High Performance Sleep-Wake Sensor Systems based on Cyclic Cellular Automata *

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Abstract

Our contribution in this paper is a scalable, easily implemented, self-organizing, energy conserving intrusion-detection sensor system applying concepts from cellular automata theory. The system self-assembles periodic wake-sensor barriers (waves) that sweep the sensor field; it is highly effective even in the case of frequent communication failures, sensor failures, large obstacles, and when intruders know sensor locations.

1 Introduction

Research in wireless sensor networks continues to intensify as technological advances are made. These advances make it possible to deploy low-cost and low-complexity sensors to monitor large areas where accessibility may be limited. One of the most common applications is event-driven: Detect and report intruders or similar specific events such as fires within some sensor field. As in most studies of the intrusion-detection problem, we focus on maximizing coverage of the sensing field, minimizing the probability that an intruder penetrates a sensor field without being detected, and minimizing the distance (or time) of penetration until detection [4, 5, 6, 7, 8, 9].

To accommodate the characteristic limitations of sensor networks, in particular limited computing capability and limited energy sources, approaches are required that are different from those needed in the development of conventional wireless networks. A standard approach to energy conservation is the use of *sleep-wake protocols* by which sensors more or less uniformly alternate between sleep and awake periods associated with relatively low and high power output: only the awake sensors actively sense events in their environments and sleep sensors avoid idle listening and overhearing . By means of a distributed algorithm defined by a local rule, sensors coordinate sleep-wake schedules with their neighbors in communication range; these communications contribute to the energy consumption in wake states.

The higher the density of sensors in (and hence the cost of) a given sensor field, the smaller the fraction needed in the wake state, the longer the sleep periods can be, and the longer the sensor field can survive without a deterioration in surveillance. Finding a design technique by which one can determine near-optimal operating points in the cost-performance spectrum is a challenging problem of clear importance – and it is this problem that we address in this paper. *More precisely, we take as fixed the basic physical characteristics such as communication range and sensing range, and introduce a protocol whereby variation of a single parameter allows one to identify a system which is self-organizing and has the elegance of local-rule logic no more sophisticated than a simple counter. Further, it has the following critically important behavior: it is scalable, fault tolerant, effective against intruders with knowledge of sensor locations, seamlessly works around obstacles effectively, and has a high performance/cost ratio.* It is striking that these additional properties essentially 'come for free,' as artifacts of our self-organizing protocol; the properties were not objectives that influenced design. This notion becomes clear in the next section.

As discussed later, we assume that clock synchronization is feasible (see e.g., [10, 11, 12, 13]), and introduce the cellular automaton(CA) dynamic [14, 15] as a model underlying our self-organizing sleep-wake protocol. Although this model has received relatively recent emphasis in applied mathematics and physics, it was actually introduced by von Neumann and Ulam in the context of cellular logic some 50 years ago. The original purpose of a cellular automaton was to model biological self-reproducing systems.

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Nowadays, CAs are used as a modeling tool for the study of physical systems in discrete time and space. In the regular lattice, each *cell*(or site) of the cellular automaton has a discrete value, typically an integer, as its state, and its state transitions at discrete time steps are governed by a universal local rule. The current value of each site at time step t depends on the values of neighboring cells which, according to a given metric, are located within a certain distance at time step $t-1$.

The remainder of this section briefly discusses relevant background in sensor system research. Section 2 covers background in cellular automata, specializing to variants of *cyclic* cellular automata, and in so doing mirrors the thought process leading to our proposed intrusion-detection scheme. Section 3 then details a system prototype and is followed by the results of extensive experiments in Section 4. Section 3 also introduces a novel technique whereby artificial nucleation centers are created so as to improve the performance of the intrusion-detection scheme. Conclusions are drawn in Section 5, which also mentions avenues for future research.

Background. In S-MAC [1], sensors follow a coordinated sleep schedule, which requires a virtual cluster and synchronization among the neighboring sensors to reduce the idle listening. T-MAC [2] introduced a sleep schedule in accordance with adaptive duty cycle by using a future-request-to send packet. Similar to S-MAC, T-MAC requires virtual cluster and synchronization. The study in [3] used graph theory to provide the optimal sleep schedule that minimizes communication latency and makes sensors active for a given fraction of time slots on an average.

In [4], the authors investigated both the characteristics of intruder movement within various models, and the impact of node failures on the performance of surveillance. The research reported in [5] proposed a lifetime-maximizing sleep-scheduling scheme that covers a sensor field with a guaranteed maximum detection delay.

The sleep-wake algorithm in [6] has two separate states: a surveillance state and a tracking state. In the surveillance state, certain sensors eventually wake up to provide a homogeneous, though not necessarily full, coverage of the field. In the tracking state, sensors wake up to provide p-coverage (coverage by at least p sensors) of a certain area where targets are detected.

The proposed power management and collaborative detection scheme in [7] is supported by synchronization and localization. In [8], the authors proposed a selective sensor activation scheme in a noisy environment. However, these intrusion detection schemes fail to detect mobile intruders who know sensor locations, intruders that are said to be "intelligent". This observation was made in [9] where the authors established a critical sensor density in a finite-width field such that intelligent intruders can almost surely find paths without being detected, if the density of sensors is below the critical value.

