Evaluating Activator-Inhibitor Mechanisms for Sensors Coordination

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Abstract: The possibility to employ reaction-diffusion models to build spatial patterns in sensor networks has been advocated in other works. Nevertheless, it has not been investigated how the biologically-inspired solutions perform in comparison to more traditional ones taking into account specificities of sensor networks like severe energy constraints. In this technical report we present some preliminary results on the comparison between a bio-inspired coordination mechanism based on activator-inhibitor interaction and a simple mechanism, where nodes do not communicate but activate their sensing circuitry according to some probability.

Key-words: Sensor Networks, Bio-Inspired mechanisms, Reaction-Diffusion models, Activator-Inhibitor models, Sensor Coordination

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Évaluation des mécanismes activateur-inhibiteur pour la coordination des capteurs

Résumé : La possibilité d’utiliser des modèles de réaction-diffusion pour construire des motifs spatiaux dans les réseaux des capteurs a été préconisés dans d’autres travaux. Néanmoins, on n’a pas été étudiée comment les solutions biologique-inspirées performent par rapport plus les traditionnels tenant compte des spécificités des réseaux de sonde comme des contraintes graves d’énergie. En cet rapport de recherche nous présentons des résultats préliminaires sur la comparaison entre un mécanisme de coordination bio-inspirée basé sur l’interaction d’activateur et inhibiteur et un mécanisme simple, où les noeuds ne communiquent pas mais activent le leur circuits de detection selon une certaine probabilité.

Mots-clés : Resaux de capteurs, mécanisme bio-inspirée, modèles de réaction-diffusion, modèles d’activateur-inhibiteur, coordination des capteurs
1 Introduction

One of the challenges of sensor networks is the development of long-lived sensor networks in spite of energy constraints of individual nodes. Depending on the specific application (type and frequency of the events to capture, size of the network) the main energy consuming activity can either be sensing or communication. In order to spare energy, nodes can periodically turn off their sensing circuitry or their radio. In both cases coordination among nodes is needed. In fact nodes can stop sensing only if other nodes in the neighborhood guarantee an adequate coverage of the area to sense. At the same time sensor networks usually rely on multi-hop communications where sensors relay data produced by other sensors to one or more data sinks. So powering down radios on sensor nodes makes such nodes unavailable for multi-hop communication. Again coordination among nodes is needed in order to maintain communication backbones in the sensor network.

This coordination could theoretically be managed by a central authority which sends specific commands to each single node, but in most cases this approach is unfeasible for large sensor networks. In fact sensors are often randomly deployed, are exposed to hostile environments, can exhaust their batteries, also communication is subject to the vagaries of the wireless channel. All these issues lead to dynamics much faster than those of wired networks, hard to manage in a centralized way. Besides central management could impose on the network a high cost in terms of bandwidth and energy for communication. So the network should be self-organizing, i.e. nodes should autonomously carry out measurement and adaptive configuration.

Computer networks research community has proposed many protocols addressing the issue of node coordination (see [4] and references there). In this paper we propose a new coordination mechanism for sensing activity based on activator-inhibitor interaction, a model used to explain pattern formation in biological system, e.g. how identical totipotent cells can differentiate in the different parts of an organism [7].

The idea to use pattern formation models in sensor networks is not completely new. For example in [5], and some following papers from Thomas Henderson, reaction-diffusion models are proposed to build a spatial pattern that could help robot operation in a given area. Research in amorphous computing [1] has been recently looking at sensor networks as an instantiation of an amorphous computer [2]. The focus of such research is mainly on developing robust primitives, appropriate methods for analysis, and designing new high-level programming languages.

Despite this research activity, to the best of our knowledge, it has not been investigated how new biologically-inspired solutions for sensor networks perform in comparison to more traditional ones. In this paper we present some preliminary results on the comparison between a coordination mechanism based on activator-inhibitor interaction and a simpler one, where nodes do not communicate but activate their sensing circuitry according to some probability.

Our preliminary results suggests that the bio-inspired mechanism is able to significantly reduce energy consumption for sensing purpose, but more investigation is needed to take into account increased communication costs.

