Monitoring Moving Objects in Rate Adaptable WSNs

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***Abstract*— In this paper we address a key challenge in wireless sensor networks: how to adaptively assign data transmission rates to individual sensor nodes that monitor and track a moving event of interest. This is necessary so as to efficiently transmit information about an event to a sink within the dual constraints of limited energy budget on each sensor nodes and paucity of radio bandwidth. We formulate the transmission rate assignment problem as a constrained optimization problem. We then present a novel heuristic algorithm involving message exchange between various sensor nodes detecting an event to determine what the transmission rates ought to be for the various nodes. We also present a simulation study to evaluate the effectiveness of our algorithm.**

I. Introduction

Wireless Sensor Networks (WSNs) are becoming more and more popular as they promise scalable, autonomous and self-organizing monitoring capabilities for harsh and hard to reach environments. The existing and potential applications of WSNs span a very wide range including microclimate control in buildings; nuclear, biological and chemical attack detection [1]; habitat monitoring [8], [13]; body protecting for martial arts [3] and counter-sniper systems [12].

WSN nodes are usually equipped with one or more sensor devices, a low duty CPU, a low power transmission radio and a power source such as batteries. As these devices are deployed in large quantities and usually in areas where human interaction can not be handled for a long time period, power efficiency becomes an important metric in the design phase of such systems. For this purpose, several power efficient algorithms and techniques are proposed including several for network and hardware layers [1].

In our work, we focus on the problem of efficient transmission rate adjustment for various sensors in a WSN network that monitor a moving event of interest. Since energy efficiency is an important factor in WSN designs, tuning the transmission rate of a sensor in an energy efficient manner is very important. This is due to the fact that usage of the radio component on a WSN node consumes a large fraction of the power required for the node to function. We base our work on the relative importance values of sensor devices. For example, in a network, if there is only one sensor node that is sensing an event, relative importance of that node grows higher compared to the other nodes in the system. Hence, more network resources shall be assigned to that node.

The rest of this document is organized as follows. In Section II, we present the previous works related to our effort in this document. In Section III, we formulate the rate assignment problem and propose our solution to it. In Section IV, we demonstrate our simulation results. And finally, in Section V, we express our future work plans.

II. Related Work

Sampling rate adjustment techniques in sensor networks are not new and several methods for achieving different goals have been presented.

In [9] a sampling rate control technique based on a feedback mechanism is proposed. Their aim is to adjust sensor sampling rates for maintaining reading accuracy while respecting the resource usage.

In [6], authors propose to use a Kalman-Filter based approach where sensor nodes can estimate the error in order to adaptively adjust their sampling rate within a given range autonomously.

[7] proposes to adapt the transmission rate according to the channel contention. If packet loss is determined as high, their algorithm decreases the transmission rate.

In [5], authors present the rate allocation problem through a linear-programming (LP) approach. Their aim is maximizing the sum of rates while maintaining network lifetime requirements.

[10] uses correlation information among successive packets and contents of those packets in order to adjust

their sampling periods.

To the best of our knowledge, there is no mechanism proposed for adjusting the transmission rate for monitoring moving objects. Furthermore, our method of using the neighbor information for this purpose has not been discussed before.

III. Problem Formulation

A. Basics

WSN nodes have the capability to adjust themselves adaptively since they are equipped with a CPU which might be programmed according to the needs of the system they are deployed for.

Our work is inspired by Hermes Middleware [11] which facilitates data acquisition from an ad hoc WSN through Web Services [4]. In this architecture, all the nodes have the ability to adjust their data transmission rates independently. A sensor node which has been assigned the data transmission rate r, wakes up every $1/r$ seconds, samples the environment on which it is deployed and transmits any measurements that are sensed. Otherwise, it stays in the doze mode in order to save energy.

