Migration Strategies of Immunity-Based Diagnostic Nodes for Wireless Sensor Network

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Abstract. In our previous studies, the immunity-based diagnostic model has been used by stationary agents in linked networks or by mobile agents on wired computer networks. We have not yet analyzed the performance of the diagnosis in wireless network where agents can move freely. In this paper, the diagnosis is applied to static and mobile sensor nodes in a 2-dimensional lattice space for wireless sensor network. Some simulation results show the strategy of going straight in the different direction can have the best detection rate. In addition, when the fraction of mobile nodes is changed, the transitions of the detection rate for the migration strategies are different.

1 Introduction

In recent year, sensor network, ad-hoc network, and ubiquitous computer have attracted much attention. Some keywords such as *wireless*, *mobile*, *distributed*, and *cooperative* in these fields are listed. These characteristics are endowed in the biological immune system. We have pursued the autonomous distributed diagnosis models inspired by the informational features of the biological immune system. The *immunity-based diagnostic model* based on the concept of the *idiotypic network hypothesis* [1] has been proposed in [2]. The diagnostic model is performed by mutual tests among agents and dynamic propagation of active states. In our previous studies, the diagnosis has been employed by stationary agents in linked networks [2] or by mobile agents on wired computer networks [3,4]. We have not yet analyzed the performance of the diagnosis in wireless network where agents can move freely.

In this paper, the immunity-based diagnostic model is applied to sensor nodes in a 2-dimensional lattice space for wireless sensor network. Each node is either static or mobile. Note that the term 'node', which is usually used in graph theory and sensor network community, is considered the same as the term 'agent' in our previous studies. Preliminary simulations are carried on both for wired networks and for wireless networks. When the immunity-based diagnosis is performed on random graph as a wired network, the capability of detecting abnormal nodes

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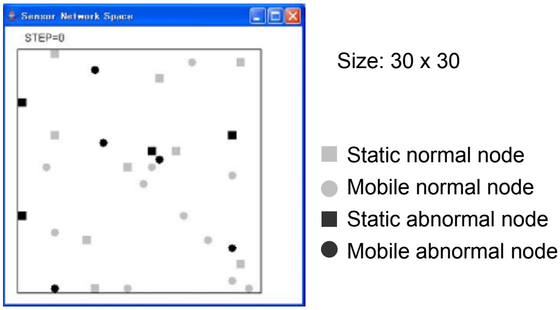


Fig. 1. 2-dimensional lattice space for wireless sensor network. There are four kinds of sensor nodes in the space.

relies on the number of edges. In wireless network where all the nodes are stationary, the detection rate depends on some environmental parameters: space size, visual distance, and the number of nodes. Next, we address some migration strategies and the fraction of mobile nodes. Some simulation results show the strategy of going straight in the different direction can have the best detection rate. Additionally, when the fraction of mobile nodes is changed, the different transitions of the detection rate for the migration strategies are observed.

2 Simulation Environment

To make it easy to analyze the performance of diagnosis, we use a simple environment for wireless sensor network. The environment is realized by a 2-dimensional lattice space with a periodic boundary condition. The size of space S x S is variable in preliminary simulations, and then is fixed in the next simulations of migration strategies.

The space consists of four kinds of sensor nodes as shown in Fig. 1. The total number of sensor nodes is defined by N. Each node is either *static* or *mobile*. Mobile nodes can move 1 distance per time step in a direction. The state of sensor node is simply represented as either *normal* or *abnormal*. The node can interact other nodes within a visual distance D. Each node can sense the state, not by itself, but only by comparisons with the others. The goal of diagnosis is to detect all the abnormal nodes by interactions among nodes.

3 Immunity-Based Diagnostic Model

The immunity-based distributed diagnostic model proposed by Ishida [2] is inspired by the concept of the *idiotypic network theory* [1]. The diagnostic model is performed by mutual tests among nodes and dynamic propagation of active states. In this study, each node has the capability of testing other nodes within the visual distance D, and being tested by the adjacent others as well. A state variable R_i indicating the *credibility of node* is assigned to each node and calculated as follows:

$$\frac{dr_i(t)}{dt} = \sum_j T_{ji}R_j + \sum_j T_{ij}R_j - \frac{1}{2}\sum_{j\in\{k:T_{ik}\neq 0\}}(T_{ij}+1), \tag{1}$$

$$R_i(t) = \frac{1}{1+\exp(-r_i(t))}, \tag{2}$$

where the credibility $R_i \in [0,1]$ is a normalization of $r_i \in (-\infty,\infty)$ using a sigmoid function. In equation (1), T_{ji} denotes binary test outcome from testing node j to tested node i as follows:

$$T_{ji} = \begin{cases} 1 & \text{if the states of nodes } i \text{ and } j \text{ are the same} \\ -1 & \text{if the states of nodes } i \text{ and } j \text{ are different} \\ 0 & \text{if node } j \text{ cannot test node } i \text{ out of view} \end{cases}. \tag{3}$$