1 Usually the number of nodes deployed is significantly higher than the minimum needed, in order to make up for random deployment and failures.
The paper is organized as follows. In Sec. 2 we illustrate the specific coordination problem we want to address. In Sec. 3 and in Sec. 4, respectively, we present the new biologically inspired coordination mechanism and the probabilistic one. In Sec. 5, performance of the two mechanisms are presented. Conclusions and future research activity are in Sec. 6.

2 Network Scenario

We consider a field where $N$ wireless sensors are uniformly at random deployed in an area $A$. The communication model is the simplest one: two sensors can communicate if their distance is smaller than $r$, the radio transmission range of each sensor. The network is quite dense, i.e. each sensor has many other sensors in its transmission range.

We assume that the most energy-consuming activity is sensing, because of power requirement of sensing circuitry or computation required to process data. For this reason, we would like some nodes to turn off their sensing circuitry in order to spare battery and increase sensor network lifetime. We assume that each node can sense up to a distance $d$, where $d >> r$. As we are going to discuss in the following section, for $d < r$ an activator-inhibitor scheme would require nodes to be able to estimate distances from other nodes.

3 The Activator-Inhibitor Mechanism

Activator-inhibitor models have been able to explain spatial concentration patterns with characteristic features known from biological systems: in this case a strong short range positive feedback (usually referred to as autocatalysis) is coupled with a long range negative feedback (usually referred to as lateral inhibition). Their interaction can produce polar and periodic patterns as well as net-like structures, able to adapt to disturbances while preserving some specific distances between activity centers. Both differential equation and cellular automata modeling approaches have been successfully applied to these systems (e.g. [7] and [3]).

Our starting point is the differential equation model in [7].

Let say $a(x, y, t)$ and $h(x, y, t)$ respectively activator and inhibitor densities in the area $A$. The following set of equations with zero flux boundary conditions can produce periodical patterns for specific values of the parameters:

$$
\begin{align*}
\frac{\partial a}{\partial t} &= \frac{ca^2}{h} - \mu a + \rho_0 + D_a \nabla^2 a, \\
\frac{\partial h}{\partial t} &= ca^2 - \nu h + \rho_1 + D_h \nabla^2 h, \\
\mathbf{n} \cdot \nabla a &= 0 \text{ on } \partial A, \\
\mathbf{n} \cdot \nabla h &= 0 \text{ on } \partial A,
\end{align*}
$$

(1)

Some illustrative costs from [6]: a photocell can absorb about 1 mW, transmission can require 1 $\mu$J per bit and execution of an instruction 0.01 $\mu$J.
where $\nabla f$ and $\nabla^2 f$ respectively denote the gradient and the laplacian of function $f$, and $\partial A$ the boundary of the area $A$.

In our algorithm, each sensor, say $i$, stores its own activator and inhibitor values (respectively $a_i$ and $h_i$) and it broadcasts them every $\tau$ seconds. With the same periodicity sensor $i$ updates its own concentration values on the basis of the information collected from its neighbours (let $N_i$ denote this set) according to the following equations, which can be derived from a discretization of Eq. (1):

\[
\begin{align*}
    a_i(t_{k+1}) &= a_i(t_k) + \tau \left( \frac{c a_i^2}{h} - \mu a_i + \rho_0 + \frac{9 D_a}{4 r^2} \sum_{j \in N_i} (a_j(t_{k+1}) - a_i(t_k)) \right), \\
    h_i(t_{k+1}) &= h_i(t_k) + \tau \left( \frac{c a_i^2}{h} - \nu h_i + \rho_1 + \frac{9 D_h}{4 r^2} \sum_{j \in N_i} (h_j(t_{k+1}) - h_i(t_k)) \right),
\end{align*}
\] (2)

where $t_{k+1} = t_k + \tau$ and $a_j(t)$ and $h_j(t)$ denote the concentration values of sensor $j$ known from sensor $i$ at time $t$. Sensors, whose activator concentration is above a given threshold ($a_{th}$) and is the highest value among the neighbours, become active turning on their sensing circuitry.

