An Energy Conservation Method For Wireless Sensor Networks Employing a Blue Noise Spatial Sampling Technique

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I. INTRODUCTION

In this work, we consider applications of wireless sensor networks where a spatially band-limited physical phenomenon (e.g., temperature, pressure, low-frequency vibrations) can be sufficiently monitored by a subset of the nodes (randomly) deployed in the environment. In other words, the total number of sensors deployed is such that if the sensors were placed uniformly within the area, the Nyquist criteria would be met in terms of spatial frequency. While such a random distribution does not provide ideal uniform coverage, it does guarantee within a reasonable likelihood that the area is covered densely enough to meet, if not exceed, the Nyquist criteria requirements within most subregions. We propose a method that determines which sensors within the more densely covered subregions should be selected to acquire data from the environment and which nodes should remain inactive in order to conserve energy. The proposed method is especially suitable for applications where it is desirable to trade spatial resolution for sensor network longevity. Our proposed method chooses sensor subsets such that the sensor positions can be mapped into the blue-noise binary patterns that are used in many image processing applications [1]. The method guarantees that the subsets would be chosen such that each subset provides a near optimal signal-to-noise ratio for the given sensor distribution and desired number of active sensors [2]. Meanwhile, the method also guarantees that the sensor nodes with the minimum residual energy are the primary candidates for deselection (i.e., they are the first to be turned off).

II. BLUE NOISE BACKGROUND

A blue noise pattern is a statistical model for describing ideal aperiodic dispersed dot patterns [3]. It is considered ideal in terms of spatial and spectral characteristics. The ideal binary blue noise pattern is a collection of similar sized dots that are stochastically distributed in a manner that is as homogenous as possible within an area, while maintaining a stochastic nature (i.e., uniform distribution is prohibited). By distributing dots in such a way, the resulting spectral content of the pattern is composed entirely of high frequency content. A subset of M dots, chosen from N possible locations within a $D \times D$ area, defines a blue-noise binary pattern if the resulting pattern has a stochastic nature, where the average distance between dots (λ_b) is given by Equation 1 and the resulting pattern has no frequency content below the blue noise principal frequency f_b given in Equation 2.

$$\lambda_b = \begin{cases} \frac{D}{\sqrt{\frac{M}{N}}} & 0 \leq M \leq \frac{N}{2} \\ \frac{D}{\sqrt{1-\frac{M}{N}}} & \frac{N}{2} \leq M \leq N \end{cases} \tag{1}$$

$$f_b = \frac{1}{\lambda_b} \tag{2}$$

General rules for generating a pattern that has blue-noise characteristics are that the dots are to be placed within the pattern such that the spectrum of the resulting pattern

1) is noisy and lacks any coherent spikes of energy and
2) has a deficiency of low-frequency energy.

Several algorithms have been proposed to generate binary blue noise patterns with various success [1], [4]–[7]. The method that is of interest to us is that proposed in [1] and improved in [5]. In their work, the authors propose a dart throwing method, which mimics a stochastic Poisson disc method. In this method, a new point is added to the point set if and only if no other point is inside a specified radius centered at the location of the new point. A low-pass spatial filter is then used to determine which points contribute the most low-frequency content (the points with the highest post-filter value). These points are subject to relocation within the regions with the least low-frequency content. The problem with this method is that the dart throwing pattern converges to uniform distribution, which is not allowed by the blue noise specifications. Thus, the low-pass filter relaxation method should stop after a certain number of iterations. The exact number of iteration steps depends on the initial pattern and has been an ongoing research challenge.

III. Application of Blue Noise Sampling to Sensor Management

In this section, we propose a method to decide which nodes in a wireless sensor network should be used to provide coverage of the environment and which should remain off for reasons of energy efficiency. Let us first consider an application where N sensor nodes are randomly deployed inside the area to be observed such that in all subregions of the area, it is likely that the density of the sensor nodes is more than necessary to meet the requirements of the Nyquist criteria. We assume an image grid within the observed area that is dense enough so that each sensor's location can be precisely mapped into a single grid point and each point on the grid is associated with no more than one sensor. If a sensor is associated with a grid point, the grid point is assigned a value of 1; otherwise, it is assigned a value of 0. The resulting binary pattern should have white noise spectral characteristics because of the way in which the sensor nodes are deployed. In our proposed method, a low-pass filter relaxation algorithm is applied to the initial binary pattern to determine which nodes are not necessary to observe the area. The characteristics of this low-pass spatial filter should depend on the nature of the variable that is being observed. More specifically, the coefficients of the low-pass filter are determined such that the frequency content of the observed variable falls within the filter's pass band. Meanwhile, the selection of the order of the filter is essentially a tradeoff between the desired performance of our proposed method and computational cost. The proposed algorithm determines which point in the filtered grid has the largest spatial-low-frequency content (the point with the highest value after the filter has been applied) and removes the most nearby sensor from the set of active sensors. These steps are carried out iteratively until the maximum filter output drops below a predetermined threshold or the number of remaining active sensor nodes drops below a certain value. The resulting pattern is shown to have blue noise spectral characteristics, guaranteeing the best possible signal-to-noise ratio for a given initial sensor placement and spatial distribution of the physical phenomena being measured [2].

