A Data-centric and Statistical-based Random Sensing Scheduler for Rare Event Detection in Distributed Wireless Sensor Networks

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Abstract: This paper presents a sensing scheduler that learns about the environment monitored and adjusts its sensing behaviour according to the variation in the environment. The aim is to preserve energy by minimising sensing events in normal situation, but response quickly and reliably when a rare-event happens. Temporally, the scheduler uses statistical long-term and short-term averages to tune its sensing frequency. Spatial neighbour coordination is incorporated to enhance information dissemination across the network and minimise detection delay.

1. Introduction

Data handling in distributed wireless sensor network for environmental monitoring has attracted a lot of attention in recent years. The challenge is that sensor networks are often distributed systems with limited resources including processing power, memory, and stringent power consumption requirement [1][2][3][4]. The works presented in this paper focus on the design of a sensing scheduler, which alternate the sensing behaviour according to some statistical properties measured in the environment in order to achieve power efficiency. A common type of sensor network application is rare-event detection. They have a similar characteristic that in majority of time the sensor networks are monitoring some normal conditions, which is not of interest of the users. When a rare event occurs, the sensor network is required to response to the event promptly and reliably and notifies the users. Examples of such applications are bridge collision monitoring, flooding detection, landslide warning system and forest fire detection [2]. Sensing of a rare-event is the trigger for further actions including reporting and network management in the sensor network and hence, we consider the work in this paper as a first step to develop a network management algorithm that fulfils the requirements of rare-event detection in sensor networks.

Traditionally, temporal samples are taken in regular intervals governed by the Nyquist frequency to avoid aliasing. In the cases when more than one frequencies are of interest and they are wide apart in temporal scale, such as wave and tidal periods in Oceanography analysis [8][9], burst sampling technique may be adopted as a mean to conserve power. Regular or burst sampling techniques are designed for recording periodic events and may not be suitable for rare-event detection. It is nor efficient in terms of power consumption that sampling frequency can be much reduced when there is no event. On the other hand if sampling frequency is set to very low interesting events may be missed.

Currently, most sensing schedulers being researched for sensor networks consider mainly redundancy in radio and sensing coverage and optimise network life by putting the covered nodes to sleep [6][7][8]. The problem is approached in a spatial aspect and temporal efficiency is not tackled. Moreover, sensing coverage can only be defined for a certain type of sensors, for example, cameras, ultrasound, *etc*, and is not applicable to point detection sensors for measurements such as temperature and pressure.

We propose a sensing schedule that response to some statistical values measured from the environment, such that sampling is sparse when the environment does not vary much, and increases according to the variation in the environment. We also incorporate neighbour coordination to combat the problem of event-detection delay due to the sparse random sampling in normal condition.

2. Temporal Design

The scheduler is based on a simple 2-states model as shown in Figure 1. p_s and p_i *are* the probability of the scheduler to change from one state to the other. At sense-state, the scheduler takes a sample[1]

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[1] *A sample is an illustrative use of the scheduler. Sense-state can be adapted to other temporal data collection methods, such as averaging of samples to minimise environmental noise and maximise power efficiency of the ADCs.*

from the environment and updates p_s *and* p_i with the current sample. The state-transitions are random probabilities, however, the probabilities are based-on a statistical property called exponential weighted moving average (EWMA) denoted in Eq.1. This quantity is used in volcanic eruptions monitoring proposed by Werner-Allen et al [5].

$$E = \alpha \cdot x + (1-\alpha) \cdot E \qquad \text{(Eq.1)}$$

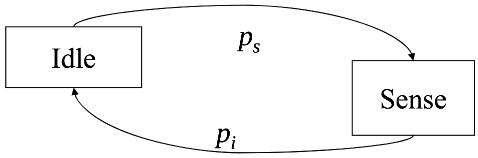

Figure 1: A simple 2-states model for the sensing scheduler

EWMA is a way of preserving memory when calculating expected values. α determines the weights of the current sample and the last average when calculating the new average. Current values are weighted more than historical values.

