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SPECIAL ISSUE ON Energy efficiency management for distributed computation and applications in sensor networks

Energy efficiency management for distributed computation and applications in sensor networks

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Distributed signal processing, learning, inference and computation has been applied to sensor networks in a broad range of applications like distributed localization, target tracking, environmental monitoring, and surveillance. Sensors are typically equipped with wireless interfaces to allow sensor-to-sensor communications in order to perform collaborative and distributed inference. The sensors can operate in either static networks or dynamic networks like vehicular ad hoc networks. However, energy efficiency of such sensor networks is a critical issue. The carbon footprint of a network can be large if the sensors are operated inefficiently.

This special issue of E-Letter focuses on the recent progresses of energy efficiency management in sensor networks. It is the great honor of the editorial team to have four leading research groups to report their solutions for meeting these challenges and share their latest results.

In the first article titled, "*Joint Design of Optimal Sensor Selection and Collaboration Strategies for Distributed Estimation",* Liu, Kar, Fardad and Varshney from Syracuse University and Intel Corporation considered sensor collaboration for distributed estimation. Collaboration cost and unknown collaboration topologies are incorporated into an optimization framework in order to determine the optimal subset of sensors that should communicate with the fusion center of the network. A joint sensor selection and collaboration convex optimization problem is formulated and solved via the alternating direction method of multipliers (ADMM). The trade-off between sensor selection and sensor collaboration for a given estimation performance is studied. The proposed approach can be applied to addressing communication problems such as cooperative spectrum sensing in cognitive radio networks.

In the second article titled "*A Sensor Scheduling Protocol for Energy-efficiency and Robustness to Failures*", Du, Fischione and Xiao from KTH Royal Institute of Technology, Sweden devise a sensor scheduling protocol that is both energy-efficient and robust to failures. A compressed data gathering (CDG) approach is utilized to improve the energy efficiency of the data gathering process. In this approach, all senor nodes combine their local measurement with data received from their children nodes in the routing tree to transmit a vector of fixed size. The sensors' measurements are then recovered at the sink nodes. A sink node coordinates the activation of sensors in each timeslot in order to take into account sensor failures and energy balancing. An optimization problem is formulated and evaluated through simulations, which show that by scheduling only a small subset of sensors to sense and transmit, monitoring accuracy can be maintained while lengthening network lifetime.

The third article is contributed by Lanza-Gutierrez and Gomez-Pulido from the University of Extremadura, Spain, and the title is *"Multiobjective Metaheuristics for Solving Two Approaches to the Relay Node Placement Problem in Outdoor Wireless Sensor Networks"*. In a sensor network, information captured by the sensor nodes are sent to a collector node using a multi-hop topology. This may lead to unbalanced energy distribution in the network with sensors using more energy than others called the bottlenecks. To avoid these, relay nodes with higher energy capacity are used. Placement of energy-harvesting relay nodes is studied and the paper proposed two multiobjective approaches that considers average energy cost, average sensitivity area, and network reliability. The approaches are studied using a synthetic sensor network dataset, which demonstrates that using a swarm intelligence algorithm gives the best average result.

The fourth paper, titled "*How to Efficiently Deploy Applications in WSNs Using Distributed Approaches*", is a contribution of Pilloni and Atzori from the University of Cagliary, towards distributed WSN applications with the purpose of extending the network lifetime. The authors highlight the benefits of distributed approaches in comparison with centralized solutions when these can be split into smaller tasks and assigned to different nodes. After characterizing the network and application models, the paper describes two different algorithms to maximize the network lifetime: The Decentralized Lifetime Maximisation Algorithm (DLMA), which executes a local optimization between neighboring nodes to locally reassign the tasks to the nodes and The Task Allocation Negotiation Algorithm (TAN), which is a multi-objective algorithm, reducing both network energy consumption and application execution time. Overall the paper shows that distributed algorithms can be used not only to improve lifetime, but also to reduce task completion time.