Remarks. Note that the zero flux boundary conditions are intrinsically satisfied because the algorithm simply redistribute activator and inhibitor among sensors in the network. We observe also that this mechanism can work only for $d >> r$. In fact for $d < r$ we should have many active sensors in the radio transmission area of a node in order to guarantee adequate coverage. This would require activator and inhibitor concentrations to vary significantly in this area, but this is not possible as long as each sensor simply average its neighbours concentration values as in Eq. (2).

Activator-Inhibitor Mechanism Configuration In order to create a pattern in the sensor network, the system should be configured to work with a fixed number of active sensor equidistant from each other. We followed the analysis in \[8\] to find out which set of parameters ($c, \mu, \rho_0, D_a, \nu, \rho_1, D_h$) is able to satisfy our condition. Such analysis sets the conditions for the stability of homogenous solutions and the existence of unstable not-homogeneous solutions of a generic reaction-diffusion system. To link up with Murray’s analysis, Equations (1) can be rewritten as:

\[
\begin{align*}
    \frac{\partial a}{\partial t} &= f(a, h) + D_a \nabla^2 a, \\
    \frac{\partial h}{\partial t} &= g(a, h) + D_h \nabla^2 h,
\end{align*}
\]

where $f(a, h) = ca^2/h - \mu a + \rho_0$ and $g(a, h) = ca^2 - \nu a + \rho_1$. Let $f_a$ be the partial derivative of $f$ with respect to $a$ evaluated in the homogeneous steady state $(a_0, h_0) = (1, 1)$, such that:

\[
\begin{align*}
    f(a_0, h_0) &= \frac{c a_0^2}{h_0} - \mu a_0 + \rho_0 = c - \mu + \rho_0 = 0, \\
    g(a_0, h_0) &= c a_0^2 - \nu h_0 + \rho_1 = c - \nu + \rho_1 = 0.
\end{align*}
\] (3)
The Murray’s conditions are:

\[
\begin{cases}
    f_a + g_h < 0 \\
    f_a g_h - f_h g_a > 0 \\
    D_h f_a + D_a g_h > 0 \\
    (D_h f_a + D_a g_h)^2 - 4 D_a D_h (f_a g_h - f_h g_a) > 0
\end{cases}
\]  

(4)

For Equations (1), these conditions are:

\[
\begin{cases}
    2c - \mu - \nu < 0 \\
    2c^2 - (2c - \mu)\nu > 0 \\
    D_h(2c - \mu) - D_a \nu > 0 \\
    (D_h(2c - \mu) - D_a \nu)^2 - 4 D_a D_h (2c^2 - (2c - \mu)\nu) > 0
\end{cases}
\]

These conditions guarantee linear stability without diffusion and unstability to small spatial perturbation. Nevertheless all these conditions do not determine the distance between every active node. In order to achieve this feature we added more conditions to isolate a single mode of the system that should guarantee a fixed distance between active sensors.

According to the [8] equations our solution to the linear problem is:

\[
w(x, y, t) = \sum_k c_k e^{\lambda t} W_k(x, y)
\]

(5)

where \(W_k(x, y)\) is the eigenfunction correlated to the wavenumber \(k\) that satisfies the following conditions:

\[
\begin{cases}
    \nabla^2 W_k(x, y) = -k^2 W_k(x, y) \\
    (n \cdot \nabla) W_k(x, y) = 0
\end{cases}
\]