2 Cyclic Cellular Automata

2.1 The Homogeneous Model

The *cyclic cellular automaton* (CCA) follows a local rule which is the same for all states[1]. Each cell can be in any state ranging from 0 to $k-1$. Let

$$\xi_t(x) : \mathbb{Z}^2 \to \{0, 1, \ldots, k-1\}$$

denote the state of cell $x \in \mathbb{Z}^2$ at integer time t. A cell x increases its state $\xi_t(x)$ to

$$\xi_{t+1}(x) = \xi_t(x) + 1 \mod k$$

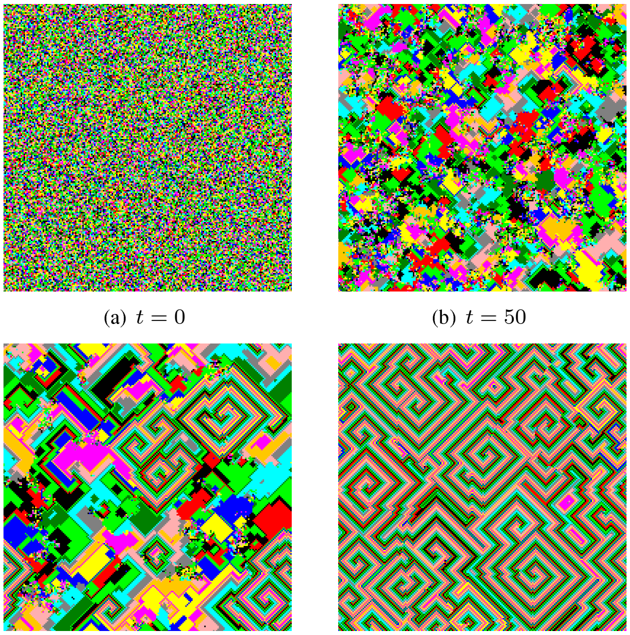
if and only if, for some given threshold θ and neighbor set $N(x)$, there are at least θ other cells $y \in N(x)$ such that $\xi_t(y) = \xi_t(x) + 1 \mod k$; otherwise, its state does not change. Our interest is restricted to the CCA in two dimensions. With a distance metric ℓ_p given, the neighbor set $N(x)$ of cell x is the set of all cells within a given distance of x. Until stated otherwise, take $N(x)$ to be the *von Neumann neighborhood*: the 4 cells within distance 1 in the ℓ_1 metric, i.e., the 4 cells that share an edge with x.

The initial state of the automaton is said to be *primordial soup*[2] if the initial cell states are i.i.d. uniform random draws from $\{0, \ldots, k-1\}$. It is a remarkable fact that, starting with primordial soup, the cyclic cellular automaton in two dimensions generates, with high probability, locally periodic *spiral-like* patterns with random chiralities; visually, the periodic dynamic takes the form of waves proceeding outward from the vortices of the spirals. The spirals are rectilinear and diagonally oriented in the sense that they consist of a sequence of straight-line segments of increasing length parallel to the diagonals. As illustrated in Figure 1(d), where each state has a distinct color, the pattern originates (or *nucleates*) in a group of neighboring cells whose states cycle through the integers $0, \ldots, k-1$.

Figure 1 illustrates the dynamic of the CCA with $k = 12$ and $\theta = 1$. At $t = 0$, the cell colors give the primordial soup of Figure 1(a). In early stages, as in 1(b) after 50 steps, isochromatic areas form randomly, expanding in waves, but no nucleation of spirals is yet to be seen. Figure 1(c) gives the pattern after 90 steps and shows the onset of spiral patterns. After enough time has elapsed, the entire automaton participates in generating periodic spiral patterns, as in Figure 1(d) after 150 steps. Eventually, the system becomes

[1] see Griffeath's web page for many references: http://psoup.math.wisc.edu/welcome.html

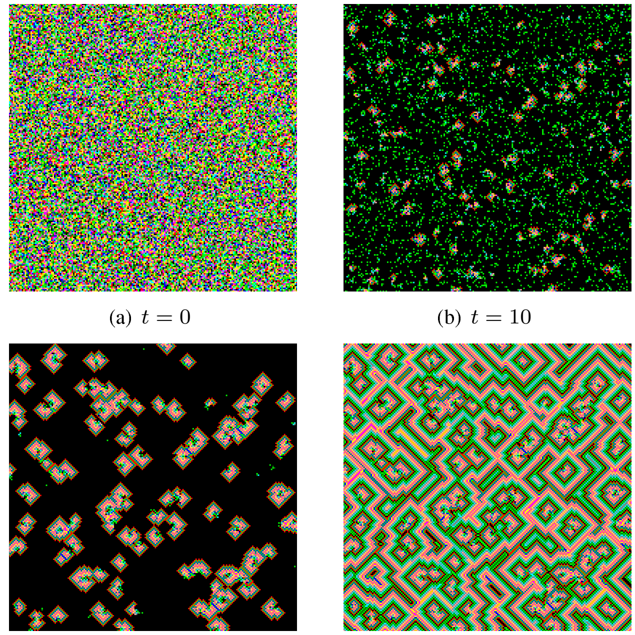
[2] The reference is to the use of CAs in origin-of-life studies of theoretical biology.



(a) $t = 0$ (b) $t = 50$

(c) $t = 90$ (d) $t = 150$

Figure 1. Cyclic Cellular Automata n $\mathbb{Z}^2$ (k=12)



(a) $t = 0$ (b) $t = 10$

(c) $t = 15$ (d) $t = 50$

Figure 2. Greenberg-Hastings Model in $\mathbb{Z}^2$ (k=12)

metastable with the lattice a collection of locally-periodic spirals where the state sequences of all cells are periodic with period k and phase changes characterize the boundaries between adjacent structures[3] A more detailed discussion of the process can be found in [16].