The initial value of credibility $R_i(0)$ in the immunity-based diagnosis is 1.0. It means the diagnosis regards all the nodes as normal. The aim of the diagnosis is to decrease the credibility of all the abnormal nodes. The threshold of credibility between normal node and abnormal one is set to be 0.5.

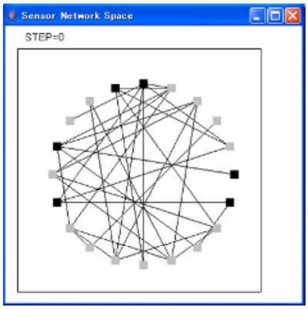
4 Preliminary Simulations

4.1 Simulation Conditions

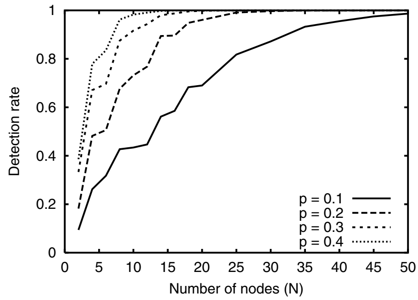
We carry on some preliminary simulations both for wired networks and for wireless networks. We firstly describe conditions for the simulations. The previous studies [3,4] say that the immunity-based diagnosis can mostly detect abnormal nodes up to $0.5N$. In this study, the number of abnormal nodes is set to be $0.3N$. For a performance measurement, we record a detection rate, that is, the fraction of abnormal nodes detected by the diagnosis model. Since all the nodes are located randomly at the start of each simulation, the detection rate is averaged over 1000 trials. Furthermore, the credibility of the immunity-based diagnosis can converge almost by 20 time steps, so that we inspect the detection rate after 20 steps.

4.2 Wired Network

The immunity-based diagnosis is performed on random graph as a wired network. Although other network models such as *small-world* and *scale free* [5] have been already applied, the results will be described in another paper for the lack of space. The random graph model includes N nodes and each possible edge independently with probability p. When $N = 20$ and $p = 0.2$, an example of random graph is illustrated in Fig. 2 (a). For the summation operators in equation (1), the accurate calculation of the credibility relies on the number of edges for each node, which is averagely $p(N-1)$ on random graph. Figure 2 (b) depicts



(a) random graph when $N = 20$ and $p = 0.2$.



(b) average detection rate vs. the number of nodes N on random graphs with various p.

Fig. 2. An example of random graph and simulation result for random graphs

the average detection rate after 20 time steps over 1000 trials vs. the number of nodes N on random graphs with various p. From the result, as expected, the detection rate of random graph depends on both N and p. When the detection rate becomes over 0.99, $N = 51, 25, 17, 12$ for $p = 0.1, 0.2, 0.3, 0.4$, respectively, and then the average number of edges for each node $p(N - 1)$ is $5, 4.8, 4.8, 4.4$, almost the same.

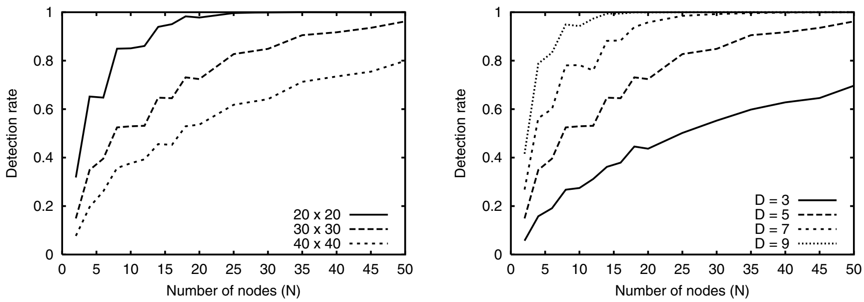
4.3 Wireless Network

In next simulations for wireless network where all the nodes are stationary, some environmental parameters are explored. It is easy to predict that the detection rate depends on the frequency of interactions between nodes, namely the density of nodes within the visual distance. In the preliminary simulations, the size of space S x S, the visual distance D, and the number of nodes N are varied. Figure 3 illustrates the average detection rate vs. the number of nodes N changing S and D. From the results, as expected, the detection rate can increase when N and D increase, but S decreases. When the detection rate becomes over 0.99, the average number of adjacent nodes is $9.26, 7.25, 5.21$ for $D = 5, 7, 9$, respectively. The numbers of necessary interactions in wireless network is not only scattered but also big compared with random graph. The reason is under study.