We define a long-term average E_{long} and a short-term average E_{short} which uses the same equation Eq.1 with $\alpha_{long} < \alpha_{short} < 1$ and we defined a quantity p_t as a normalised ratio of the two averages:

$$p_t = \left| \frac{E_{long} - E_{short}}{E_{long} + E_{short}} \right| \qquad \text{(Eq.2)}$$

The temporal components of p_s and p_i are:

$$\begin{aligned} \hat{p}_s &= k_1 + (1-k_1) \cdot p_t \\ \hat{p}_i &= 1 - p_t \end{aligned} \qquad \text{(Eq.3)}$$

Without k_1, $\hat{p}_s$ is simply p_t and $\hat{p}_i$ is the reverse of p_t, which means that sampling probability increases with the difference of long-term average and short-term average. k_1 is an integrity threshold that make sure sampling probability does not fall to zero when the average difference is very small. When the environment is stable, the sensor nodes are asynchronously sampling at a random rate close to k_1 both temporally and spatially. One can visualise a problem when k_1 is very small, there would be long delay for the detection of an event. The experiment set in Figure 2 demonstrates how k_1 affects the time for network to be aware of a change occurs to the whole network. Time taken for a full awareness of the change in the network is an exponential relationship to k_1.

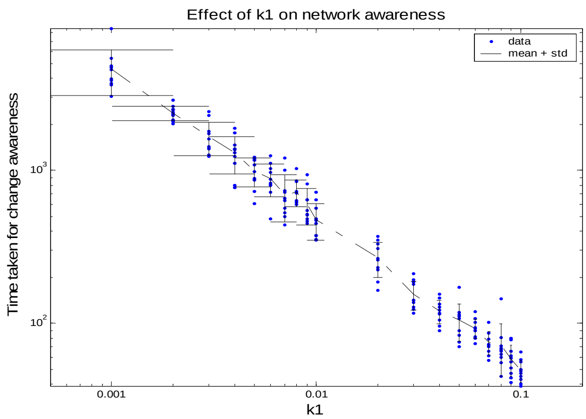

Figure 2: Relation of k_1 and network awareness (log scale). α_{long} = 0.01, α_{short} = 0.05. Environment changes from 0 to 50 at time 200.

On the other hand, a small $k_1$sets a small 'peeping' rate when nothing interesting is happening in the environment, meaning a higher energy efficiency in long term.

3. Spatial Coordination

A small k_1 setting can enhance energy saving in the network; however, the sensing rate is so slow after the settling period that it would take a long time for the sensor nodes to pick up on the events happen in the environment. Therefore, we introduce neighbour coordination to tackle the problem of detection delay. The basic idea is that when a single node senses some change in the network, it alerts its neighbours with its discovery. We include a spatial component, distance $\overline{d_i}$ to the equation in determining p_s and p_i. Distance of this node i and it neighbours j is defined in Eq. 4 and is the summation of the absolute differences of p_t.

$$\bar{d}_i = \frac{1}{n}\sum_j \left| p_{t_i} - p_{t_j} \right| \qquad \text{(Eq. 4)}$$

Finally, Eq. 5 for p_s and p_i are such that probability of sensing is high when either $\bar{d}_i$ or p_t are high; probability of idling is low when both p_t and $\bar{d}_i$ are low.

$$\begin{aligned} p_s &= k_1 + (1-k_1)(1-(1-\bar{d}_i)(1-p_t)) \\ p_i &= (1-p_t)(1-\bar{d}_i) \end{aligned} \qquad \text{(Eq.5)}$$

In the model developed, we used a push-approach to the information dissemination problem among neighbours. A sensor node sends a report to its neighbours when its p_t is above a defined threshold ($p_t > T$), which indicates a significant change in the environment measured. Currently, p_s and p_i are updated at every time step, *i.e.*, even at idle state because the messages received from a node's neighbour may change the sensing schedule of a node. To minimise the communication expenses, a node which has broadcasted its p_t to its neighbour will wait M time steps before considering re-broadcasting its p_t information. T is set to 0.8 and M is set to 10 in the experiment in this paper.

4. Experiments and Results

As a demonstration of the scheduler ability to adapt to the environmental changes, we have built a two dimensional 100x100 torus which contains 100 nodes. The background value changes from a constant of 0 to 50 at time 50. To simplify the scenario, there is no randomness built into the background environment.