Now, let us consider an application where the number of sensor nodes is much more than sufficient to meet the Nyquist sampling criteria. In such applications, spatial resolution can be traded for energy efficiency, meaning that a smaller subset of M sensor nodes ($M < N$) could be used to observe the area. The subset of M nodes is to be determined on the fly such that it constitutes a blue noise pattern while exercising care with respect to the residual energy of the sensor nodes. Once again, the method assumes a similar image grid as that in the previous paragraph. However, here we map energy costs - assigned to be a monotonically decreasing function of the residual energy of the sensor nodes - to the image grid instead of the binary value as we did previously. In this case, the low-pass filter is used to determine which grid points are critical in terms of energy as well as low spatial-frequency content. Sensors closest to the grid points which have the maximum post-filter value are subject to be excluded from the active subset. These steps are repeated iteratively until the active subset consists of M sensor nodes or the PSNR reaches a suitable level. Following the selection algorithm, the active subset of M nodes is used to observe the area for a certain time interval. After this interval, the selection algorithm is repeated again with updated energy information of the sensor nodes within the network.

Finally, we propose another energy-efficient sensor selection approach. In this approach, active sensor subsets are created in a similar manner as in the first approach. However, rather than deterministically deselecting nodes in areas of the largest spatial-low-frequency content, nodes are deselected with a weighted probability proportional to their post-filter value. With the introduction of this random factor, many active subsets, each providing the necessary blue-noise sampling characteristics, can be calculated. It is possible to schedule the use of each of these subsets so that the total lifetime of the monitoring application is maximized. This optimization can be performed through a simple linear programming approach.

IV. Simulations

We simulated a network of 5000 sensors randomly deployed within a 128×128 grid, of which a given number were activated to monitor a bandlimited phenomenon. We compared the blue noise sampling approach with the random selection of sensors (essentially, a white noise sampling approach). Typical locations of activated sensors using the blue noise sampling method and using the random method are shown in Figures 1a and 1b, respectively.

Following the selection of nodes, the original images were reconstructed from the sensor samples and the mean square errors were calculated. As expected, the

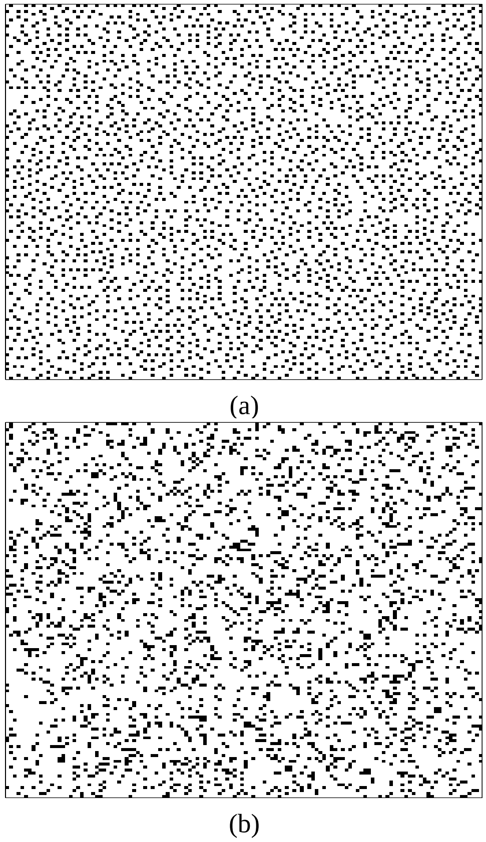

Fig. 1. Typical plot of the activated sensor locations using the blue noise sampling method (a) and using the random method (b)

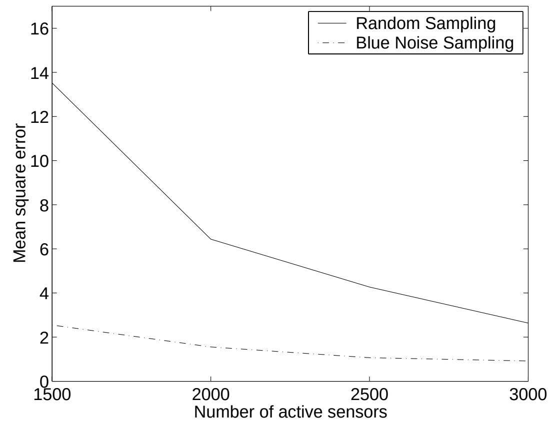

Fig. 2. Mean square error for blue noise sampling and random sampling

mean square error increases as the number of sensors selected decreases, as can be seen in Figure 2. However, the blue noise sampling method shows more immunity to the decreased sampling rate and its relative performance is best for a smaller number of activated sensors, reducing mean square error by as much as 85% compared to the random selection method when selecting 1500 active sensors.

We plan to run extensive simulations using the energy-aware sampling methods to observe the tradeoff between power consumption/network lifetime and accuracy of phenomenon measurement. We would also like to implement these selection in the ns-2 network simulator to observe the translation of number of activated sensors to actual power savings and network longevity when factors such as routing and MAC layer overhead are considered.

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