Distributed Inference in Wireless Sensor Networks: Some Recent Results[1]

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Distributed inference (e.g., detection, estimation, learning, etc.) is one of the primary applications of wireless sensor networks. This paper presents an overview of recent results by the author and co-workers in this area. The focus is on results in distributed learning and sensor scheduling, but some issues relating to energy efficiency are also discussed briefly. This work is summarized here:

Distributed Learning [4]-[6]: Learning is used in detection and estimation problems when no probablistic model relating an observation X to a quantity Y to be inferred is available. The basic idea of learning is to replace a probabilistic model with a set $\{X_i, Y_i\}_{i=1}^n$ of examples of observations that have been marked with correct inferences. In a centralized setting, this is a classical problem, and algorithms can be constructed that are consistent, i.e., that achieve the minimal Bayes risk asymptotically as the number of independent and identically distributed (i.i.d.) examples increases without bound (i.e., as $n \to \infty$). In a distributed setting, the examples are not available at a central site, and the question naturally arises as to whether it is still possible to achieve consistency. This question is explored under various network models in [4] and [5]. For example, one such situation is that in which i.i.d. examples are distributed among n sensors, which are queried about a new observation X. In this framework, consistency can be achieved at a fusion center if each sensor transmits one bit (per decision) to the center for (binary) detection, or $\log_2(3)$ bits per decision for (real) estimation. Other problems, such as sensor specialization, are also considered in these works. Another issue, explored in [6], is the use of local collaboration among distributed sensors to estimate a signal field. A message-passing algorithm, based on successive orthogonal projections, is developed in [6] that iteratively determine a "best" approximation (within the constaints of the network topology) to a centralized least-squares estimate of the field.

Sensor Activation and Scheduling [7]-[9]: Another type of problem of interest is the placement, scheduling and/or activation of sensors to achieve optimal trade-offs between performance at the application layer and network properties such as energy consumption and the number of sensors. These issues are addressed variously in [7]-[9], for the problem of detecting a correlated signal field against background noise. The basic tool used here is the error exponent for the miss probability in fixed-level Neyman-Pearson detection of a correlated signal field against a white Gaussian noise background:

$$-\lim_{n\to\infty} \log P_M(n)/n \ ,$$

where $P_M(n)$ denotes the miss probability based on n sensors. For linear-Gaussian state-space signal models, this quantity is derived in closed-form in [9]. It is seen, for example, that the behavior of the error exponent as a function of signal correlation depends critically on the signal-to-noise ratios of received sensor transmission. The implications of this and other phenomena for the above-noted trade-offs are explored in [7] and [8].

Energy Efficiency Issues [1]-[3]: A primary motivation for the work described in the preceding paragraphs is to examine the efficacy of sensor networks operating with limited energy, and thus with limited communication capabilities. Further issues of energy efficiency in sensor networks are explored in [1]-[3]. For example, [1] examines the relative energy efficieny of analog versus digital communications in an estimation network, with the conclusion that analog communication can be superior in this regard under certain circumstances. The issue of energy efficiency in general wireless multiple-access networks is examined in [2], in which a game-theoretic framework is used to examine the optimal utility (measured in bits-per-Joule) of multiple transmitting terminals competing for the same radio resources. Finally, [3] examines the use of collaboration among clusters of sensors at the physical layer (in the form of beam-forming) to reduce the power required for transmission of sensor data to an access point or fusion center.

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