The final paper is "*Optimization of Information Neighbors for Energy-constrained Diffusion*", by Hu and Tay from Nanyang Technological University, Singapore. This paper proposes a multi-hop diffusion strategy for distributed estimation in a WSN, in which parameter estimates at each sensor is based on information a set of information neighbors instead of the physical neighbors. The information neighbors can be more than one hop away from the sensor. They showed that it is possible to optimize the information neighborhood of each sensor so that the local energy budget and network-wide energy budgets are satisfied. A mixed integer linear program is formulated, and a distributed and adaptive algorithm can be used to select the information neighbors and combination weights for each node.

Energy management in sensor networks is nowadays a critical issue that still limits widespread adoption of related technologies in different fields of application. Therefore, increasingly efficient solutions will be under research and development in the years to come. While this special issue is far from delivering a complete coverage on this exciting research area, we hope that the four invited letters give the audiences a taste of the main activities in this area, and provide them an opportunity to explore and collaborate in the related fields. Finally, we would like to thank all the authors for their great contribution and the E-Letter Board for making this special issue possible.

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Joint Design of Optimal Sensor Selection and Collaboration Strategies for Distributed Estimation

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1. Introduction

Wireless sensor networks consist of a large number of spatially distributed sensors that often cooperate to perform parameter estimation; example applications include environment monitoring, source localization and target tracking [1-2]. Under limited resources, such as limited communication bandwidth and sensor battery power, it is important to design an energy-efficient architecture for distributed estimation.

Recently, the problem of distributed estimation with sensor collaboration has attracted significant attention [3-5], where collaboration refers to the act of sharing measurements with neighboring sensors prior to transmission to a fusion center (FC). In [3], the problem of sensor collaboration was studied by assuming an orthogonal multiple access channel (MAC) setting with a fully connected network, where all of the sensors are allowed to collaborate. It was shown that the presence of sensor collaboration smooths out the observation noise, thereby improving the quality of the signal and the eventual estimation performance. In [4], optimal power allocation schemes were proposed given star, branch and linear network topologies. The problem of sensor collaboration over a coherent MAC was studied in [5], where it was observed that even a partially connected network can yield performance close to that of a fully connected network. The works [3-5] assumed that there is no cost associated with collaboration, that the collaboration topologies are fixed and given in advance, and that the only unknowns are the collaboration weights used to combine sensor observations.

In this letter, we present a tractable optimization framework to solve the collaboration problem with non-zero collaboration cost and unknown collaboration topologies. We incorporate energy costs associated with selected sensors while determining the optimal subset of sensors that communicate with the FC. For the joint design of optimal sensor collaboration and selection schemes, we describe collaboration through a collaboration matrix, and associate (a) the cost of sensor collaboration with the number of nonzero entries of a collaboration matrix (i.e., its overall sparsity), and b) the cost of sensor selection with the number of nonzero rows of the collaboration matrix (i.e., its row-sparsity). We show that there exists a trade-off between sensor selection and sensor collaboration for a given estimation performance.

This letter highlights our recent work [6] on joint design of optimal sensor collaboration and selection strategies. More of our contributions to problems of resource management in sensor networks, such as sensor scheduling, energy-aware field reconstruction, and sensor selection with correlated noise, can be found in [7-9].

2. Sparsity-Aware Sensor Collaboration

In this letter, the task of the sensor network is to estimate a random parameter θ which follows a Gaussian distribution with zero mean and variance η^2. In the collaborative estimation system, sensors first acquire their raw measurements via a linear sensing model. Individual sensors can then update their observations through spatial collaboration, which refers to (linearly) combining observations from other sensors. The updated measurements are transmitted through a coherent MAC. Finally, the FC determines a global estimate of θ by using a linear estimator. We show the collaborative estimation system in Fig. 1.