We see already the suggestion of an idea for using CCAs in the design of a self-organizing intrusion-detection scheme for sensor networks. Identify cell centers with sensors (the lattice with the sensor field), and choose a grid size so that adjacent sensors are within communication range. Now think of selecting one of the colors in the periodic bands of each spiral and making it a wake state (the same for all spirals). Deleting the remaining $k - 1$ colors corresponding to sleeping sensors, we would have a collection of wake-sensor barriers spanning the entire field. Moreover, in keeping with local periodicity, *these barriers are effectively in motion*, sweeping the field in waves, so that, even if immediate detection does not occur, it does so at the arrival of the next wave. To exploit this general idea, several issues must be dealt with. First and foremost, we need a version of the CCA which produces only the wake-sensor barriers, a problem we solve in the next subsection. Second, a more realistic model places the sensors in the continuous plane $\mathbb{R}^2$ and may have to place them at random rather than deterministically. This problem is addressed in the last subsection. Other issues include a guarantee that the desired wave-like, wake-sensor process does not die out. This *fixation* problem will be addressed in the next section along with other details of full sensor system design.

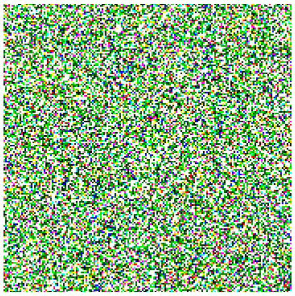
[3] One acquires much greater insight into the evolution of the CCA, and the derivatives to be discussed later, if one can view the CCA "in motion," rather than as a sequence of snapshots. For this, we urge the reader to go to the web site http://www.ee.columbia.edu/∼kjkwak/ca. There, the reader will be told how to conduct his or her own experiments and see the patterns evolve as a function of time.

2.2 Greenberg-Hastings Model in Z^2

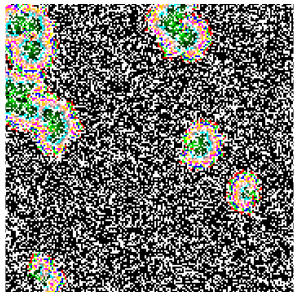
The *Greenberg-Hastings model* (GHM)[17]-[18] is a simplified cyclic cellular automaton that emulates an excitable medium. In the GHM, the rule uniform over all states in the CCA is instead restricted to a single state, taken for convenience to be the state 0. Returning for the moment to general neighbor sets, the state transition rule involves the same parameters θ, k, and N as before, and is as follows: The state of cell $x \in \mathbb{Z}^2$ evolves according to the local rule:

1. If $\xi_t(x) = i > 0$, then $\xi_{t+1}(x) = i + 1 \mod k$.
2. If $\xi_t(x) = 0$ and at least θ neighbors are in state 1, then $\xi_{t+1}(x) = 1$; otherwise, there is no change in state: $\xi_{t+1}(x) = 0$.

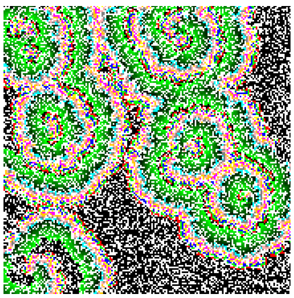
Thus, the state of a cell is incremented *automatically* if it is nonzero. But if it is 0, then it is incremented only *by con-*



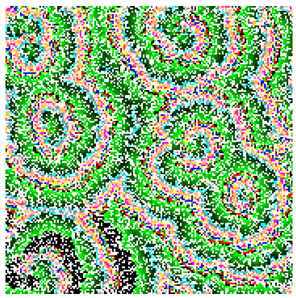
(a) $t = 0$



(b) $t = 10$

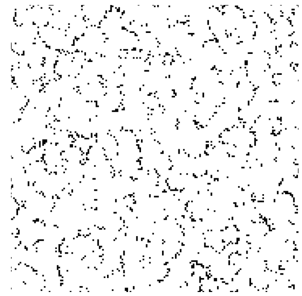


(c) $t = 15$



(d) $t = 50$

Figure 3. Greenberg-Hastings Model in $\mathbb{R}^2$ (k=20)



(a) k=12

(b) k=20

Figure 4. Greenberg-Hastings Model in $\mathbb{R}^2$

tact, as in the homogeneous CCA, i.e., only if enough of its neighbors are in state 1. In the excitable-medium applications, excitation is the transition from state 0 to state 1.

We now adopt a threshold $\theta = 1$, as before, but the expanded *Moore* neighborhood N_x in which cell x is the central cell in a 3×3 array of cells, i.e., N_x contains just those 8 cells that touch x at an edge or vertex.

