a Quadratic Integrate-and-Fire (QIF) neuron (Hansel and Mato, 2001); both models have been extensively studied in the literature.

The passive LIF neuron is modelled by a differential equation, which describes the temporal evolution of a potential $V_p$. If $V_p$ exceeds a threshold $\vartheta$, the neuron fires a spike and is reset to the resting potential $V_{\text{reset}}^p$.

$$\begin{cases} \frac{dV_p}{dt} = -\lambda(V_p(t) - V_{\text{rest}}) + I_{\text{exc}}(t), & \text{if } V_p < \vartheta \\ \text{else fires a spike and } V_p \text{ is set to } V_{\text{reset}}^p \end{cases} \quad (1)$$

where $\lambda$ is the relaxation constant. $I_{\text{exc}}(t)$ models instantaneous synaptic interactions. The set of presynaptic neurons is denoted by **Pre**, such that there exists a communication channel from every neuron in **Pre** toward the current neuron. Denoting **Train**$_i$ the spike train of the $i^{\text{th}}$ neuron in **Pre**,

$$I_{\text{exc}}(t) = w \sum_{i \in \mathbf{Pre}} \sum_{j \in \mathbf{Train}_i} \delta(t - t_j^i), \quad (2)$$

where $w$ is a synaptic weight, $\delta(.)$ is the Dirac distribution and $t_j^i$ is the firing time of the $j^{\text{th}}$ spike from the $i^{\text{th}}$ presynaptic neuron.

The active QIF neuron is described by the evolution of the potential $V_a$, compared to the resting potential $V_{\text{rest}}$ and an internal threshold $V_{\text{thres}}$. Additionally, it receives an internal signal $I_{\text{clock}}$ modelling a gap junction connection:

$$\begin{cases} \frac{dV_a}{dt} = \lambda(V_a(t) - V_{\text{rest}})(V_a(t) - V_{\text{thres}}) \\ \qquad + I_{\text{inh}}(t) + I_{\text{clock}}(t), & \text{if } V_a < \vartheta \\ \text{else fires a spike and } V_a \text{ is set to } V_{\text{reset}}^a \end{cases} \quad (3)$$

The choice of this neuron model (Izhikevich, 2007) is motivated by the bistability of the QIF neuron if the reset threshold is greater than the internal threshold ($V_{\text{reset}}^a \geqslant V_{\text{thres}}$). If $V_{\text{reset}}^a < V_{\text{thres}}$, the membrane potential $V_a$ stabilizes on $V_{\text{rest}}$ when there is no external perturbation, and the neuron thus exhibits an integrator behavior. When $V_{\text{reset}}^a \geqslant V_{\text{thres}}$, the neuron displays a bursting behavior and fires periodically.

## An Agent Slice of Life

In observing state, the agent decision is thus controlled from the passive LIF neuron (Eq. (1)), the active QIF neuron (Eq. (3)) and an internal clock unit. Both spiking neurons receive the spikes emitted by other neighbor foraging agents (external factors); additionally, the active neuron receives the $I_{\text{clock}}$ signal emitted by the agent internal clock. The active neuron is activated by the internal signal, and inhibited by the external signals, whereas the passive neuron is only activated by the external signals. Depending on whether the active (respectively the passive) neuron fires first, the agent goes foraging (resp. sleeping).

When the observing agent sees none or few other foraging agents (i.e. receives no or few spike signals from them), the internal signal $I_{\text{clock}}(t)$ is not counteracted by any external inhibitions and the active neuron fires; it wins the competition and the agent goes foraging (first and third periods in Fig. 2). When in foraging state, the active neuron is bursting and periodically sends spikes to neighbor agents (which process them only if they are in observing state). The agent stays foraging for a time $t_f$ and then switches to the sleeping state for a time $t_s$. This switch is triggered by an internal delay between the clock unit and the active neuron.

If the observing agent perceives many foraging agents, the passive neuron receives many excitatory external signals and it fires first (second period in Fig. 2); the agent switches to sleeping state for a time $t_s$.