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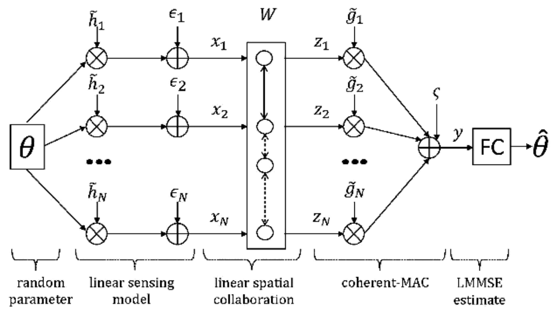

Figure 1: Collaborative estimation architecture.

As shown in Fig.1, the sensor collaboration process is described by

$$\mathbf{z} = \mathbf{W}\mathbf{x}, \quad \mathbf{W} \in \Re^{N \times N},$$

where **z** denotes the message after collaboration, **W** is the collaboration matrix that contains weights used to combine sensor measurements, and **x** is the vector of raw sensor measurements. We note that the nonzero entries of **W** correspond to the active collaboration links among sensors. For example, $W_{mn} = 0$ indicates the absence of a collaboration link from the *n*th sensor to the *m*th sensor. Conversely, $W_{mn} \neq 0$ signifies that the *n*th sensor shares its observation with the *m*th sensor. Thus, the sparsity structure of W characterizes the collaboration topology.

The *sensor collaboration cost* is given by

$$Q_{\mathbf{W}} = \sum_{m=1}^{N} \sum_{n=1}^{N} C_{mn} \|W_{mn}\|_0,$$

where C_{mn} is the cost of sharing an observation from the nth sensor with the *m*th sensor, and $\|\cdot\|_0$ denotes the l_0 norm of a vector (or scalar) which returns 1 if $W_{mn} \neq 0$ and 0 otherwise.

Next, we define the sensor selection cost. Partitioning the matrix **W** rowwise, the non-zero rows of **W** characterize the selected sensors that communicate with the FC. The *sensor selection cost* is then given by

$$S_{\mathbf{W}} = \sum_{n=1}^{N} b_n \big\| \|\mathbf{w}_n\|_2 \big\|_0,$$

where b_n is the cost of selecting the *n*th sensor, $\mathbf{w}_n$ denotes the *n*th row of **W**, and $\|\cdot\|_2$ is the Euclidean norm of a vector.

After sensor collaboration, the resulting signal is transmitted to the FC through a coherent MAC, which leads to the *transmission cost* T_{W}. At the FC, the linear minimum mean squared-error estimator is used to estimate the random parameter θ. The resulting estimation performance is evaluated in terms of *Fisher information* J_{W}. Both the transmission cost T_{W} and Fisher information J_{W} can be expressed as explicit functions of the collaboration weights,

$$T_{\mathbf{W}} = \mathbf{w}^T \mathbf{\Omega}_{\mathrm{T}} \mathbf{w} \qquad J_{\mathbf{W}} = \frac{\mathbf{w}^T \mathbf{\Omega}_{\mathrm{JN}} \mathbf{w}}{\mathbf{w}^T \mathbf{\Omega}_{\mathrm{JD}} \mathbf{w} + \sigma^2},$$

where $\mathbf{w}=[\mathbf{w}_1, \ldots, \mathbf{w}_N]^T$ is a vector that consists of the entries of **W** in a rowwise manner, the coefficient matrices are positive semidefinite which were defined in [6, Appendix A], and σ^2 is the variance of channel noise.

Motivated by scenarios where saving energy is our primary goal in resource management, we design optimal sensor collaboration and selection schemes by minimizing the energy consumption subject to an information constraint,

$$\underset{\mathbf{W}}{\text{minimize}} \;\; Q_{\mathbf{W}} + S_{\mathbf{W}} + T_{\mathbf{W}} \quad \text{subject to} \;\; J_{\mathbf{W}} \geq J_0, \qquad \text{(P0)}$$

where $J_0 > 0$ is a given information threshold. In the above problem, the l_0 norm that appears in the sensor collaboration cost Q_{W} and the selection cost S_{W} promotes the sparsity of the collaboration matrix **W**. Therefore, we refer to (P0) as a sparsity-aware sensor collaboration problem for distributed estimation.

