Adaptive Sampling for Wireless Sensor Networks

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Abstract — **This paper proposes an adaptive three-stage approach for accurate field estimation using a wireless sensor network that can significantly reduce energy consumption. Under a piecewise smooth field assumption, this method nearly achieves the minimax error rate $n^{-1/2}$, where n is the number of available sensors, while activating only $n^{3/4}$ of the sensors in the network. This approach can save significant energy compared to dense, non-adaptive sampling.**

I. Wireless Sensing of Two-Dimensional Fields

Assume that n sensors are arranged on an $\sqrt{n} \times \sqrt{n}$ square lattice over the unit square, and that the two-dimensional field being sensed is twice-continuously differentiable everywhere except near possible one-dimensional boundaries (or "edges") where the field changes sharply. Each sensor can make a measurement of the field at its location which is contaminated with white Gaussian noise with variance σ^2.

The basic problem addressed by our method is that of estimating and communicating an estimate of the field to a *fusion center*. Since the field is piecewise smooth, in principle we can achieve the desired level of accuracy by activating more sensors in non-smooth regions and fewer sensors in the smooth regions. Because sensor activation, measurement acquisition, and communication contribute significantly to the energy expenditure of wireless sensor networks, an adaptive sampling strategy can result in significant energy savings in two ways. First, by adaptively sampling the field, fewer sensors are activated. Second, since fewer measurements are collected, the number of communications required to achieve an accurate estimate is reduced. To quantify the energy required to transmit a field estimate, we assume a simple multihop communication protocol, where $e(n)$ is the energy required to send one bit over one hop.

II. Adaptive Sampling

The following theorem summarizes the performance of field estimation using the adaptive sampling method described below:

Theorem 1: *Assume a field consisting of C^2 regions separated by C^2 boundaries. Then the proposed field estimation method requires $O\left[e(n) \cdot n^{3/4}\right]$ units of energy. The distortion (MSE) of the resulting field estimate is $D(n) = O\left[n^{-1/2}\log n\right]$.*

The MSE above is of the same order as the best that one can achieve for a piecewise smooth field using all n sensors and $O\left[e(n) \cdot n\right]$ units of energy [1]. Thus, we achieve the same performance, but using the proposed method we reduce the amount of energy required by a factor of $n^{1/4}$. Put another way, if m is the number of sensors *activated* in the estimation process, then the distortion decays like $O[m^{-2/3}]$, the minimax rate for nonparametric estimation of one-dimensional curves (i.e., curves with box-counting dimension 1).

The three primary stages of the proposed method are (1) **Preview**, which forms a low resolution estimate of the field, (2) **Backcast**, which activates additional sensors in non-smooth areas, and (3) **Refinement**, which produces the final, high resolution estimate. Employing a multiresolution complexity regularized estimator developed in our earlier work [1], we are able to control the distortion in both the Preview and Refinement stages.

Preview: The unit square is partitioned into $n^{1/2}$ smaller "subsquares", and in each subsquare, $n^{1/4}$ sensors are activated; thus, $n^{3/4}$ "Preview" sensors are activated in total. These sensors are used to form an initial estimate of the field, which is passed to the fusion center. With high probability, the Preview partition will be composed of small cells in regions close to any boundary present in the field and larger cells in smoother regions of the field. It follows that the resulting high-resolution MSE can achieve the target rate of $n^{-1/2}$ to within a log factor in cells in the smoother regions. This stage requires $O\left[e(n) \cdot n^{3/4}\right]$ units of energy, and $O\left[n^{3/4}\right]$ sensors must be on to facilitate the multihop communications.

Backcast: The fusion center transmits a message to the smallest cells of the Preview partition (*i.e.*, those remaining subsquares that were not aggregated together due to the presence of a boundary), activating all available sensors in those cells. Assuming that the boundary is a one-dimensional curve, only $O\left[n^{1/4}\right]$ preview subquares will contain the boundary and require fine-tuning. Thus, the total energy consumed in Backcast is $O\left[e(n) \cdot n^{3/4}\right]$.

Refinement: The newly activated sensors are used to generate a refined estimate of the field in the smallest cells of the Preview partition. It is then possible to simply fit a line to the refined estimate and transmit the boundary and linear surface fit coefficients to the fusion center. This requires a total $O\left[e(n) \cdot n^{3/4}\right]$ units of energy. Note that this process uses all the sensors in each of the smallest preview subsquares and hence nearly achieves the minimax error rate of $n^{-1/2}$.Further details and derivations are available in a technical report available on-line [2].

References

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