A Convex Optimal Sensor Selection Method for Wireless Sensor Networks: Abstract

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In wireless sensor networks (WSNs) based applications, a key requirement is the need to design sensor operations that would conserve precious onboard battery energy and yet satisfy application quality-of-service (QoS) requirements. Sensor operations include sensor-to-sink communication, onboard processing/filtering of sensor measurements etc, while application QoS could be the maximum event position estimation error allowable in a remote event monitoring application. An obvious strategy to reduce the overall consumption of battery energy would be to select only a small subset of the total number of deployed sensors to satisfy application requirements. However, it is a challenging task to determine which subset of the sensor deployment will suffice, if at all. In this paper, we consider a remote monitoring application where it is required to estimate the location of an event with optimal precision using minimum number of sensors. Based on some reasonable approximations, we formulate the sensor selection problem as a convex optimization problem. We then come up with a solution to this optimization problem which we refer to as the convex optimal sensor selection (COSS) algorithm to select only a proper subset of the sensor deployment required to observe the event and accurately estimate the location of the event. Finally, the proposed COSS algorithm has been tested through extensive simulations and hardware experiments under realistic conditions.

As an illustrative example, we assume that an array of n light sensors are placed at known locations, $\mathbf{r}_i$, to track a mobile lamp's position $\mathbf{q}^*$ based on the light intensity measurements, $s_i[k]$, which is presented as a real light intensity, $y_i[k]$, contaminated by an additive unbiased noise $v_i[k]$, i.e., $s_i[k] = y_i[k] + v_i[k]$. Note that $y_i[k]$ is a function of the distance from sensor i to the lamp and hence a function of the lamp position. The well-known fact that we exploit in our COSS algorithm is that averaging more samples will contribute to better noise rejection, as well as more precise estimation. Let p_i be a normalized sampling rate of sensor i, which samples $p_i N$ times for light measurements over each time interval of duration, say T, where N is a constant. Thus, over each T time slot, sensor i sends its average measurement data denoted by $\bar{s}_i[k]$ to the sink.

The first task of the COSS algorithm is to estimate the position of the target through a standard least squares (LS) approach with all the sensors activated. The result is the a priori estimate, say $\hat{\mathbf{q}}_A[k]$ given by:

$$\hat{\mathbf{q}}_A[k] = \arg\min_{\mathbf{q}} \frac{1}{2}\sum_{i=1}^{n}(\bar{s}_i[k] - y_i(\mathbf{q};\mathbf{r}_i))^2. \tag{1}$$

The next step in our COSS algorithm is to estimate what the optimal sampling rate, p_i, of the sensors are to be over the next time interval and beyond. This is achieved by solving a specially constructed sampling rate optimization problem shown below, such that most sampling rates are close to zero after the optimization. Which means, that only those sensors whose sampling rates are above a certain threshold are selected.

$$\begin{aligned} \hat{\mathbf{p}}[k] &= \arg\min_{\mathbf{p}} \Psi(M(\mathbf{p};\hat{\mathbf{q}}_A[k])), && (2)\\ \text{subject to} &: \mathbf{p} \geq 0, \mathbf{1}^T\mathbf{p} = 1, && (3)\end{aligned}$$

In the above equations, M is the Fisher information matrix (FIM) whose inverse represents the "size" of the estimation error, $cov(\hat{\mathbf{q}}) = M^{-1}$, and the function Ψ is the D-optimality criterion defined as $\Psi(M) = -\ln\det(M)$ in the literature of optimal experimental design. One method to solve the above sampling rate optimization problem is a multiplicative method developed for D-optimization. It can be proved that since the cost function (2) used to estimate $\mathbf{p}$ is a convex function with convex constraints, only a small subset of sensors is required to establish precise estimates.

Once the p_i are estimated, and only the sensors with high sampling rates are selected, denoted by the set say $\mathbb{S}_S[k]$, subsequently, the a posterior estimate $\hat{\mathbf{q}}_B[k]$ of the lamp's position is obtained by solving the following LS problem:

$$\hat{\mathbf{q}}_B[k] = \arg\min_{\mathbf{q}} \frac{1}{2}\sum_{i\in\mathbb{S}_S[k]}(\bar{s}_i[k] - y_i(\mathbf{q};\mathbf{r}_i))^2. \tag{4}$$

In our simulation experiments, we found that $\hat{\mathbf{q}}_B[k]$ is normally much closer to $\mathbf{q}^*[k]$ than $\hat{\mathbf{q}}_A[k]$. In addition, our COSS algorithm applied to real hardware conformed that $\hat{\mathbf{q}}_B[k]$ is a more precise estimate of $\mathbf{q}^*[k]$ than $\hat{\mathbf{q}}_A[k]$. Figure 1 is a frame from our movie [1] that demonstrates our sensor selection testbed. Our current analytical work is focused on the following two critical issues:

- The event location estimation error is approximately equal to the minimal estimation error as predicted by the Cramér-Rao lower bound (CRLB).
- The number of sensors selected is no more than the upper limit that allowed by the Carathéodory's theorem as applied to our formulation.

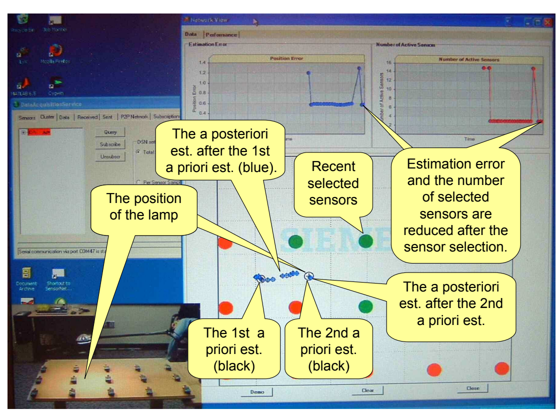

Fig. 1. A screen shoot of our sensor selection testbed.

[1]This video and other experiment results are available at `http://cc.usu.edu/~zhensong/SensorSelection`.