5 Simulations of Migration Strategies

5.1 Migration Strategies

When all the nodes cannot move, adjacent nodes are always identical. If mobile nodes are installed, each node would have a lot of opportunities of interactions. However, generally speaking, the mobile nodes require some additional mechanisms with respect to both hardware and software. The hardware items are not only moving mechanisms such as wheels and legs but also battery or energy for movement. Therefore, the number of mobile units would be as small as possible.



(a) space size S is varied while $D = 5$. (b) visiual distance D is varied while $S = 30$.

Fig. 3. Average detection rate after 20 time steps over 1000 trials vs. the number of nodes N changing S and D when all the nodes are stationary

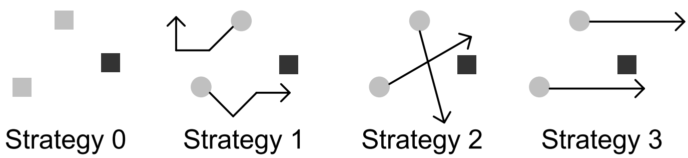


Fig. 4. Migration strategies indicated by the arrow. In strategy 0, all the nodes are stationary.

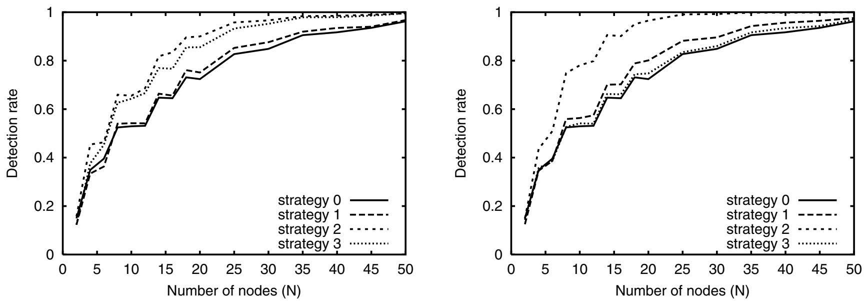
In addition, software mechanisms for migration and collision avoidance need to be implemented. Mobile node can also have more complicated capabilities, for example, learning and cooperation. The following simple migration strategies including static case as illustrated in Fig. 4 are firstly applied:

Strategy 0: All the nodes are stationary.
Strategy 1: Each mobile node can walk randomly.
Strategy 2: Each mobile node can go straight in a random direction.
Strategy 3: Each mobile node can go straight in the same direction.

5.2 Simulation Results

Based on the results of the preliminary simulations as shown in Fig. 3, two parameters S and D are fixed as $S = 30$ and $D = 5$ in the simulations of migration strategies. The other conditions are the same as the preliminary simulations.

Figure 5 depicts the average detection rate vs. the number of nodes N for each migration strategy when half or all the nodes are mobile. The results demonstrate that the detection rate of strategy 1 of randomly walking nodes is similar to strategy 0 of all static nodes, while the performance of strategy 2 can be improved most. In addition, the detection rate of strategy 3 is better than strategy 0 in Fig. 5 (a), but the same in Fig. 5 (b).



(a) half the nodes are mobile. (b) all the nodes are mobile.

Fig. 5. Average detection rate after 20 time steps over 1000 trials vs. the number of nodes N for each migration strategy

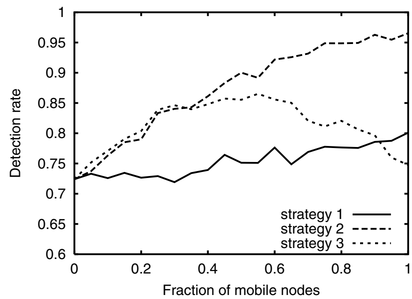


Fig. 6. Average detection rate vs. the fraction of mobile nodes for each migration strategy when $N = 20$

Relevant simulations are carried out changing the fraction of mobile nodes when N is set to be 20. Figure 6 illustrates the average detection rate after 20 time steps over 1000 trials vs. the fraction of mobile nodes for each migration strategy. From the result, the following points are observed:

– The detection rate of strategy 1 slightly increases as the fraction of mobile nodes become higher.
– The performance of strategy 2 grows, but keeps constant over the fraction of mobile nodes 0.8.
– In strategy 3, there is a peak of the detection rate near the fraction of mobile nodes 0.5.

