Adaptive Random Sensor Selection for Field Reconstruction in Wireless Sensor Networks

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1. INTRODUCTION

Wireless sensor networks (WSNs) allow for the sampling of a physical phenomenon over long periods of time and across extended geographical areas [1]. Once reported to a central collecting unit, the samples may be used to reconstruct the developing of the physical phenomenon of interest – also referred to as *signal* or *sensor field* – in both time and space. Work in information theory [3] shows that a reliable signal reconstruction is possible if a sufficiently large number of nodes sample the signal at sufficiently close time and space intervals. Clearly, the achievable quality of the reconstruction can be maximized by letting the highest possible number of nodes collect and report samples. However, on typical sensor nodes, sensing and communication modules require the largest amount of energy and their continuous use can rapidly deplete node batteries [1]. Limiting the number of nodes actively participating in sensing and communication is thus the most effective way to increase the lifetime of both single sensor nodes and the network as a whole [2, 5]. *Sensor selection* algorithms can be used to schedule individual sensing activity in order to balance the accuracy of the reconstruction with energy consumption. In real WSNs deployments, the irregular spatial distribution of the nodes typically produces nonuniform sampling geometries that and reconstruction techniques able to deal with scattered samples must thus be used. In this context, the ACT reconstruction algorithm [3, Chapter 6] is one of the most computationally efficient and robust techniques known in literature and appears as a perfect fit to perform field reconstruction in WSNs. In particular, the ACT can deal with both very irregular sampling geometries and presence of noise in the data. However, the more the sampling geometry resembles a uniform grid, the better the performance of the ACT. With these considerations in mind, we investigate sensor selection strategies able to generate, given the constraints of the physical network topology, sampling geometries providing limited number of samples but still enabling the ACT to work properly. To this scope, we resort to random sensor selection strategies [2] and propose an adaptive method to determine, in a distributed fashion, the probability of activation of single sensor nodes. Our preliminary experimental results show that our approach succeeds in making the ACT able to reconstruct the sensor field with good accuracy, thereby using a lower number of sensors with respect to other random sensor selection strategies.

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2. ADAPTIVE RANDOM SELECTION (ARS)

In a random sensor selection (RSS) scheme sensor nodes can autonomously decide whether to be active or not according to their *probability of activation* p. To enforce some uniformity on the sampling patterns resulting by random node activations, nodes in scarcely populated neighborhoods should have high probability of activation, while nodes in clusters of nearby located nodes should be assigned low values of p. To this scope, each sensor node can determine its probability of activation by considering the number and positions of its neighbors. Indeed, information about the communication neighborhood of a node must be collected anyway in order to find a routing path towards the data sink. In our work, we assume that the network relies on the CTP[1] data collection protocol, whose beacons can be easily modified to include also the position of the sending nodes. We can thus assume a node n_i holds an updated list of the $N_{tx,i}$ nodes that are within its transmission range, along with their positions s_j, $j = 1,..,N_{tx,i}$. To compute the probability of activation, we resort to the following heuristic. First, the neighbors are divided into N_{sets} sets $S_{ik}, k = 1,..,N_{sets}$. If the network is deployed on a line (1-dimensional case), the node n_i can assign each neighbor n_j to its "left" ($|s_i| >= s_j$) or "right" (($|s_i| < s_j$) neighborhood. If the nodes are deployed on a plane (2-dimensional case), the sets correspond to $N_{sets} = 4$ circular sectors spanning the circle centered on the node and having radius δ. In both the 1- and 2-dimensional case, only the $N_{\delta,i}$ neighbors whose distance d_{ij} to n_i is strictly smaller than δ are included in the sets. The value of δ is signal-dependent and relates to the maximal tolerated distance between any two adjacent samples. If δ is not known a-priori, the ACT algorithm allows to estimate its value along with the computation of the reconstruction. If all sets are non-empty, the node computes, for each neighbor n_j, the quantities $\phi_{ij} = 1 - \frac{d_{ij}}{\delta}$. To understand the meaning of this factor one should recall that, considered alone, the node n_i is "responsible" for covering an entire sector of radius δ and centered at n_i. But a node n_j with distance $d_{ij} < \delta$,

[1] www.tinyos.net/tinyos-2.x/doc/html/tep123.html (TinyOS TEP 123)

can "relief" the node n_i from part of its "sensing responsibility". To account for the contribution of all neighbors in a sector k, the factor $\Psi_{ik} = 1/(1+\sum_{j=1}^{N_{\delta,i}} \phi_{ij})$ is computed for all sets. For each set k the value Ψ_{ik} represents the probability of activation p_{ik} the node n_i should assume to "cover" the region span by the set k. An appropriate aggregate (e.g., minimum or average) of the Ψ_{ik} is then chosen as the activation probability p_i of the node n_i. For an empty set the probability of activation is 1 and in this case we force the p_i to be 1 too.

