Dissertation titled:

Energy-Efficient Sensing Strategies for Wireless Sensor Network-based IoT Applications

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Abstract:

This dissertation aims at providing frameworks for energy-efficient optimized sensing at the node-level and network-level in wireless sensor network (WSN)-assisted IoT applications. Correlation inherent in the monitoring process allows performing sparse/parsimonious sensing without compromising the sensing quality, thereby saving energy. Further, these under-sampled measurements are utilized to estimate the process signal and generate its heat-map across the entire WSN field.

In the first part, a novel centralized adaptive sensor selection framework to improve the durability of a densely deployed WSN monitoring a spatio-temporal process is developed. Owing to the correlation inherent in the process, the idea of turning-ON/activating a few sensor nodes (SNs) selected by jointly optimizing the sensing quality and energy efficiency of the WSN is proposed. A feedback mechanism is developed to adapt the size of the active SNs set as per the estimated variations of the underlying process. Further, a joint Principal Component Analysis-Sparse Bayesian Learning (PCASBL) scheme is presented that estimates the process signal across the entire WSN field (including both active and sleeping SNs). The PCA-based transformation matrix gives a sparse representation to the process signal, while the SBL uses an approximate overcomplete dictionary to estimate it. The energy efficiency and stable sensing performance of the proposed framework are validated using both synthetic and real data of a WSN in the simulation studies.

Subsequently, to circumvent energy and communication overheads and scalability issues associated with the centralized setting, the problem of decentralized sensor selection in an energy-constrained WSN monitoring a spatio-temporal process is addressed. An adaptive edge computing framework and its variants are proposed which distributedly optimize a critical trade-off between the sensing accuracy and energy efficiency of the SNs. The centralized sensor selection problem is decoupled into multiple sub-problems, each solvable at an edge node elected as head of a coverage region containing a set of SNs. These sub-problems are adapted to variations of the underlying process in respective regions. Further, the proposed approach maintains energy balance among the SNs to avoid outage of network coverage. The process signal across all the SNs in each region is estimated using PCA-SBL scheme. To limit the accumulation of estimation error in the sensor selection and estimation tasks, a retraining logic is designed to indicate the requirement of network retraining in the upcoming measurement cycle. The results from extensive simulation studies illustrate that, compared to the closest competitive decentralized approach, the proposed framework provides up to 84% higher energy efficiency (network lifetime) and improves energy balance among the SNs without impacting the sensing quality. The efficacy of the proposed decentralized framework is tested on synthetic as well as real WSN data-sets.

Further, the energy efficiency aspect is looked upon for sensing multiple processes simultaneously (i.e., multi-sensing (MS)). An adaptive MS framework for a network of densely deployed solar energy harvesting wireless nodes is presented. Each node is mounted with heterogeneous sensors to sense multiple cross-correlated slowly varying parameters/signals. The spatial and temporal correlations

inherent in the monitored parameters are exploited to adaptively activate a subset of sensors of a few nodes and turn-OFF the remaining ones. For this, a multi-objective optimization problem that jointly optimizes the sensing quality and network energy efficiency is solved for each monitored parameter. To further increase the energy efficiency, network, and node-level collaborations-based MS strategies are proposed. These strategies further reduce the active sensors sets by utilizing spatial proximity (SP) of nodes with active sensors (obtained from the MS) and cross-correlation (CC) among the observed parameters at each node respectively and thus, named as MS-SP and MS-CC. A retraining logic is also developed to prevent the degradation of the sensing quality in MS-SP. Further, a multi-sensor data fusion technique is presented for jointly estimating all the parameters across the field nodes using under-sampled measurements sensed by MS-CC based active sensors. For this ill-posed estimation scenario, double sparsity due to spatial and cross-correlation among measurements is used to derive a PCA-based Kronecker sparsifying basis, and the SBL framework is then used for joint sparse estimation. Extensive simulation studies using synthetic (real) data illustrate that the proposed MS-SP and MS-CC strategies are respectively 48.2 (52.09)% and 50.30 (8.13)% more energy-efficient compared to respective state-of-the-art techniques while offering stable sensing quality. Further, heat-maps of the estimated field signals corresponding to synthetically generated and parsimoniously sensed multi-source parameters are also provided which may aid in source localization IoT applications.

The frameworks proposed so far in the dissertation provide the sensing decision for a single measurement cycle in one go/run. In the last part of the dissertation, an energy-efficient framework for multi-step ahead sensing (i.e., taking sensing decisions for multiple measurement cycles in advance) of a temporal process is proposed. Unlike existing schemes in the literature, the temporal variations of the monitored process are directly used in finding optimized sensing instants of a sensing window for a SN. A concept of age of sample (AoS) is introduced, and expressions for the AoS and average AoS functions are derived that capture freshness of sensed samples (or inter-sample time). To incorporate the effect of process variations, weighted AoS (WAoS) and its average functions are developed. The framework optimizes this average WAoS function and energy efficiency of the SN to select a few temporal sensing instances of a sensing window while maintaining a predefined sensing quality. To make the optimization problem solvable, an upper bound on the average WAoS is derived and used. Using the few sensed measurements, the process signal across the entire sensing window is estimated by leveraging the inherent temporal correlation. To address the non-stationary aspect of the monitored process, the length of the sensing window is adapted according to the changing correlation of the process. Simulation studies on real data-sets illustrate that, on comparison with the closest existing scheme, the proposed scheme provides 30.1% gain in sensing quality while consuming nearly the same sensing energy. Further, it consumes 22.4% lesser sensing energy to maintain nearly the same sensing quality.