The reasons for the first and third points can be easily explained. The detection rate relies on the number of testing and tested adjacent nodes during 20 steps. In strategy 1, randomly walking nodes stay almost near the initial location in 20 steps, so that adjacent nodes are not so varied. Since mobile nodes of strategy 3 move at the same speed in the same direction, the interaction between mobile nodes is always constant, and only the interaction between a mobile node and a static node is changed. Therefore, when all the nodes are stationary or

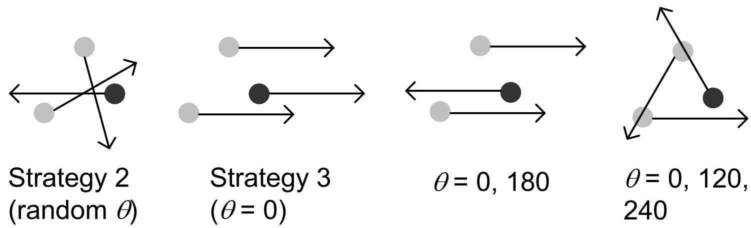


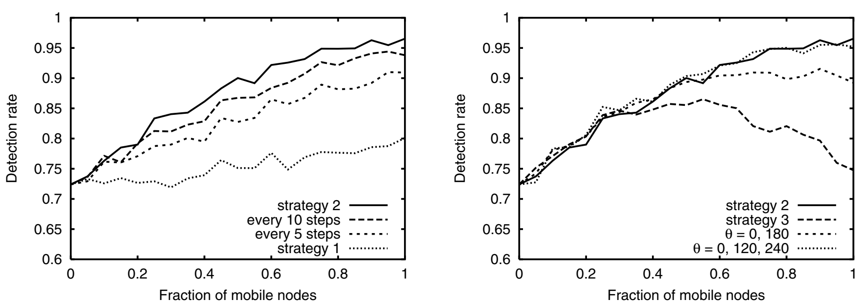
Fig. 7. Migration strategies with different assignment of direction θ

mobile, that is, the fraction of mobile nodes is 0 or 1, the detection rate marks the worst value because the interaction between nodes never changes. The reason for the second point is under investigation.

Some changes for strategy 2 with the best performance can be considered, for example, the following migration strategies:

– Each mobile node can change the direction every some steps. It is expected that the performance of the strategy would exist between strategy 1 and 2 because the interval of changing the direction is 1 in strategy 1 and ∞ (exactly 20) in strategy 2.
– Each mobile node can go straight in a differently assigned direction θ as shown in Fig. 7. Strategy 2 and 3 assign θ to mobile nodes randomly and identically, respectively. It is predicted that the detection rate of the other strategies would be between strategy 2 and 3.

To confirm the predictions given above, we perform additional simulations. From the simulation result in Fig. 8 (a), the first prediction comes true. However, the second prediction is a little different from the result as shown in Fig. 8 (b). The introduction of the opposite direction can highly improve the worst detection rate of strategy 3 when all the nodes are mobile. The strategy with $\theta = 0, 120, 240$ can realize the same performance as strategy 2, so that the random assignment of direction is not necessary. We will clarify the reason theoretically in future.



(a) the interval of changing the direction is changed.

(b) the assignment of direction θ is changed.

Fig. 8. Average detection rate vs. the fraction of mobile nodes for the migration strategies when $N = 20$

6 Conclusions and Further Work

In this paper, the immunity-based diagnostic nodes with the simple migration strategies are implemented in the 2-dimensional lattice for wireless sensor network. Some simulation results show the strategy of going straight in the different direction can have the best detection rate. The random assignment of directions to mobile nodes is not necessary. Furthermore, when the rate of mobile nodes is changed, the different transitions of the performance by the migration strategies are observed.

In further work, we will go on analyzing the performance of migration strategies by both simulations and mathematical models. This paper has focused only on the mutual diagnosis between sensor nodes. Since real wireless sensor networks are given applications or tasks, the migration strategies should be examined in response to applications.

Acknowledgements

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