3. Joint Sensor Collaboration and Selection via Convex Optimization

In this section, we present an efficient optimization approach for the joint design of sensor collaboration and selection schemes. First, we convexify (P0) by using an iterative reweighted l_1 minimization method and a linearization method. The resulting convex problem is then solved via the alternating direction method of multipliers (ADMM).

Convexification.

Due to the presence of the l_0 norm, (P0) is combinatorial in nature. A method for solving it is to relax the l_0 norm to a weighted l_1 norm [10]. This leads to the following optimization problem

$$\begin{aligned}&\underset{\mathbf{w}}{\text{minimize}} \quad \mathbf{w}^T \mathbf{\Omega}_{\mathrm{T}} \mathbf{w} + \|\mathbf{\Omega}_{\mathrm{C}} \mathbf{w}\|_1 + \sum_{n=1}^{N} d_n \|\mathbf{w}_n\|_2 \\ &\text{subject to} \quad \mathbf{w}^T (J_0 \mathbf{\Omega}_{\mathrm{JD}} - \mathbf{\Omega}_{\mathrm{JN}}) \mathbf{w} + J_0 \sigma^2 \le 0,\end{aligned}$$

where $\mathbf{\Omega}_{\mathrm{C}}$ is a diagonal vector given by diag($\alpha_1 c_1, \ldots, \alpha_L c_L$), $L=N^2$, $\mathbf{c} = [c_1, \ldots, c_L]^{\mathrm{T}}$ is the rowwise vector of the collaboration cost matrix C formed by $\{C_{mn}\}$, $d_n=\beta_n b_n$ for $n = 1, \ldots, N$, $\{\alpha_i\}$ and $\{\beta_n\}$ denote the weights that are iteratively updated in order to ensure that the last two terms in the objective function are good proxies for the l_0 norms they replace, namely,

$$\alpha_i \leftarrow 1/(w_i + \varepsilon), \quad \beta_n \leftarrow 1/\|\mathbf{w}_n\|_2 + \varepsilon.$$

Here ε is a small positive number which ensures that the denominator is always nonzero.

The resulting l_1 optimization problem involves a convex objective function and a nonconvex quadratic constraint. This nonconvex constraint can be recast as a difference of convex functions [11]

$$J_0 \mathbf{w}^T \mathbf{\Omega}_{\mathrm{JD}} \mathbf{w} + J_0 \sigma^2 - \mathbf{w}^T \mathbf{\Omega}_{\mathrm{JN}} \mathbf{w} \le 0.$$

We linearize the convex function $\mathbf{w}^T \mathbf{\Omega}_{\mathrm{JN}} \mathbf{w}$ around a feasible point $\boldsymbol{\gamma}$, and obtain

$$J_0 \mathbf{w}^T \mathbf{\Omega}_{\mathrm{JD}} \mathbf{w} + J_0 \sigma^2 \le \boldsymbol{\gamma}^T \mathbf{\Omega}_{\mathrm{JN}} \boldsymbol{\gamma} + 2\boldsymbol{\gamma}^T \mathbf{\Omega}_{\mathrm{JN}} (\mathbf{w} - \boldsymbol{\gamma}), \quad (1)$$

whose left hand side is an affine lower bound on the convex function $\mathbf{w}^T \mathbf{\Omega}_{\mathrm{JN}} \mathbf{w}$. This implies that the set of $\mathbf{w}$ that satisfy the linearized constraint is a strict subset of the set of w that satisfy the original constraint.

After linearization, we obtain a convex problem

$$\begin{aligned}&\underset{\mathbf{w}}{\text{minimize}} \quad \mathbf{w}^T \Omega_{\mathrm{T}} \mathbf{w} + \|\mathbf{\Omega}_{\mathrm{C}} \mathbf{w}\|_1 + \sum_{n=1}^{N} d_n \|\mathbf{w}_n\|_2 \qquad \text{(P1)} \\ &\text{subject to} \quad \text{convex quadratic constraint (1),}\end{aligned}$$

where non-smooth norms appear in the objective function. In what follows, we will employ ADMM to find the optimal solution of (P1).