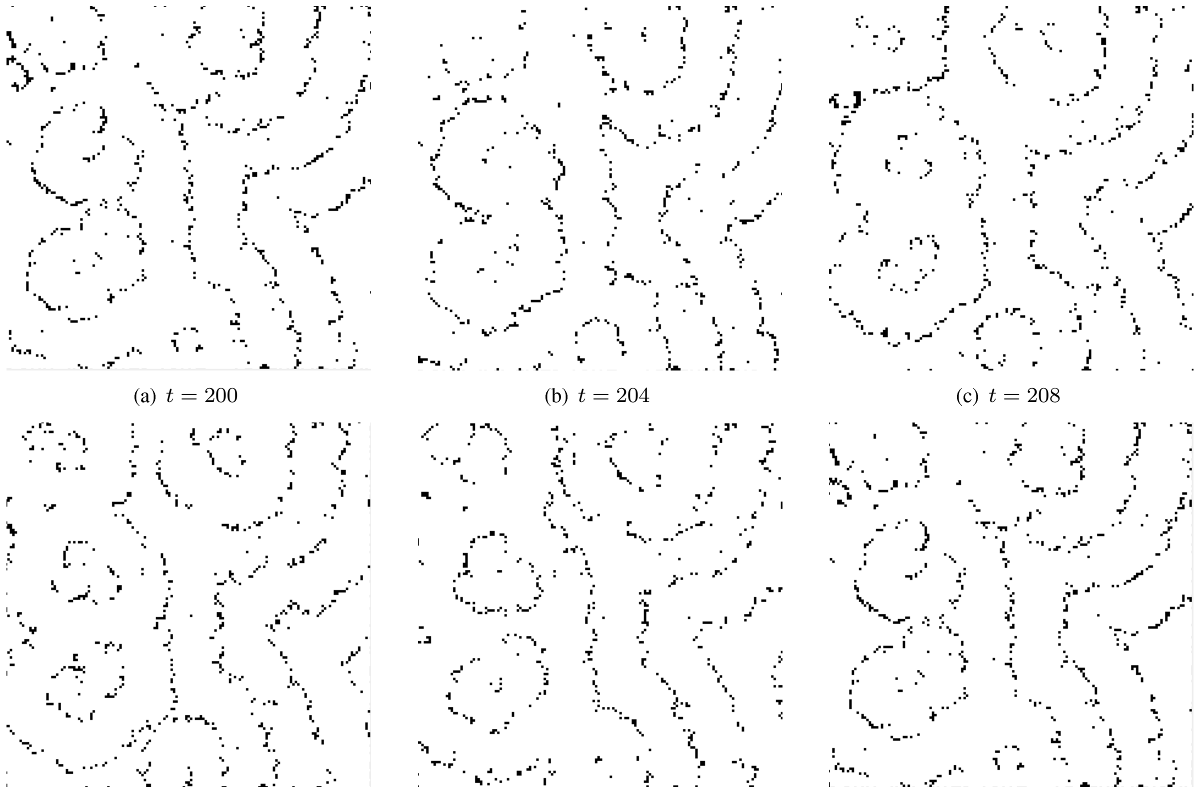
A sample of our extensive experiments is shown in Figure 2, where the color black denotes state 0. From primordial soup, the GHM pattern first transitions to one with many black cells, cells in state 0 waiting for a neighbor in state 1. Several steps later many expanding rectilinear figures begin to appear with a nascent local periodicity; and the fraction of black cells begins to reduce substantially. After many steps, one sees a locally periodic collection of rectilinear figures, rather similar to the CCA, except that, with current parameter values, they are closed figures rather than spirals.

2.3 Greenberg-Hastings Model in R^2

In actual sensor fields, the sensor locations should be modeled as points in $\mathbb{R}^2$, and in the applications (scales) of interest here, these points will be closely approximated by Poisson patterns in two dimensions. Neighborhoods are now defined by Euclidean distance; a point is in N_x if and only if it is within a given distance r_c of x. These changes create a new automaton model directly adaptable to sensor systems. We call this automaton the CGHM, the C standing for 'continuous,' and call the classical, discrete version the DGHM. Whether the properties of the discrete models are preserved in our new continuous model becomes a question of fundamental importance. To investigate whether the CGHM retains the vital property of periodicity, we implemented a simulation of the CGHM with a communication radius $r_c = 1.5$. We sited 40,000 points independently and uniformly at random within a 200×200 square field, and started the process again in primordial soup, in this case the uniform product measure on 20 states $\{0, \ldots, 19\}$.

As in Figure 3(b), most cells linger in state 0 many steps before acquiring a neighbor in state 1. Once that happens these cells soon commence periodic behavior; in the aggregate the points begin to generate periodic wave patterns as in the DGHM. In contrast to the DGHM, the CGHM was observed to generate circular wave patterns, or patterns corresponding to the periphery of intersecting circles. We also observed that, although the CGHM preserves periodic behavior, it requires larger k and a longer transient period than the analogous behavior of the DGHM. Figure 4 shows the points in state 0 at $t = 100$ with $k = 12$ and $k = 20$. They form many small, generally curved line segments when $k = 12$ as in Figure 4(a) but they form the closed periodic waves when $k = 20$ as in Figure 4(b). Figure 5 gives some feeling for visible wave motion by showing a number of closely spaced snapshots.

Note that the nucleating centers, or *seeds* play a central role in both the CGHM and the CGHM. The existence of such seeds prevents a *fixation* or dying out of the process; in these automata fixation occurs only in state 0. We return shortly to the problem of assuring the existence of seeds.



