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 paper 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.

I. 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[1]. 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.

[1]Usually the number of nodes deployed is significantly higher than the minimum needed, in order to make up for random deployment and failures.

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 [3] 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 [6].

The idea to use pattern formation models in sensor networks is not completely new. For example in [4], 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 [**?**] has been recently looking at sensor networks as a instantiation of an amorphous computer [1]. 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.

The paper is organized as follows. In Sec. II we illustrate the specific coordination problem we want to address. in Sec. III and in Sec. IV we respectively present the new biologically inspired coordination mechanism and the probabilistic one. In Sec. V performance of the two mechanisms are presented. Conclusions and future research activity are in Sec. VI. An extended version of this paper is available as INRIA Research Report [8].

II. Network Scenario

We consider a field where N wireless sensors are uniformly randomly 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 sensor 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[2]. 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 $d >> r$.

III. 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. [6] and [2]).

Our starting point is the differential equation model in [6].

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 can produce periodical patterns for specific values of the parameters:

$$\begin{aligned} \frac{\partial a}{\partial t} &= \frac{ca^2}{h} - \mu a + \rho_0 + D_a \left(\frac{\partial^2 a}{\partial x^2} + \frac{\partial^2 a}{\partial y^2} \right), \\ \frac{\partial h}{\partial t} &= ca^2 - \nu h + \rho_1 + D_h \left(\frac{\partial^2 h}{\partial x^2} + \frac{\partial^2 h}{\partial y^2} \right). \end{aligned} \tag{1}$$

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 τ 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):

$$a_i(t_{k+1}) = a_i(t_k) + \tau \left(\frac{ca_i^2}{h} - \mu a_i + \rho_0 + \frac{9D_a}{4r^2} \sum_{j \in N_i} (a_{j,i}(t_{k+1}) - a_i(t_k)) \right),$$

$$h_i(t_{k+1}) = h_i(t_k) + \tau \left(ca_i^2 - \nu h_i + \rho_1 + \frac{9D_h}{4r^2} \sum_{j \in N_i} (h_{j,i}(t_{k+1}) - h_i(t_k)) \right),$$

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

IV. 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

[2]Some illustrative costs from [5]: a photocell can absorb about 1 mW, transmission can require 1 μJ per bit and execution of an instruction 0.01 μJ.

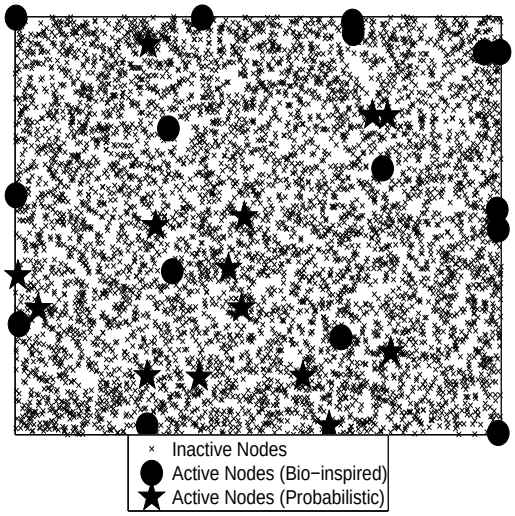

Fig. 1. Sensor activated by the two mechanisms.

active sensor will be required in comparison to the bio-inspired mechanism in order to guarantee the same sensing coverage. Sensing coverage (α) is evaluated as the fraction of the area A where events are sensed by at least one sensor.

V. 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[3] varies less than 0.008τ between two consecutive global updates.

a) 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 [7] to find out which set of parameters $(c, \mu, \rho_0, D_a, \nu, \rho_1, D_b)$ 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:

$$\begin{aligned} \frac{\partial a}{\partial t} &= f(a,h) + D_a \nabla^2 a, \\ \frac{\partial h}{\partial t} &= g(a,h) + D_h \nabla^2 h. \end{aligned}$$

[3]Concentrations at each nodes are initially set equiprobably to a high (1.8) or a low (0.2) concentration value.

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:

$$\begin{aligned} f(a_0,h_0) &= \frac{ca_0^2}{h_0} - \mu a_0 + \rho_0 = c - \mu + \rho_0 = 0 \\ g(a_0,h_0) &= ca_0^2 - \nu h_0 + \rho_1 = c - \nu + \rho_1 = 0 \end{aligned} \tag{2}$$

The Murray's conditions are:

$$\begin{cases} f_a + g_h < 0 \\ f_a g_h - f_h g_a > 0 \\ D_h f_a + D_a g_h > 0 \\ \left(D_h f_a + D_a g_h\right)^2 - 4 D_a D_h \left(f_a g_h - f_h g_a\right) > 0 \end{cases} \tag{3}$$

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

b) 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

TABLE I

NETWORK PARAMETERS

A	1x1	N	6125	μ	0.75
r	0.0228	d	0.22	ν	0.8
D_a	0.000222273	τ	0.003	ρ_0	0.25
D_h	0.00580619	c	0.5	ρ_1	0.3

to the number of active sensors (S in Table II). This corresponds to the case where the sensing field really coincides with the 1x1 area with N nodes we are simulating. 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[4]. The difference among the two is significant due to border effects (see remarks below).

Table II 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 (α) 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 [7] 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.

VI. 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 II shows also that a high number of message

[4]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.

TABLE II

RESULTS (95% CONFIDENCE INTERVALS)

	Bio-inspired	probabilistic	
		p_1	p_2
S	[14.91,16.59]	[24.65,27.30]	[30.42,33.00]
S_{eq}	[9.87,11.18]	[20.04,22.06]	[25.04,27.10]
α	[0.93,0.95]	[0.93,0.96]	[0.95,0.97]
$\alpha_{90\%}$	0.92	0.88	0.92
M	[90038,111880]	-	-

is needed in order to establish the pattern starting from a clean slate status. 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.

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