Overall, the competition between the passive and active neurons thus fully determines the observing agent decision. It is worth noting that the SpikeAnts system is asynchronous[3]. Its temporal dynamics is highly non-linear; in

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[3] Differential equations are solved by finite differences, with fixed precision depending on the computational resources.
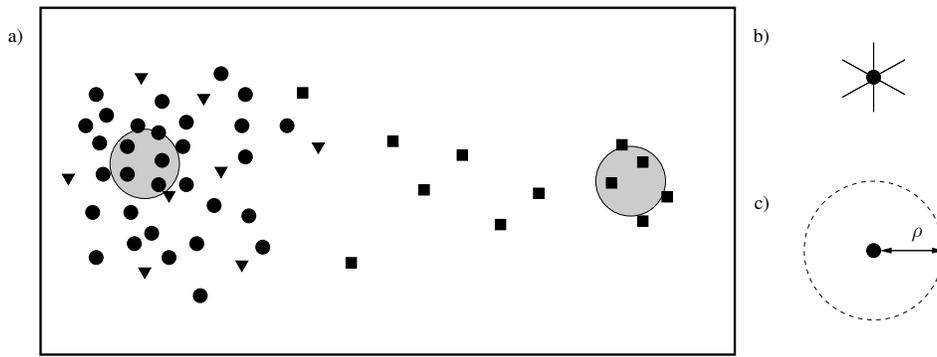
Figure 3: *SpikeAnts* simulation in 2D environment. (a) The arena includes a nest and a food regions (disk); foraging, sleeping and observing agents are respectively indicated with squares, circles and triangles. (b) Proximity zone of an agent. (c) Communication range $\rho$.

practice, the number and pace of the spikes received before making a decision vary from one observing period to another. There is no time limit for the observing state; an agent remains in observing state until making a decision.

## Investigating Temporal and Spatial Couplings

In a first study (Chevallier et al., 2010), the temporal couplings induced by *SpikeAnts* have been experimentally studied within an abstract setting, considering each agent as a node in a random graph with a given connectivity rate. Each agent had a fixed position and a fixed, sparse, set of neighbors. In particular, no traveling time from the nest to the food source was accounted for in the foraging activity. Such an abstract setting however does not account for the fact that real and artificial agents alike are moving in a spatial environment, and can hardly be considered as material points.

A more realistic simulated environment is investigated in the present paper. This section introduces the experimental setting and goals.

### Spatial interactions

The study considers a large square 2D arena, the dimension of which is circa 160 times the size of the individual agent. The arena includes the nest, or sleeping place, and the food source, or foraging place (Fig. 3(a)). The region centered on the nest (respectively the source) with radius $\gamma$ is referred to as nest (resp. source) region. The region centered on the nest with radius $2\gamma$ is referred to as domestic region ($\gamma$= 3% of the arena size in the experiments).

Each agent moves with a constant speed; its communication range $\rho$ is constant (Fig. 3(c)). The agent is endowed with a set of elementary behaviors:

- In observing state, the agent moves inside the domestic region, with constant speed, except when it sees another agent, where the collision avoidance behavior is executed (see below). Foraging agents within its communication

range send excitatory (resp. inhibitory) signals to its passive (resp. active) neuron.

- Upon the firing of its active neuron, the agent switches to the foraging state for a given time $t_f$. Whatever its current position, it goes directly to the food source with constant speed, except when it sees another agent, where the collision avoidance behavior is executed. When arriving in the source region, the agent moves inside this region until the foraging time $t_f$ is elapsed.

- When switching from foraging to sleeping state, the agent goes directly to the nest region with constant speed, except when the collision avoidance behavior is executed. When arriving in the nest region, the agent moves inside the domestic region until the sleeping time $t_s$ (starting at the end of the foraging period) is elapsed.

- When switching from observing to sleeping state, the agent stays in the nest region, moving with constant speed, except when the collision avoidance behavior is executed.