Considering our domain bi-dimensional, with \(0 \leq x \leq L_x\) and \(0 \leq y \leq L_y\), a solution to the previous conditions is the eigenfunction \(W_k\):

\[
W_k(x, y) \propto \cos \left( \frac{n \pi x}{L_x} \right) \cos \left( \frac{m \pi y}{L_y} \right)
\]

\[
\nabla^2 \left( \cos \left( \frac{n \pi x}{L_x} \right) \cos \left( \frac{m \pi y}{L_y} \right) \right) = - \left( \frac{n^2 \pi^2}{L_x^2} + \frac{m^2 \pi^2}{L_y^2} \right) \cos \left( \frac{n \pi x}{L_x} \right) \cos \left( \frac{m \pi y}{L_y} \right)
\]

where \(n\) and \(m\) are integers. In our simulations the sensors are deployed in a unit square field, hence both \(L_x\) and \(L_y\) are equals to one. Moreover we want the same period in both the dimension \(x\) and \(y\), so we want \(n\) and \(m\) be the same integer value \(n_0\). Therefore our eigenvalue \(k_c^2\) will be:

\[
k_c^2 = \frac{n_0^2 \pi^2}{L_x^2} + \frac{n_0^2 \pi^2}{L_y^2} = 2n_0^2 \pi^2
\]
In order to isolate only one mode in the system we extend the Murray’s conditions at Eq. (4) adding two more conditions.

\[
\begin{align*}
\frac{D_h f_a + D_a g_h}{2D_a D_h} &= k_c^2 \\
\sqrt{\left(\frac{D_h f_a + D_a g_h}{2D_a D_h}\right)^2 - \frac{4D_a D_h (f_a g_h - f_h g_a)}{2D_a D_h}} &< \frac{\pi^2}{L^2}
\end{align*}
\]

The first one establishes the minimum of the function \(h(k^2)\) to our choosed \(k_c^2\) value, this should guarantee our mode to be stimulated. The second one prevents other modes to interfere with our choosed \(k_c^2\). This is possible only when there is no combination of \(m\) and \(n\) that verifies the condition \(m^2 + n^2 = 2n_0^2\). For instance the value \(n_0 = 5\) stimulates the mode \(k_c^2 = 50\pi^2\), but even the combination of \(m = 1\) and \(n = 7\) leads to the same value of \(k^2\), and vice versa. Therefore all these values of \(n_0\), such as \(n_0 = \{5, 10, 13, 15, 17, \ldots\}\), should be avoided in the choice of the number of the activated zone.

This would allow us, for given sensor network characteristics (like the radio range, sensing range and number of nodes), to derive mechanism parameters in order to guarantee a given coverage. Nevertheless our simulations show that, while the system exhibits patterns whenever the conditions prescribes it, the number of active nodes can be very different from what expected. This can be a consequence of the discretization of Eq. (1). For this reason we considered for the bio-inspired mechanism the parameter setting specified in Table 1 and, after having derived the number of active nodes by simulation, we chose the sensing range in order to have a sensing coverage near to 95%.

4 The Probabilistic Mechanism

In the probabilistic coordination mechanism each node independently activates its sensing circuitry with probability \(p\). This mechanism does not require any form of communication among nodes, but we can expect that more active sensor will be required in comparison to the bio-inspired mechanism in order to guarantee the same sensing coverage. Sensing coverage \((\alpha)\) is evaluated as the fraction of the area \(A\) where events are sensed by at least one sensor.

**Probabilistic Mechanism Configuration** In order to determine the activation probability \(p\) for the probabilistic mechanism, we can use the following formula valid for an infinite Poisson field:

\[c = 1 - e^{-\lambda \pi d^2}\] [9], where \(\lambda\) is node density (= \(N\) in our case). This relation provides quite good results ???. The probabilistic mechanism appears on the whole easier to configure.

5 Performance Evaluation

We want to study which active sensor patterns arise with the two mechanisms and how efficient they are in terms of sensing coverage of the field and power consumption. In this section we present some preliminary results obtained through a Java simulator we developed. Figure 1 shows exemplificative
patterns of active sensors obtained with the two mechanisms. For a specific sensor placement we have run many simulations of the two mechanisms, logging the final number of active nodes and their positions. For the bio-inspired mechanism, we have also logged the number of messages \( M \) exchanged until the whole concentration \( \tau \) varies less than 0.008\( \tau \) between two consecutive global updates.