Typically, there is a $< min, max >$ transmission range dictated by the overall network design considerations and the nodes can not adjust their transmission rates beyond this range. Lower bound is introduced in order to differentiate between a damaged sensor and a sensor that is functional but not sensing anything significant; thereby ensuring that the sensor is operational. This is similar to heartbeat messaging [2]. Upper bound avoids network inefficiency due to unnecessary usage of power and radio bandwidth. We call such a network as Rate-Adaptable Wireless Sensor Network (RA-WSN).

In a RA-WSN, the most straightforward strategy for allocating the transmission rates for each node might be assigning the same data rate statically to all of the nodes and keeping this rate constant during whole operation time. Even though this will yield a theoretically acceptable result, the network will be wasteful under this schema since the nodes that are detecting an event are assumed to be equal to all of the other nodes, even those that only peripherally detect the event in question. Conversely, an efficient rate adaptation mechanism assigns higher frequencies to more important nodes so that they can have access to more network resources. Thus, our aim is to find relative weights of the nodes in the system and assign more resources to them by having them transmit their data at higher transmission rates.

In an event-driven sensor network, the transmission rates of nodes can be assigned according to the proximity

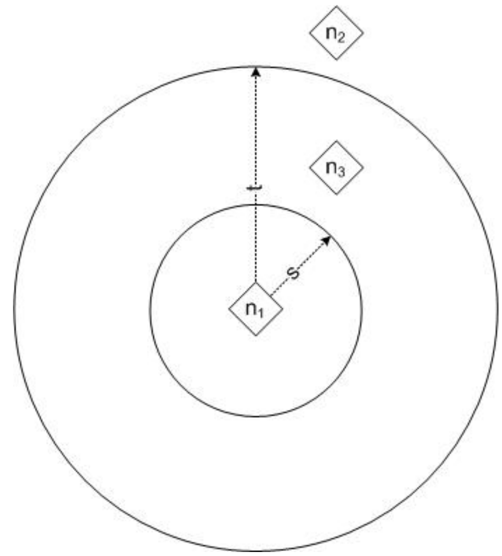

Fig. 1. Transmission Range v.s. Sensing Range

of the nodes to the event. Indeed, a node that is very close to an event will have higher priority than a node which is further away from the event. Besides, if the event is a moving object that has to be monitored (such as fire spreading), the importance of the nodes that are close to the event are more likely to be affected by it in future. This kind of information can be used for estimating the importance of the evacuation zones and scheduling evacuation procedures for areas in case of fire spreading.

In order to come up with an efficient transmission rate mechanism, it is required to have exact information on the positions of the nodes, and a localization mechanism for estimating the positions and proximity of the nodes to the event. Even though there are mechanisms proposed for localization in WSNs, poor reliability and low accuracy of these systems make them unattractive for this purpose. There are also centralized methods such as [14] for determining efficient static WSN deployments. We propose a mechanism which is totally distributed and one which uses message exchange between neighbors in order to eliminate the need for exact location information of the event and the nodes.

In our work, we combine different measurements in order to estimate the relative importance of each node: readings of a particular node‘s sensor and those from its neighbors received through wireless medium. For the sake of simplicity, we assume that the nodes are armed with a single sensor and the event we are monitoring can be detected through that sensor. Usually, the ranges of the sensor devices on the nodes are very limited and require several sensors to cooperate in order to come up with a reasonable estimate. Wireless range, on the other hand, is much larger than the sensor range and enables communication between different nodes. Figure 1 illustrates this behavior. Node n_1 can sense events in its vicinity, those that are bounded within a circle of radius s. The circle with radius t, on the other hand, represents the transmission range of the node. In this example, n_1 can sense and detect events occuring within the circle of radius s, it can wirelessly communicate with n_3 even though it is outside this circle but within the circle of radius t, and finally, it can neither sense any event nor communicate with any node outside the circle of radius t, for example node n_2.