- The collision avoidance routine is triggered whenever an obstacle or another agent is located in the proximity zone of the current agent (Fig. 3(b)). The obstacle side is detected as the side (left or right) with higher average sensor activation, and the agent rotates in the opposite direction with a given angle $\alpha$ ($\alpha = 5^o$ in the experiments). It goes straight ahead in the subsequent time steps (unless some further obstacle enters in its proximity zone, in which case the collision avoidance is triggered anew). When its proximity zone becomes empty again, the agent rotates back to its initial direction.

### Goal of experiments

The experiments are meant to answer two main questions. The first one concerns the temporal couplings between the swarm agents. In the former graph-based setting, several

behavioral regimes were observed depending on the connectivity of the neighborhood graph (agent sociability), ranging from asynchronous behaviors to synchronous aperiodic and synchronous periodic. A 2D environment however involves several sources of variability, which might prevent the swarm from reaching a synchronous behavior. Firstly, the transitions from observing to foraging states are no longer instantaneous as agents must travel from the nest to the source. Secondly, the set of neighbors of each agent varies as the agent moves in observing state, whereas the connectivity was fixed in the previous experiments. Lastly, the agent activity might be perturbed as the collision avoidance routine is executed in priority whenever the agent meets an obstacle or another agent. The question thus is whether the regimes observed in the fixed graph-based setting are still observed in 2D simulations, and whether the transitions from one regime to another depend on the same design parameters.

The second question concerns spatial couplings, and the possible impact of synchronous behavior on the collective foraging efficiency. Whereas synchronous activity is ubiquitous in many living societies and complex systems, the benefits of synchrony remain actively debated. On the one hand, when agents move in a synchronous way as a flock, the chances of collision expectedly decrease and more agents might make it to the source. On the other hand, in asynchronous mode some agents might be deviated from their route to the source due to repeated collision avoidance ("traffic jams"); but it might also be the case that asynchronous agents better share the collective space and the frequency of traffic jams decreases. In order to investigate further the foraging efficiency, two indicators are proposed. The first one counts the *number* of agents arriving at the food source; the second one measures the overall foraging *time*, i.e. the overall number of time units spent by agents in the source region.

## Experimental setting

The experimental setting used to answer the above questions goes as follows. Each agent is simulated as a Khepera robot with eight infra-red sensors and a radio communication module. The communication range $\rho$ is constant, covering 20% of the arena unless indicated otherwise. Each foraging agent broadcasts its activity signals to all agents with distance less than $\rho$; each observing agent receives the signals of foraging agents on an individual basis. In other words, the simulated setting involves no centralized communication among agents.

At the beginning of each simulation, every agent is sleeping and wakes up after some time, independently and uniformly drawn in $]0, 2t_s[$. Each simulation involves 50,000 time steps. All reported results are averaged over 10 independent runs for a given parameter setting. As already mentioned, the *SpikeAnts* model is deterministic; the only source

of variation among simulations comes from the swarm initialization and the uniform agent wake-up times.

Every agent obeys the same *SpikeAnts* model with same parameters as in Chevallier et al. (2010). Foraging and sleeping times are chosen such that their ratio is not an integer, to avoid spurious synchronization effects: $t_f = 541$ and $t_s = 457$ time steps. Spiking neurons are simulated using a clock-driven simulator and Runge-Kutta method for differential equation approximations with a small time step of 0.1ms to achieve numerical stability.

## Experimental Results

This section reports on the temporal and spatial couplings observed in the 2D simulation of *SpikeAnts*.

### Emergence of Temporal Self-Organization

The temporal coupling at the population level is displayed in Fig. 4, reporting the number of active agents *vs* the simulated time step. Three behavioral regimes emerge depending on the parameter setting. An *asynchronous* regime (Fig. 4, (A)) is observed for low communication ranges; agents individually and asynchronously decide to go foraging, with an average number of 30 foraging agents in each time step out of 100 agents. Another *synchronous aperiodic* regime sees the emergence of sub-populations of agents, that synchronously decide to go foraging; still the size of the foraging subpopulation varies from one period to another one, and the foraging subpopulations with same size gather distinct agents in each period (Fig. 4, (B)). Finally, the *synchronous periodic* regime involves a few persistent subpopulations (two in Fig. 4, (C)), which alternate and go foraging. The agent trajectories in all three regimes are shown in Fig. 5, displaying different spatial patterns.