(a) $t = 200$ (b) $t = 204$ (c) $t = 208$

(d) $t = 212$ (e) $t = 216$ (f) $t = 220$

Figure 5. Dynamics of Greenberg-Hastings Model in $\mathbb{R}^2$ (k=20)

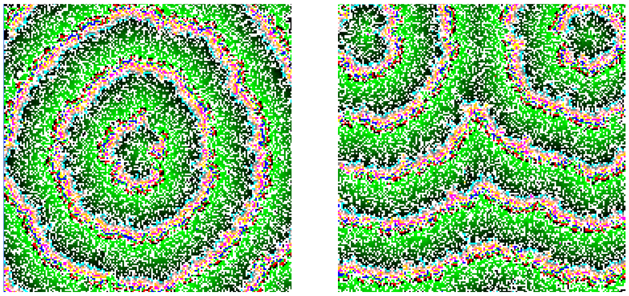
3 A Prototype System for Experimentation

This section briefly outlines the essential characteristics of a sensor system implementing a CGHM-based sleep-wake protocol. Given the feasibility of more elaborate sensor systems, there are clearly no new implementation challenges in the CGH system. However, performance is another matter, and this will be the subject of the next section.

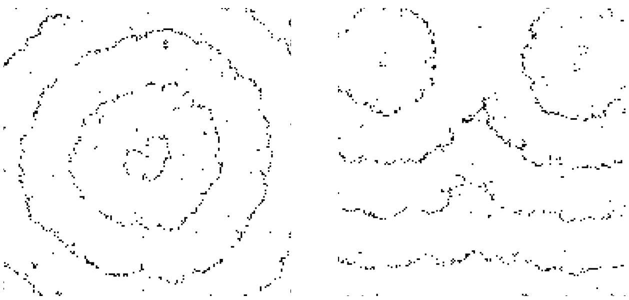
Implementation entails manufacture of sensors of a single, uniform type (with sensors programmed to perform the functions given below), then sensor deployment in the targeted field yielding distributions approximating primordial soup in two dimensions: a Poisson pattern of locations over the field and a uniform product measure describing the sensor states. Both of these approximations can be moderately crude. Indeed, as we shall see later, we can dispense with the randomization of the initial states almost entirely. Following this set-up, sensor operation begins in a power-intensive but brief initialization phase, and then continues in its long-term, low-power operational phase.

Initialization implements a global synchronization of the sensors. This stage is common to all synchronous wireless networks, and is a nontrivial operation even if the only problem is that of reliable communications. Nothing new is needed from this function for present purposes, however, so without further discussion, we refer the reader to [10, 11, 12, 13] for high-precision synchronization techniques.

After initialization, the synchronous sensor system is driven by a clock, each sensor moving through a state sequence determined by the CGHM. Detailed operation is defined by just those functions performed within a clock cycle. The clock cycle is divided into two fixed-duration disjoint intervals: a passive interval I_{pass} and an active interval I_{act}. Sensors are passive during I_{pass} in the sense that no change of state is made and no communication with neighbors takes place: sensors in nonzero states are in a minimal-energy sleep mode and sensors in state 0 are sensing their environments for targeted events. Unless an alarm is to be broadcast, the passive interval is followed by an active interval during which sensors in state 0 or 1 turn on their radios and communicate with their neighbors. A sensor in state 1 broadcasts a signal signifying that it is in state 1. Sensors in state 0 listen for such signals to determine whether there exists at least one neighbor in state 1. By the end of I_{act} each sensor in a nonzero state increases its state by 1 mod



(a) 1 Seed: All sensors (b) 2 Seeds : All sensors



(c) 1 Seed : Wake sensors (d) 2 Seeds : Wake sensors

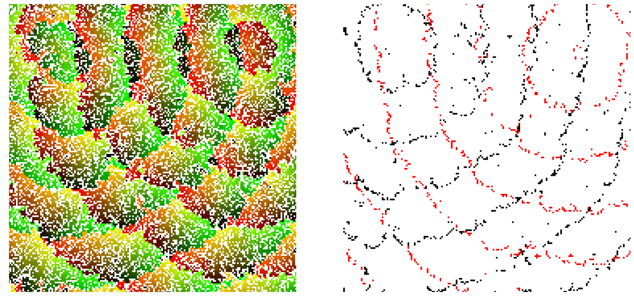
Figure 6. Planting Single-Phase Artificial Seeds with k=30

k; a sensor in state 0 transitions to state 1, but only if it has received a broadcast message from at least one neighbor in state 1; otherwise, it remains in state 0.

If an intrusion or other targeted event has been detected by one or more sensors in a given clock cycle, then these sensors enter an alarm mode wherein an alarm message is transmitted to one or more base stations. For fast response, a longer communication radius is generally needed in alarm mode, and hence a higher power output. We omit the details of responses to alarms as they do not involve any new features not present in other proposed or existing systems.

Planting Artificial Seeds. If k is not too large, then remarkably, the system as designed will work well with very high probability, i.e., the probability that the CGHM process starting in primordial soup will fixate is vanishingly small.[4] The locations of nucleating centers (seeds) will be unpredictable as will be the wake-state wave action they induce, but good performance is assured. Note that fixation is in state 0 so that there will be no sacrifice in surveillance, but the lifetimes of the sensors will be reduced. On the other hand, in the interests of low energy consumption and hence a low duty cycle $1/k$, we will want to take k large. And k does not have to be very large ($k > 20$ will do) before the risk of fixation becomes too great. *Planting seeds*, i.e., deploying artificial nucleation centers, is a handy and effective solution for larger k. Any collection of sensors containing a $k-cycle$ serves as a seed. As the term suggests, a k-cycle in the synchronous sensor system is a sequence of sensors $x_0, \ldots, x_{k-1}$ such that, for all $k = 0, \ldots, k-1$, $\xi_t(x_i) = i$ and $x_{(i+1) \bmod k}$ is in communication range of x_i. Clearly, a k-cycle, which cycles endlessly through the k states, spending one clock period in each state, is trivial to put together, and renders fixation impossible. In so doing, as shown in Figure 6, the desired periodic wake-sensor waves will be produced over the sensor field. Figure 6(b) shows the aggregate wake-sensor state at time step 200 with $k = 30$ when 2 artificial seeds with the same state space are planted and function independently. One is at the top left and another at the top right. As the waves from the two seeds come together, they form a big wave which propagates toward the bottom of the sensor field. As an added advantage of seeding the sensor field, there is no need to "prepare" the primordial soup of sensor states. The evolution to periodic waves will occur independently of the initial states of the sensors outside the implanted k-cycles.