Our adaptive random sensor selection (ARS) strategy takes into account changes in the topology of the network by automatically including information from the routing table of CTP in the computation of p_i. The ARS can also follow changes in the dynamics of the observed signal field by adapting the value of the spatial resolution δ.

3. PRELIMINARY RESULTS

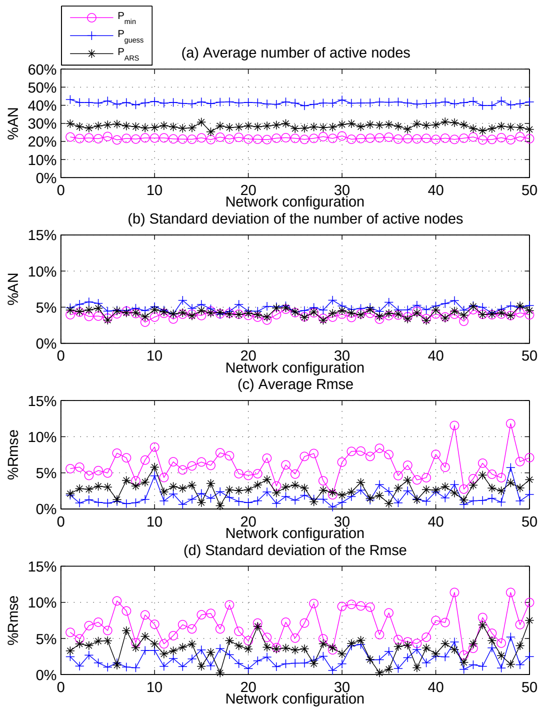

Figure 1: Average values of the $\%AN$ and $\%Rmse$ for 50 different network configurations (a),(c) along with the correspondent values of the standard deviation (average over 50 trials) (b),(d).

To gather preliminary results on the performance of the ARS, we consider a sensor network of $N_{tot} = 100$ nodes distributed uniformly at random over a segment of length $L_x = 100m$ (1-dimensional case). The transmission range R_{tx} and the spatial resolution δ are fixed and both equal to $5m$. As an example of sensor field f we use the physical process model used in the Castalia[2] simulator (with parameters $N_{sources} = 1$, $V = 1$, $K = 0.05$, and $a = 3$). For this setting, we generate 50 random network configurations and let our ARS algorithm run 50 times. For each configuration and round, we measure two main performance metrics: the percentage of active nodes $\%AN$ (i.e., ratio between the number of nodes that participate in sensing and the total number of nodes), and the relative root mean square (rms) error of the reconstruction $\%Rmse$ (given the signal f and its reconstruction $\hat{f}$ we have $Rmse = \|f - \hat{f}\|^2/\|f\|^2$). We compare the performance of the ARS to that of a simple random selection scheme that uses two different values of the probability of activation p (kept fixed and equal for all nodes in all rounds). The first value, dubbed p_{min}, is computed so that the expected number of active nodes $p_{min} \cdot N_{tot}$ equals the number of nodes that would have constant internode spacing δ if they were deployed uniformly over the sector $[0, L_x]$. The second value, dubbed p_{guess} is chosen as $p_{guess} = 2 \cdot p_{min}$. Previous work has showed that random sampling typically requires more than twice the sampling rate of regular sampling to provide for a reliable reconstruction [4]. Therefore, p_{guess} represents a more realistic estimate of the required probability of activation in the plain random selection scheme. We run our experiments on the Matlab[3] computing environment.

Figures 1*(a)* and 1*(b)* report the average $\%AN$ obtained for 50 different network configurations along with the correspondent standard deviation (over 50 trials). This figure shows that the number of nodes selected by the ARS is slightly higher than the correspondent figure for the RSS with p_{min}, but significantly lower compared to the RSS with p_{guess}. This slightly higher effort is however praised by significantly better reconstruction performance, as showed in figure 1*(c)*, which reports the $\%Rmse$ for all the three considered sensor selection schemes. ARS thus offers reconstruction accuracy comparable to that obtained with the RSS with p_{guess} (and far better with respect to the RSS with p_{min}) but requires far less nodes to actively sample the signal. In other words, when the ACT is used to perform field reconstruction at the base station, the ARS can provide sampling geometries that favor the reconstruction process.

4. REFERENCES

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