Our work reported in this paper are predicated on the following set of reasonable assumptions:

1) Events are semantically defined by the users and imposed on the system externally. For example, the nodes might be armed with light sensors and the event might be defined as “Light reading greater than 4000 lux”. Moreover, we also assume that only one event can occur at one time.
2) Each node in the WSN operates in a sleep-wake mode, i.e., a node sleeps for a pre-determined amount of time, and then wakes up to sense any event for a certain amount of time, transmits its reading if necessary, and then goes back to sleep.
3) Each event manifests itself within a node‘s sensing range for a finite amount of time. And within this finite time interval, the nodes can detect and comprehend the event. And of course, this can happen only if the node‘s wake up interval overlaps with time interval during which the event manifests itself within the nodes sensing range.

As an example, in Figure 1, if an event occurs in the sensing range of n_1, n_1 will become relatively more important to other nodes whose sensing ranges do not contain the event, and hence it increases its transmission rate. However, assuming the event is not in the sensing range of n_2 and n_3, they will transmit at the same lower transmission rate since they will not be able to detect the event. Intuitively, n_3 is more important than n_2 since it is closer to n_1‘s sensing range. Thus, it is more likely that n_3 will sense the event sooner than n_2, consequently, n_3 is expected to be assigned more resources than n_2.

B. Monitoring Event Propagation

WSNs can be used to monitor the movement of an object, say a car as in Figure 2. Since the sensors that are close to the object are more important, they are expected to transmit at a higher rate, where the others‘ importance values depend on their relative position to the event passing by. This figures demonstrates that the two nodes that are closest to the object are transmitting with high frequency (marked with “H”), three nodes that might be interest to the system in future, transmit with medium rate (marked with “M”) and all the others transmit with lower rate.

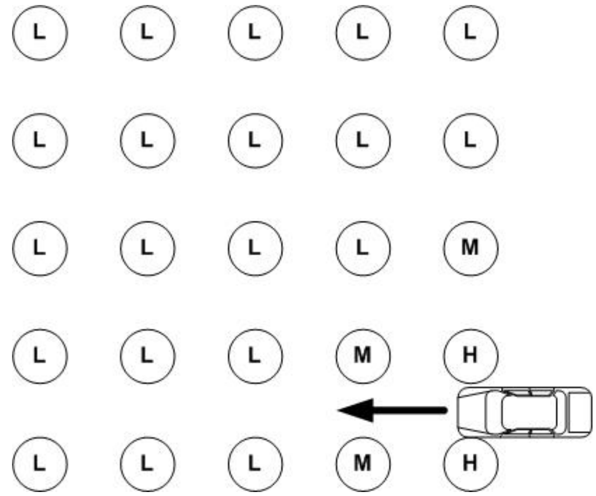

Fig. 2. Monitoring a moving object through a WSN.

In Figure 3, a nodes‘ sensing range with radius r is illustrated. An event manifests itself within the sensing range of the node. If the transmission rate of the node i is p_i, the number of times node n_i detects and transmits the event is $\frac{t_i}{1/p_i}$ where $t_i = l_i/v$ and l_i is the distance the object has to traverse. Hence, the probability that n_i detects this event is $P_i = min\{\frac{l_i \times p_i}{v}, 1\}$. Given such a sequence of sensor nodes, the probability that all the nodes detect the event is

$$P = \prod_{i=1}^{s} P_i. \tag{1}$$

Notice that if $P = 1$, then the system can monitor the event at each step. Such a system is highly desirable and this equality can be assured if all the transmission rates in the system are assigned very high values. However, notice that this will make the system underutilized since then the nodes that do not detect an event are assigned high rates too. We represent the cost associated with this problem as follows. Let x_i represent the event: detection of event by node n_i. If n_i detects an event $x_i = 1$, otherwise $x_i = 0$. Then we represent the overall cost due to unnecessary high rate assignment as follows,

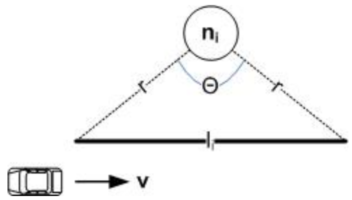

Fig. 3. Sensing Range of a WSN node.