[4] Accurate analytical estimates of this probability as a function of k are not known, even in the original discrete version.



(a) 2-Phase: All sensors (b) 2-Phase : Wake sensors

Figure 7. Planting Bi-Phase Artificial Seeds with k=30

If the application calls for the detection of events like fires in the interior of the field, then the system of Figure 7 can be recommended for a broad set of performance objectives, as illustrated in Section 4. But if penetration of an intruder crossing a boundary is to be detected, then the gaps between waves along the right and left boundaries could be of concern (although any intruder entering one of these gaps is forced to exit the field in front of an approaching wave, if the intruder is to remain undetected).

To further protect against intrusions, or to speed up detection generally, one may deploy *bi-phase* sensors in a two-seed synchronous system to obtain the results in Figure 7. The sensors are now designed to maintain two out-of-phase CGHMs simultaneously. In particular, a bi-phase sensor maintains a state pair $(\xi_t^1(x), \xi_t^2(x))$ with each state following independently, but in lock step, the transitions defined for the CGHM. *Now, however, the sensor is in its wake state whenever either or both of the two states becomes 0.* In equilibrium, the bi-phase CGHM is periodic in both ξ^1 and ξ^2, with the two states maintaining a fixed phase difference. For the two-seed system in Figure 7, one obtains the two independent, intersecting periodic waves. The bands where detection can be avoided (temporarily) in Figure 6(d) are now 'tiles' with circular sides which greatly reduce the time and distance of successful penetration. The cost, of course, is the near doubling of the total time spent in wake states (the in-phase sensors in which the two component states are the same avoid this doubling, but other effects tend to increase the overall fraction of the time spent in wake states. For example, some sensors will be isolated, e.g., those near the boundary, and these will fixate. An interesting observation drawn from the experiments was that the total number of wake sensors was also periodic, with a period of k. For example, with $k = 30$ the number varied from about 750 to about 900 in one of the experiments; the fraction varied from about 0.033 (which is $1/k$) to 0.04. We return to more of this data in the next section.

4 Experimental Results

This section returns to the claims made in Section 1 and briefly demonstrates the basis for each. First, it is clear that the protocol inherits its self-organizing property from the CCA on which it is based. A similar remark applies to the properties whereby it is fully distributed, needs no central control, and is scalable: the sensor (local-rule) design does not change with the size of the sensor field or the density of the sensors, and the number of sensors grows no faster than the area of the sensor field. Also, the impenetrable, periodic wake-sensor barrier waves make knowledge of sensor locations alone of no use to the intelligent intruder beyond penetrations that must stay very close to the boundary.

We consider next, in order, performance (times-to-detection), fault tolerance, and accommodating obstacles.

The communication and sensing radii are $r_s = r_c = 1.5$, *the neighborhood threshold is* $\theta = 1$, *and the sensor density is 1 throughout all of our experiments.*

4.1 Performance

Choose a point x uniformly at random in the sensor field at a random time after the CGHM has stabilized, and define the corresponding *detection time* D as the time that elapses until x falls within the sensor radius of some wake sensor. The point x is to be considered the site of some targeted object or event. Of course, this time will usually be 0 when x is chosen within sensing range of a wake-sensor wave. Thus, D's distribution will have an atom at the origin. We conducted many experiments with artificial seeds planted at the upper left and upper right corners of a 150×150 sensor field. We compared the average detection times in the single-phase and bi-phase systems; the results are shown in Table 1. For a cost (energy) measure, we also computed the average number of wake sensors. Table 2 shows the densities obtained by dividing these numbers by the total number of sensors. The average detection time of the bi-phase case is almost half of that in single-phase case when k is at most 30 or so. But the density of wake sensors is also almost twice that of the single-phase case, as we noted in the previous section. So as a bottom-line message on performance, the product of these quantities, used as a figure of merit measuring performance vs cost, stays between .4 and .5 for $20 \leq k \leq 40$ but decreases for smaller k, more so for the single phase system. It should be noted that, as expected, in none of our many performance experiments did a wave fail to detect a point that was chosen between it and the preceding wave.

k	Single-Phase 2 seeds	Bi-Phase 2 seeds
15	4.87	2.76
20	8.96	3.88
25	10.95	5.52
30	12.57	5.92
35	15.24	9.95
40	15.57	10.13

Table 1. Average Detection Time (in clock cycles)

We can compute a conservative estimate on $\mathbf{E}D$ that is in fact rather good. In the simple mathematical model of Figure 8, we take the periodic waves to be regular and the distance between adjacent waves at its maximum kr_c with r_c per clock cycle being the rate of the wave motion.