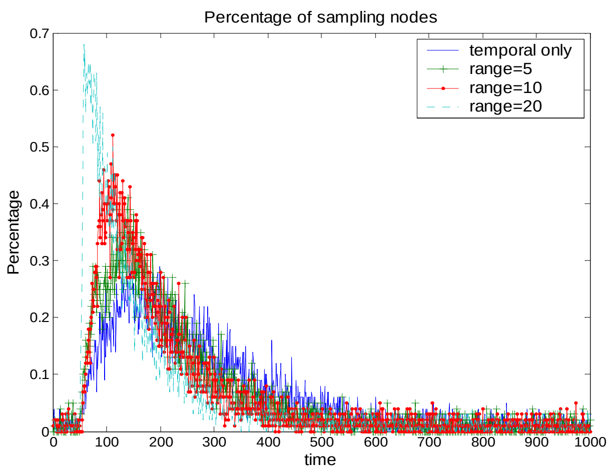

Figure 3: Percentage of sampling nodes over time. Ranges denote the radio range that a node would be considered as a neighbour to another node.

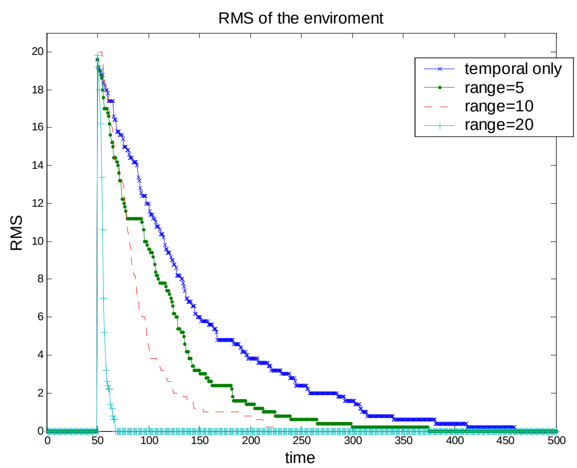

Figure 4: Environmental RMS over time.

Figure 3 is the result of the sampling situation in the network over time. From time 50 onwards, the sensor nodes in the network gradually realise there is a change to the environment and increase their sampling probability accordingly until their long-term average has adjusted to the new value. The percentage of node sampling in the network eventually settles to a value close to k_1, which is set to 0.01 in this experiment. Figure 4 shows the environmental RMS, which is defined as:

$$RMS = \left(\sum_{all\ sensors} (environmental\ value - value\ sensor\ node\ last\ measured)^2 \right)^{\frac{1}{2}}$$

In both figures, we compare the results of using just temporal statistics with the addition of neighbour coordination. A large neighbour range means a node has more neighbours on average. We can see that the RMS converges much quicker to zero when neighbour range is 20, meaning a much faster response of the network to the environmental changes. Information disseminates much more efficiently across the network. Also in Figure 3, the percentage of sampling nodes rises much faster with a larger neighbour range and converge quicker to k_1.

5. Conclusion and Discussion

We have explored a simple, distributed, and self-organised solution to sensing scheduler that can learn about the environment and adjust its sampling behaviour to the changes, such that when there is not much variations in the environment the percentage of sampling nodes in the network converge to a value close to k_1 as defined in Eq. 3. We have also incorporated neighbour coordination to enhance information dissemination across the network and hence, minimise detection delays. The solution is scalable that it is not affected by the addition and removal of sensor nodes in the network.

The works presented in this paper serve as a first steps to the design of a network management algorithm. The concept of altering sensing behaviour based on the data measured can be an efficient way of conserving energy. There are a lot of areas to be explored in our future research.

- In the model, we assume that the information sent by a neighbour is immediately received and processed. This is much deviated from a real network that transmission delays exists dependent on the Media Access Control (MAC) protocol and radio can be turned off to preserve energy. An efficient MAC protocol in line with the scheduler design is required to complete the research in the sensing scheduler.
- The equations and models in this paper are based on a single sensory parameter. We could modify them to fuse data obtained from multi-sensors to improve detection accuracy.
- Reporting of a rare-event is another interesting area to research on. This would include the definition of a rare-event and a routing algorithm for sending information back to the user.

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