$$C = \sum_{i=1}^{s} (1 - x_i) \times p_i. \quad (2)$$

The transmission rates of the various sensor nodes that observe the event can be assigned by solving the following optimization problem:

$$\begin{array}{rl} \textbf{Min} & C \\ \textbf{s.t.} & P = 1 \\ & \forall i \in Nodes,\, min < p_i < max \end{array}$$

In order to solve the above optimization problem, which is rather complicated, we need the exact information about the route of the object and the speed of the object. In a sense, this is contradictory to our original goal, since the whole aim of the system is to monitor the object. Thus, rather than solving the optimization problem head on, in the following sections, we present a simple heuristic algorithm that confirms to our goal. As we will see shortly, our algorithm combines sensor readings with messages from neighboring nodes in order to assign appropriate transmission rates to different nodes.

C. Neighbor Informed Rate Adaptation Algorithm (NIRAA)

We now present our heuristic algorithm which involves neigboring sensor node message exchanging in order to adaptively assign relative importance values to each of the nodes in the system.

Our algorithm uses two kinds of information in order to estimate the transmission rates of the nodes: readings from the associated sensor device on the node and the neighbor information received through wireless medium. In a network where none of the sensors detect an event, all the sensors are assigned the lowest transmission rate in order to ensure minimal energy requirements. If a node detects an event through its sensor device, it automatically assigns itself the highest data rate possible. Nodes that are not detecting an event but are in close proximity to the ones that are detecting an event are in different status. Such nodes are not as important as the ones that are detecting an event, but clearly they are more important than the ones that are far away from the event. Moreover, in case the event is a moving object, the possibility that these nodes will detect the event in near future is much higher than the far away nodes. Hence, we propose to use a discrete rate assignment method which assigns one of the three rates to the nodes: HIGH, MEDIUM and LOW. HIGH and LOW rates are imposed by the system, where we choose MEDIUM as the average value of the former two. Notice that the choice of MEDIUM rate might have a big effect on the overall performance of the system. Nevertheless, we leave the calculation of finding the optimal MEDIUM rate for a network as a future work and adopt the basic averaging method in this work.

In the example in Figure 2, when n_1 detects the event defined by the system, it automatically assigns high transmission rate to itself and consequently broadcasts an EventDetected message. The receivers that intercept this message understand that a close node has detected an event and elevate themselves to a higher transmission rate. Notice that a node that receives an EventDetected packet can be detecting the event itself, in which case it will increase its transmission rate to the highest; otherwise it will transmit at a medium rate since it is not as important as the nodes that are detecting the event, but it is more important than the nodes that are neither detecting the event nor have received the EventDetected messages. Algorithm 1 summarizes this mechanism.

Algorithm 1 NIRAA

```
if LocalEventDetected() then
    Rate = MAX
    AlertNeighbors()
else if NeighborAlertReceived() then
    Rate = MEDIUM
else
    Rate = LOW
end if
```

All of the nodes also deploy a timeout mechanism which ensures that the transmission rates are reset to LOW rate if neither an EventDetected packet is received nor the event is detected locally.

IV. SIMULATIONS

We executed several simulations in order to investigate the performance of our proposed algorithm with comparison to constant rate networks. Our aim is to achieve maximum P (Equation 1) with minimum Cost (Equation 2). In order to accomplish this objective, we implemented a discrete time moving object simulator

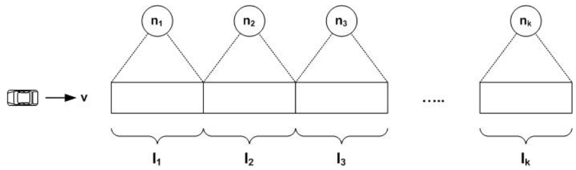

Fig. 4. One dimensional simulation route.

using Matlab. Our implementation assumed a single dimensional route for the moving object as can be seen in Figure 4. Moreover, we assumed that only neighbor nodes can hear each other, i.e. $\forall n_i$, only n_{i+1} and n_{i-1} is in the communication range of n_i.