There is a distance $2r_s < kr_c$ between waves where a

k	Single-Phase 2 seeds	Bi-Phase 2 seeds
15	0.0714	0.1331
20	0.0548	0.1016
25	0.0445	0.0827
30	0.0378	0.0699
35	0.0336	0.0611
40	0.0295	0.0539

Table 2. Fraction of Wake Sensors

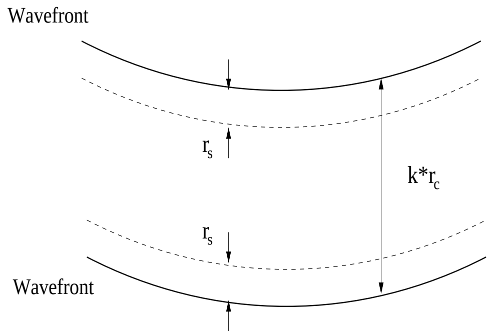


Figure 8. Wake sensors along a wavefront

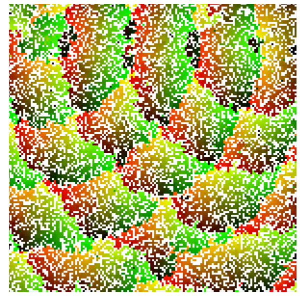
randomly chosen point will be within the sensing radius of a wave in front or behind, so $\Pr(D = 0) = 2r_s/kr_c$. (See Figure 8.) Given that a point chosen at random does not fall within a sensing radius, it falls uniformly at random in an interval of duration $(kr_c - 2r_s)/r_c$ clock cycles, and hence waits a (conditional) average of $(kr_c - 2r_s)/2r_c$ clock cycles. Thus,

$$\mathbf{E}D \approx \left(1 - \frac{2r_s}{kr_c}\right) \frac{kr_c - 2r_s}{2r_c}$$

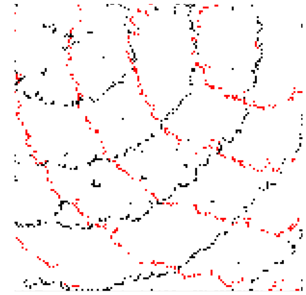
With $r_s = r_c = 1.5$ this gives the table below (experiments with a single-phase 1 seed at the center of sensor field), which shows excellent agreement between the experimental results and the conservative analytical estimate. (As we are dealing with estimates whether we talk about the data or the mathematical model, we round off the results to the nearest integer to avoid the suggestion of a precision which is not actually in the results.) Note that, in the limit of large k, the relative effect of r_s can be ignored and the result tends to $k/2$ clock cycles as expected.

k	Experiments	Estimates
15	6	6
20	8	8
25	11	11
30	13	13
35	15	16
40	18	18

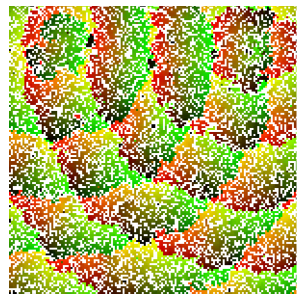
Table 3. Estimates of Average Detection Time (in clock cycles)



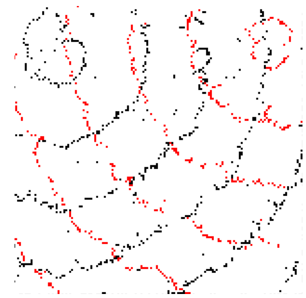
(a) 10% link failure - All sensors



(b) 10% link failure - Wake sensors



(c) 30% link failure - All sensors



(d) 30% link failure - Wake sensors

Figure 9. Link Failure (2-phase 2 seeds with *k*=30)

4.2 Fault Tolerance

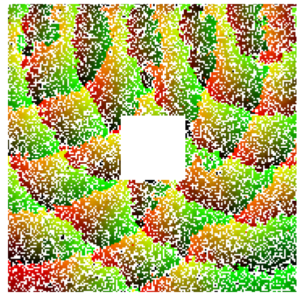
Wireless links are always vulnerable to interference and collision. As described in Section 3, our scheme of communication is restricted to message broadcasting. If a broadcast message from a sensor in state 1 fails to reach neighboring sensors in state 0, the dynamics of proposed scheme can be expected to deteriorate. We tested our system with a fixed link-failure probability p to illustrate how link failures affect system dynamics. Link failure probabilities $p = .1, .3$ are considered in Figure 9. As p increases, the wake-sensor wavefronts sustain more 'hollows' owing to failures to successfully receive broadcast messages from neighboring sensors in state 1. However, a critical self-healing property can be seen to occur: the hollows are soon repaired by other neighboring nodes within next few clock cycles as the wavefront propagates. Note that, when the sensor density is such that there are several neighbors within communication range on average, even high link failure probabilities can be sustained without significant damage to performance; the probability that a sensor fails to receive a broadcast message from *all* of its neighbors is quite small.

These experiments with link failures also imply that the dynamics of our system will not be affected even in cases where the assumptions on uniform sensor density and a fixed communication radius do not hold.

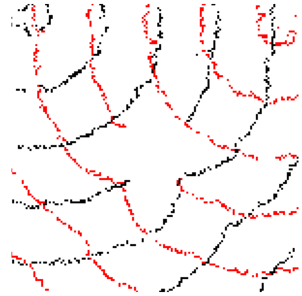
We also found that our system performance is independent of the assumption of a uniform product measure on the initial states, so long as we plant more than one artificial seed. Even if all sensors outside the seeds have the same initial state, they will quickly reach state 0 and wait for the broadcast messages from a seed to propagate to them. In short, our CGHM scheme is remarkably robust to variations in sensor and sensor-field properties.