The emergence of these regimes has been explained from a few *SpikeAnts* design parameters (Chevallier et al., 2010). The first factor is the communication range $\rho$, given as percentage of the arena covered when agents broadcast/receive the foraging signal. For a low $\rho$, the agent decision is based on a few local cues; for a high $\rho$, every agent can reliably estimate the number of currently foraging agents. The second factor is called *receptivity* and characterizes the strength of interactions between agents; it is expressed as the ratio between the connection weight $w$ and the sub-threshold range (depending of the resting potential $V_{\rm rest}$ and the firing threshold $\vartheta$): $\left| \frac{w}{\vartheta - V_{\rm rest}} \right|$. With a high interaction strengths, a few spikes can trigger the agent decision; small variations in the received information lead to different decisions. With a low interaction strength, agent decisions are based on many signals; the number of spikes needed to reach the threshold is high and the agent decision thus is more stable.

The transition between all three regimes is made precise using an entropy indicator defined as follows. Let $n_t$ denote the number of foraging agents at (simulated) time $t$,
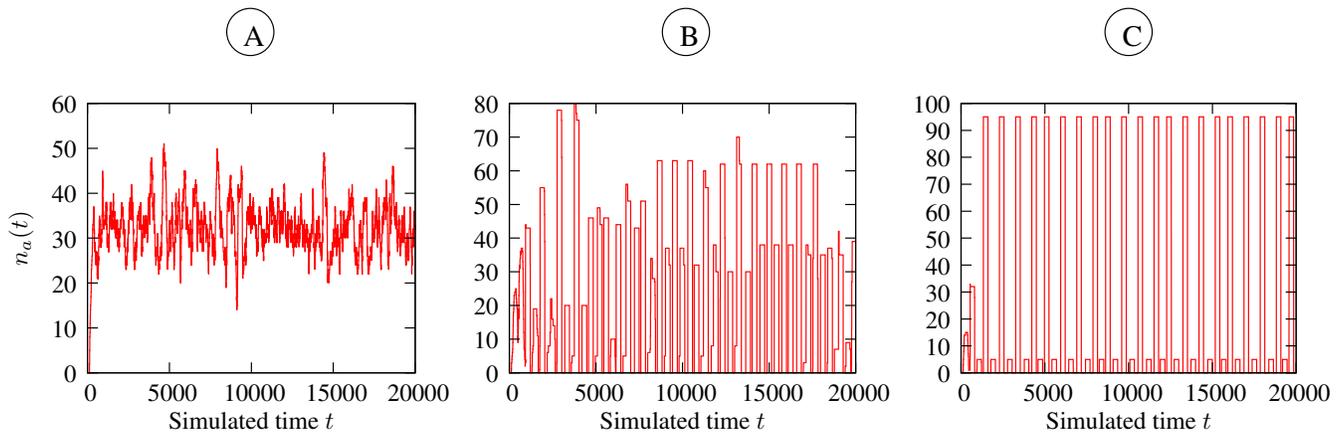
Figure 4: Three behavioral regimes emerge in the population: (A) Asynchronous, (B) Synchronous aperiodic and (C) Synchronous periodic. Each graph reports the number of active agents *vs* the simulated time step.
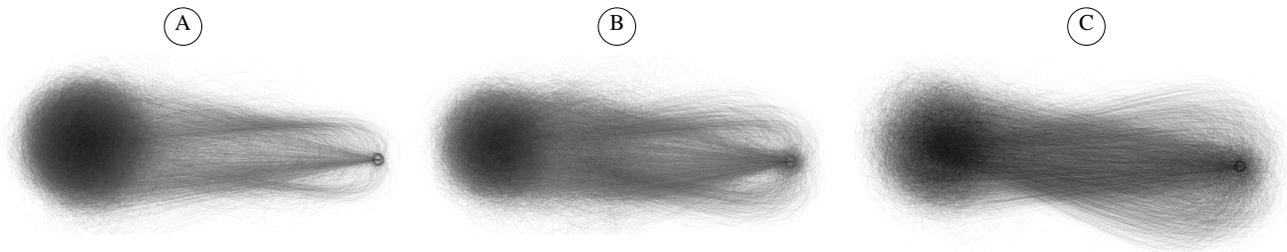