Clearly, two factors are dominant in the performance outcomes of different algorithms: velocity of the object and the number of nodes on the route. As the velocity of the object increases, the probability that a node will detect the object decreases as the object will traverse the node's sensing area faster. Number of nodes, on the other hand, affects the probability of detection in the inverse way as the aim is continuous real-time monitoring of the object with highest granularity possible, i.e. all the nodes on the route have to reliably detect and inform a sink about the object.

We first executed experiments in order to see the velocity effect on the performance. We compared the results with three different constant rate assignments, namely low, medium and high constant rate assignments. In this experiment, we kept the number of nodes constant at 10, assigned uniformly distributed random numbers to the sensing range of the nodes in the range $[50, 100]$ and chose $< min, max >$ range as $< 1, 10 >$. We chose the medium rate as the average value of min and max values, i.e. 5.5. As can be seen from Figure 5, for velocity values smaller than 400, our NIRAA algorithm performs very well, close to the high rate assignment. Notice that low rate assignment performs worst in this experiment and can only perform well for velocity values less than 100. As the velocity values gets higher and higher, our algorithm starts to perform badly and finally, for very large velocity values, it performs as the low rate assignment.

Figure 6, on the other hand, shows the cost values (i.e. objective function defined earlier) associated with different assignment methods. It is expected that high rate assignment is the costliest of all the methods; low rate is the cheapest and medium rate lies between the former two. Our algorithm, on the other hand, performs very close to the low rate assignment for velocity values lower than 400, and gets closer to low rate assignment

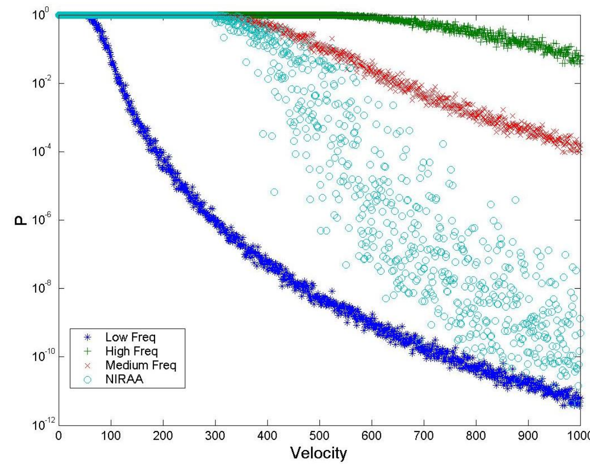

Fig. 5. Node detection probabilites v.s. velocity of the object to monitor.

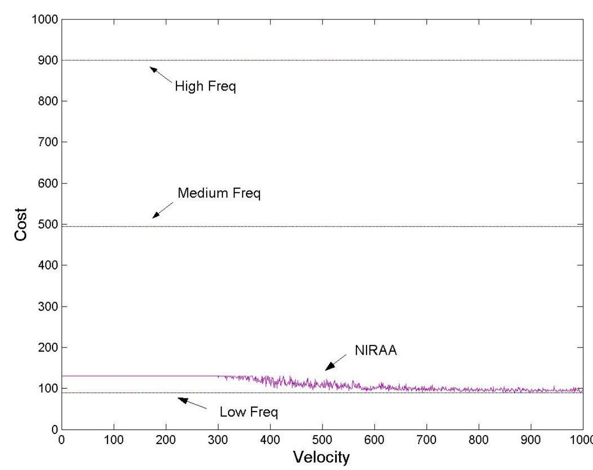

Fig. 6. Cost v.s. velocity of the object to monitor.

for large velocity values. Hence, we can conclude that our algorithm performs very well for monitoring moving objects with low-to-medium velocity values. Our algorithm promises the efficiency and quickness of high rate assignment with the cost of low rate assignment.