In order to determine the activation probability \( p \) for the probabilistic mechanism, we can use the following formula valid for an infinite Poisson field: \( c = 1 - e^{-p\lambda\pi d^2} \) \cite{9}, where \( \lambda \) is node density (= \( N \) in our case). This relation provides quite good results ???. The probabilistic mechanism appears on the whole easier to configure.

**Sensing Costs** Energy consumption for sensing purpose is clearly related to the number of active nodes. In particular we can evaluate it in two different ways. In the first case we just consider sensing cost to be proportional to the number of active sensors (\( S \) in Table\( ^2 \)). This corresponds to the case where the sensing field really coincides with the 1x1 area with \( N \) nodes we are simulating.

\[3\] Concentrations at each nodes are initially set equiprobably to a high (1.8) or a low (0.2) concentration value.
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Table 2: Results (95% confidence intervals)

<table>
<thead>
<tr>
<th></th>
<th>Bio-inspired</th>
<th>probabilistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S$</td>
<td>[14.91,16.59]</td>
<td>[24.65,27.30]</td>
</tr>
<tr>
<td>$S_{eq}$</td>
<td>[9.87,11.18]</td>
<td>[20.04,22.06]</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>[0.93,0.95]</td>
<td>[0.93,0.96]</td>
</tr>
<tr>
<td>$\alpha_{90%}$</td>
<td>0.92</td>
<td>0.88</td>
</tr>
<tr>
<td>$M$</td>
<td>[90038,111880]</td>
<td>-</td>
</tr>
</tbody>
</table>

In the second case we consider sensing cost to be proportional to an equivalent number of sensors (say it $S_{eq}$) where each active node is weighted considering which fraction of its sensing area (a circle with radius $d$ centered in the sensor) is inside the unitary area. This corresponds to consider an infinite sensing field with $N$ sensors per area unit. The difference among the two is significant due to border effects (see remarks below).

Table 2 shows average performance of the bio-inspired mechanism and of the probabilistic one for two different values of the activation probability: $p_1 = 0.416\%$ and $p_2 = 0.509\%$. They have been selected in order to achieve approximately the same performance of the bio-inspired mechanism, respectively in terms of average coverage probability ($\alpha$) and minimum coverage guarantee in 90% of the cases ($\alpha_{90\%}$). The results show how sensing cost is much higher for the probabilistic algorithm. When our target is the average coverage (then we consider $p_1$), the number of sensors activated is 100% higher in comparison to the bio-inspired mechanism for the infinite field. The reaction-diffusion process proves to be able to space away the concentration maxima. The performance gap is smaller on the unitary field (only 60%). In fact, as we can note from Figure 1 and as it is predicted by the theory in reaction-diffusion systems many concentration maxima are on the boundaries of the area. These maxima correspond to active sensors which only partially contribute to the coverage of the unitary area (but they would contribute to the coverage of adjacent areas). This effect is particularly significant in cases where the number of sensors to be activated in the reference area is quite small (i.e. "large" $d$ values). Finally when we consider minimum coverage guarantees, the bio-inspired algorithm offers even better performance. Probabilistic forwarding exhibits a much higher variability in placement of active nodes, so that the average number of active sensors with the probabilistic mechanism has to be from 100% up to 160% higher under the two scenarios in order to guarantee the same minimum coverage level.

6 Conclusions and Future Research

From the previous results it appears that the bio-inspired mechanism is able to spare energy for sensing purpose, activating a smaller number of sensors. At the same time Table 2 shows also that a high number of message is needed in order to establish the pattern starting from a clean slate status.

\footnote{Note that sensing coverage should be evaluated differently for the infinite field scenario taking into account that also nodes out of the unitary area contribute to its coverage.}

RR n° 0123456789
Message exchange is needed until an almost stable configuration is reached and active nodes are individuated. Should nothing change, the initial communication cost would become negligible after a long enough network operation time. In reality active nodes can go out of battery or can undergo temporary failures. For this reason the algorithm should run continuously in order to keep track of the changing scenario and select new active nodes if necessary. An analysis of this issue requires assumptions on sensor failure phenomenon and is out of the purpose of this short paper. Therefore it is left for future research.

References