Figure 5: Trajectories followed by agents during a representative run, respectively in asynchronous (A), synchronous aperiodic (B) and synchronous periodic (C) regimes. Darker lines indicated the most often visited paths.

with $0 \leqslant n_t \leqslant M$ and $M = 100$ is the overall number of agents. Let $p_n$ denote the percentage of time steps such that $n_t = n$. The foraging entropy is classically defined as $H = -\sum_{n=0}^{M} p_n \log p_n$. The phase diagram, reporting the entropy *vs* the two control parameters of agent sociability and receptivity, is displayed in Fig. 6.

The asynchronous regime is characterized by a medium entropy value (circa 3) as the $n_t$ values are tightly distributed around a mean value. This regime emerges in populations with low communication range and high interaction strength. For a medium communication range and weak interactions, a synchronous aperiodic activity is observed, with high entropy ($H \approx 4$) as the sub-population sizes vary from 10 to 80 agents. A stable synchronous periodic regime, characterized by a low entropy value ($H \approx 1$ since the sub-population sizes are very stable), is observed for a large communication range and strong interactions. On Fig. 6, the synchronous periodic regime emerges for a communication radius which cover nearly all the arena ($\rho =80\%$). Complementary experiments show that for a smaller $t_f/t_s$ ratio the transition from asynchronous to synchronous regimes is shifted on the left, and occur for smaller communication range ($\rho= 30\%$, results omitted for brevity).
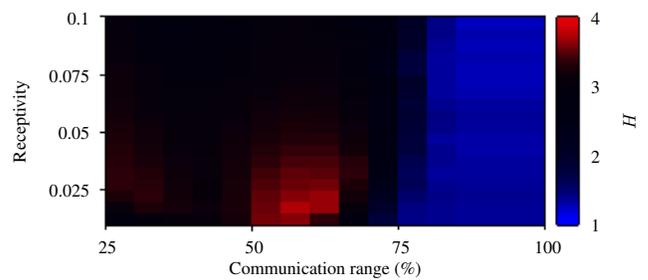


Figure 6: Phase diagram of the temporal coupling: foraging entropy vs the agent sociability ($x$ axis) and receptivity ($y$ axis).
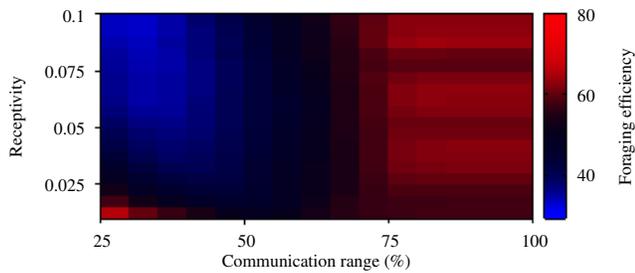
Figure 7: Foraging efficiency defined as the percentage of foraging agents that arrive in the source region.



Figure 8: Foraging loss $L = \frac{t_r - t_{\min}}{t_{\max} - t_{\min}}$, measuring the foraging time wasted in the travel from the nest to the source.