In our second experiment, we executed simulations in order to see the effects of the number of nodes placed on the route of the moving object. (Note, we are not increasing the density of nodes in the vicinity of an event; rather we are increasing the number of nodes while keeping the density more or less constant. Such a scenario would be required for example to detect a fire or a toxic gas leak that are spreading in space and time). This time, we kept the velocity of the object constant at 500 units and varied the number of nodes. Since

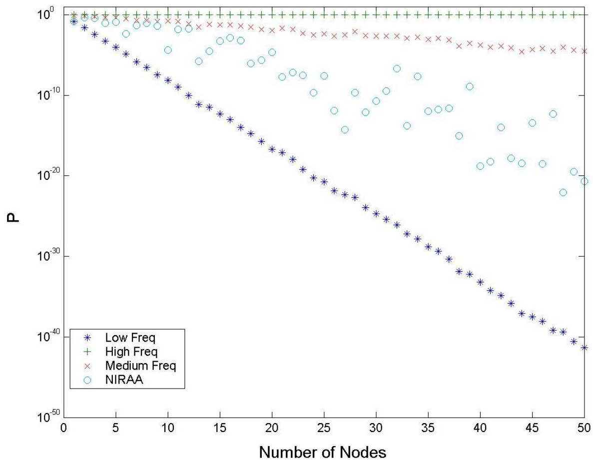

Fig. 7. Node detection probabilities v.s. number of nodes.

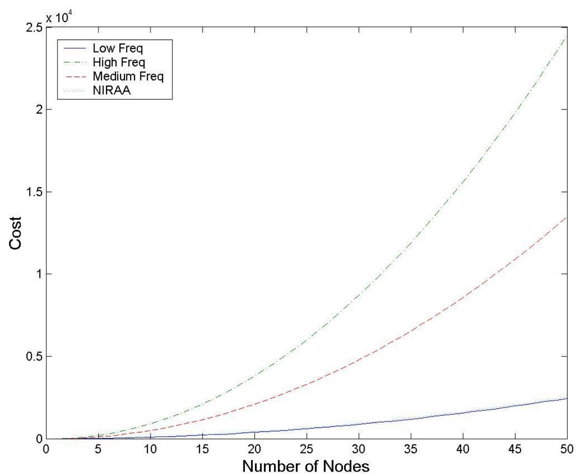

Fig. 8. Cost v.s. number of nodes.

our target is maximum granularity, our results show that increasing the number of nodes worsens the probability of detection. This is because of the fact that as the number of nodes in the system increases, the *probability that all the nodes detect the object* decreases. Figure 7 illustrates this phenomenon. Figure 8 demonstrates the cost comparison of all four mechanisms for increasing number of nodes. This figure suggests that the costs incurred by utilizing our algorithm are very close to those incurred by assigning low transmission rates to all the nodes, independent of the number of nodes in the system. In terms of efficiency, our algorithm performs better than low rate assignment but incurs the same cost.

V. Conclusions and Future Work

In this work, we presented a novel neighbor informed transmission rate adjustment algorithm (NIRAA) for Rate Adaptable Wireless Sensor Networks to detect and track an event as it propagates through space and time. Our algorithm adjusts the transmission rates of the neighbors of a node which detects an event, in order to maximize the probability of detection while minimizing the costs associated with unnecessary high transmission rate assignments. We presented simulation results for one dimensional routes and concluded that for events that propagate with a low-to-medium velocity, our transmission rate assignment mechanism performs closer to high rate assignment mechanism while incurring a cost value close to low rate assignment mechanism.

In our future work, we plan to extend our mechanism for multi-dimensional routes. As the degree of freedom increases in such routes, the choice of the *medium rate* gains more importance. We intend to calculate the optimal medium rate value for different network and object characteristics.

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