Solution via ADMM.

The major advantage of ADMM is that it allows us to split (P1) into a convex quadratic program with only one quadratic constraint and a proximal operator [12] of a sum of l_1 and l_2 norms, where the former can be efficiently solved by exploring its KKT conditions, and the latter admits an analytical solution. ADMM is performed based on the augmented Lagrangian function [13] of (P1), where we alternatively solve the resulting two subproblems. We refer the readers to [6, Sec.VI] for details on the proposed ADMM algorithm.

3. Performance evaluation

In this section, we illustrate the performance of our proposed sparsity-aware sensor collaboration methods through numerical examples.

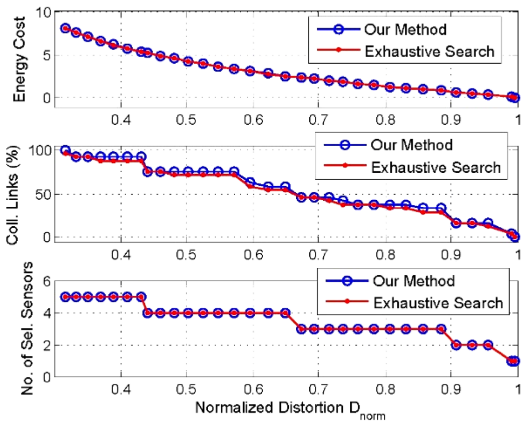

Figure 2: Performance evaluation of sensor selection and collaboration

In Fig.2, we show the energy consumption, number of collaboration links and selected sensors as functions of the normalized estimation distortion D_{norm} that provides the information threshold. For comparison, we also present the optimal results obtained from an exhaustive search, where $N = 5$ sensors are assumed in this example. We observe that the proposed approach assures near optimal performance for all values of estimation distortion. Moreover, the energy cost, number of collaboration links and selected sensors increases as D_{norm} decreases, since a smaller estimation distortion enforces more collaboration links and activated sensors.

In Fig.3, we present specific sensor collaboration and selection schemes by increasing the sensor selection cost under a given estimation distortion $D_{\text{norm}} = 0.7$. In the figure, the solid line with an arrow represents the collaboration link between two sensors, and the dashed line from one sensor to the FC signifies that this sensor is selected to communicate with the FC. As we can see, in the left plot in which sensor selection cost is lower, three sensors are selected to communicate with the FC, and three collaboration links are established. While in the right plot in which sensor selection cost is higher, fewer sensors are selected and more collaboration links are established. This exhibits a trade-off between sensor collaboration and sensor selection.

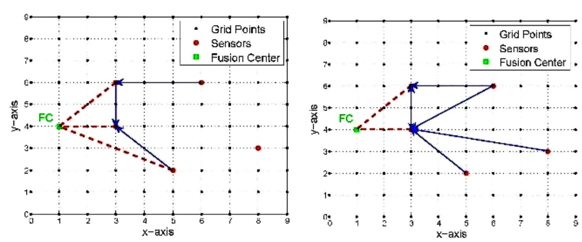

Figure 3: Trade-off between collaboration & selection

4. Conclusion

In this letter, which is based on our recent work [6], we described a novel framework for the joint design of optimal sensor collaboration and selection schemes in the distributed estimation context. We showed that optimal sensor collaboration and selection schemes can be designed by promoting the elementwise and rowwise sparsity of the collaboration matrix. The formulated sparsity-aware optimization problem is nonconvex in nature, and we convexified the problem by using a reweighted l_1 norm and the convex restriction method, and solved the resulting convex program via ADMM. It was empirically shown that there exists a trade-off between sensor collaboration and sensor selection for a given estimation performance. The methodology of sparsity-aware sensor collaboration could provide valuable insights into addressing communication problems such as cooperative spectrum sensing in cognitive radio networks.

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