## Mixed Benefits of Synchronous Foraging

As mentioned earlier on, it was expected that synchronous regimes would benefit the foraging activity through decreasing the chance of collisions. The foraging efficiency measuring the fraction of foraging agents making it to the source is displayed in Fig. 7; on average, 80% of the foraging agents arrive in the source region in synchronous periodic regime, as opposed to less than 40% in asynchronous regime. The lower foraging efficiency in asynchronous regime is related to the "price of anarchy": more chances of collisions slow down the agents on their way to the source region, to the point that the foraging period ends up for most agents before they even reach the source, and they go back to the nest with empty hands.

Additional experiments are conducted to examine the sensitivity of the synchrony benefits when increasing the foraging time $t_f$. For larger $t_f$ values, all agents eventually arrive at the source sooner or later. It thus comes naturally to consider the agent traveling time $t_r$. By construction, $t_{min} \leqslant t_r \leqslant t_{max} = t_f$, where $t_{min}$ is the minimum time needed to go from the nest to the source. Let us accordingly define the *foraging loss* as the excess time wasted in the travel from the nest to the source, $L = \frac{t_r - t_{min}}{t_{max} - t_{min}}$. A contrasted picture then appears (Fig. 8): the foraging loss is minimum in asynchronous regime (less than 50%), and it increases when the swarm switches to synchronous aperiodic or periodic regimes (up to 65%). Agent paths shown on Fig. 5 corroborate these results: agents in synchronous regimes display more spatially distributed trajectories than in asynchronous regime, thus increasing the traveling time.

This experiment suggests that synchronous foraging entails opposite effects: while less agents arrive at the food source in asynchronous regime, the overall foraging time remains higher than for synchronous regimes. Additional experiments will examine these mixed effects in more depth.

## Discussion and Perspectives

This paper has presented the distributed, decentralized and deterministic swarm model *SpikeAnts*, accounting for the em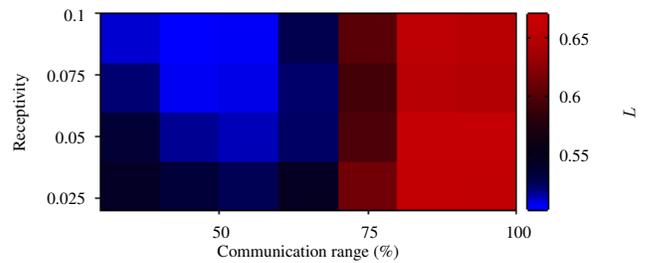ergence of synchronous behaviors and division of labor in a foraging swarm. Depending on the communication range and interaction strength among agents, the swarm behavior ranges from an asynchronous regime, where every agent independently makes its decisions, to a synchronous periodic regime where two persistent sub-populations alternate and go foraging.

A most interesting and unexpected experimental result concerns the mixed effects of synchrony. Quite a few authors have advocated the benefits of synchrony for division of labor: temporal coactivation of individuals enhance the information exchange and the cohesion of the population (Robinson, 1992; Bonabeau et al., 1998b; Delgado and Solé, 2000); synchrony also provides an intrinsic mechanism of mutual exclusion (Hatcher et al., 1992). In a 2D framework however, agent synchronization entails some spatial couplings through the collision avoidance mechanism. The experimental evidence suggests that synchronous flocking behaviors decrease the chances of collision (and more agents arrive at the target destination), but increase the traveling time (and agents have less time to achieve the task when arrived at destination).

Additional experiments will be needed to investigate these effects, and a first perspective is to implement *SpikeAnts* on a physical robotic platform. As already mentioned, *SpikeAnts* was designed to comply with limited memory and computational resources. Along the same lines, *SpikeAnts* will be extended to deal with several tasks of diverse priorities (e.g., collecting energy and rescuing the swarm robots out of energy). The question is whether and when the swarm will demonstrate several sub-populations attending the different tasks in a synchronous way, and how the division of labor may take place depending on the experimental setting.

A further question regards how the collective regime will be modified under external perturbations in the environment, and how the swarm adapts its response. A yet further stage will be to consider autonomous and adaptive agents, e.g. controlling their foraging time or interaction strength depending on their internal state and individual agenda.

## Acknowledgments

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