4.3 Accommodating Obstacles

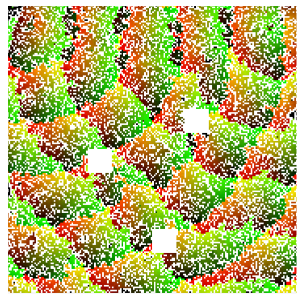
In many environments (e.g., the outdoor environment), one often finds obstacles (e.g., huge rocks, swamps, etc) in the sensing field. These obstacles form holes in the distribution of sensor locations and many intrusion-detection schemes do not adequately cover the affects of such obstacles in an otherwise uniform field. Of course, in good system designs, the performance of intrusion/event detection away from the obstacles should not be affected by these obstacles. This is in fact a property of the CGHM sensor. To illustrate the effects of obstacles, we experimented with one big obstacle (40×40) and three small obstacles (15×15) in a 180×180 sensor field. Figure 10 shows that our proposed scheme can seamlessly work around both the one huge obstacle and the small obstacles; the system continues to generate periodic waves sweeping the area outside the holes in coverage created by the obstacles. In particular, the wake sensors sweep the obstacle along its boundary and form a closed wave pattern as soon as they pass the obstacle, so that the intruders nearby any obstacle can be detected.



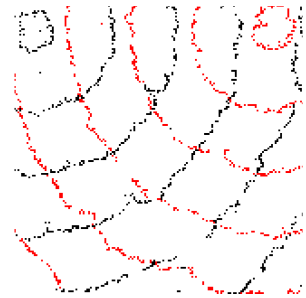
(a) One Obstacle - All sensors



(b) One Obstacle - Wake sensors



(c) Three Obstacles - All sensors



(d) Three Obstacles - Wake sensors

Figure 10. Working around Obstacles (k=30)

5 Conclusions

Low power, limited computing/storage capabilities, and limited communication/sensing ranges are standard properties asked of the sensors in large-scale surveillance/monitoring systems. From this point of view, the CCA's simplistic local-rule logic and its astonishing distributed self-assembly and self-organizing properties make it an ideal defining infrastructure for sleep-wake sensor systems. The Greenberg-Hastings CCA was chosen as just the right variant to generalize to sensors scattered at random over a sensor field in $\mathbb{R}^2$. We verified through extensive experimental performance studies that the periodic wake-sensor barrier waves met exceptionally high standards for intrusion detection and targeted event sensing. Moreover, the general approach, supplemented by artificial seed implantation, led to a scalable, unexpectedly robust system: one that was very tolerant of errors, locally self-healing, able gracefully to accommodate obstacles, and could "defend" against the intelligent intruder.

Our goal in this paper has been a convincing demonstration of the performance and outstanding overall effectiveness one can expect in practice, an argument to the effect that the systems effort needed to test and adapt the system to the real world of sensor applications is a worthwhile investment that should be made. This is the next goal in our research agenda.

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Appendix

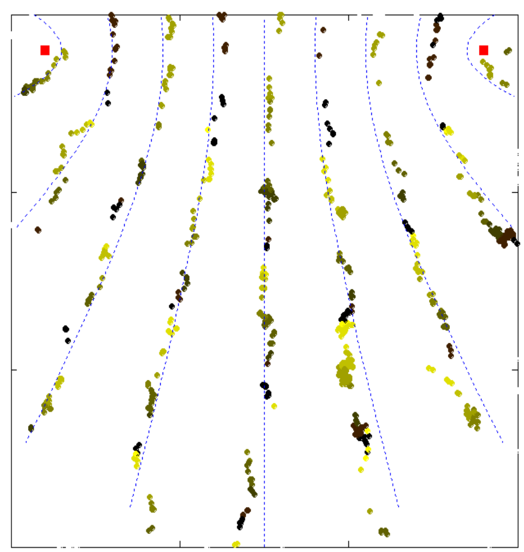

Figure 11. Node Trace

The Figure 7 represents a snapshot of the active sensors. To understand the dynamics of this picture, we plotted the locations of the sensors in state (0,0), at different times. At any given instant, these are the points of intersections of the curves (wave fronts) formed by the wake sensors activated by either of seeds, that is the "corners" of the partition of the plane shown in the figure. As time progresses, the wake state changes, but the periodicity of the evolution implies that these corner points will be (with fluctuations which are small for large k) corresponding to the points which have the diagonal state at any given time. As the excitation propagates roughly along the straight lines and isotropically, these sensors have the property that the difference in the distances from the two seeds remains constant.

Thus, if $x^{(i)}, y^{(i)}$ are the seed locations for $i = 1, 2$, then the points lie on a curve of the form

$$\sqrt{(x - x^{(1)})^2 + (y - y^{(1)})^2} - \sqrt{(x - x^{(2)})^2 + (y - y^{(2)})^2} = const$$

We have plotted a family of these hyperbolic curves (the dashed lines) in Figure 11. These are superimposed on the experimental data giving the corresponding locations of the 'same-state' sensors, i.e., those whose component states are the same, at (approximately) a random time in equilibrium. The red squares are the seeds.

These curves have another important interpretation: they describe the approximate trajectory which an intelligent intruder will have to follow to avoid detection. Indeed, the intruder will have to keep bounded distance to the center of the piece of partition of the plane formed by the fronts of wake sensors. These centers are also diagonal states, $(k/2, k/2)$, whence the claim follows.