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Cooperative Sensing for Wireless Sensor Networks

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***Abstract*—**Wireless Sensor Networks (WSNs), which sense environmental data with battery-powered nodes, require multi-hop communication. This power-demanding task adds an extra workload that is unfairly distributed across the network. As a result, nodes run out of battery at different times: this requires an impractical individual node maintenance scheme. Therefore we investigate a new Cooperative Sensing approach that extends the WSN operational life and allows a more practical network maintenance scheme (where all nodes deplete their batteries almost at the same time). We propose a novel cooperative algorithm that derives a piecewise representation of the sensed signal while controlling approximation accuracy. Simulations show that our algorithm increases WSN operational life and spreads communication workload evenly. Results convey a counterintuitive conclusion: distributing workload fairly amongst nodes may not decrease the network power consumption and yet extend the WSN operational life. This is achieved as our cooperative approach decreases the workload of the most burdened cluster in the network.

***Keywords*—**Cooperative signal processing, power management, signal representation, signal approximation, wireless sensor networks.

I. Introduction

Wireless Sensor Networks (WSN) are increasingly popular as a tool to remotely monitor the environment, built infrastructures or other assets. A WSN comprises several units (nodes) capable of sensing environmental data (e.g. temperature, humidity, vibrations) and transmit information using wireless routing strategies. Employing cheap yet versatile battery-powered wireless nodes allows users to quickly deploy a large sensor network without the need for mains power or permanent communication infrastructures. This flexibility, however, comes at the cost of managing the power requirements of WSN nodes, as this dictates the operational life of a node for a given battery capacity.

Multi-hop communication dominates power consumption of nodes in a large WSN [1] hence we focus on this component to reduce node power requirements. When the onboard radio hardware cannot be modified (or alongside improvements), the goal becomes reducing the amount of data a node communicates. Lowering power requirements of an individual sensor extends its operational life and reduces the frequency of maintenance operations to replace its battery. However, we argue that focusing on single-node power is not the key to extend the operational life of an entire WSN. Multi-hop communication induces an unfair workload across the network: nodes closest to the sink relay every message originated in the network. As a result, these nodes bear the highest power demands and will be the first to exhaust their batteries, disconnecting all sensors from the end user.

We propose a distributed sensing algorithm that enables groups of nodes to compress data while meeting user-defined reconstruction accuracy. This approach reduces multi-hop communication and lowers power requirements of nodes close to the sink, extending WSNs operational life. Furthermore, by levelling power costs across the network, it aligns operational life prospects for all nodes (assuming equal capacity batteries). This allows scheduling a single maintenance operation to replace batteries in all nodes at once: a shift from individual node maintenance scheme to network maintenance scheme.

WSN communication efficiency can be improved by coding sensed data to achieve compression. For example, each node may individually exploit signal correlation over time [2], [3] or cooperate with others to remove spatial redundancy [4]-[6] or both [7], [8]. These approaches may reduce power consumption of individual nodes, but overlook the unfair workload distribution addressed by our work.

This work makes two main novel contributions:

- A power-efficient Cooperative Sensing algorithm that enables nodes to approximate, with a set accuracy, the sensed signal by piecewise polynomial models. In most cases this demands less power than a conventional WSN.
- The ability of Cooperative Sensing to reduce the power demands imposed on nodes close to the sink. This extends the WSN operational life, even when no net power reduction is attained compared to a Conventional WSN. This also allows replacing individual node maintenance with more efficient network maintenance.

In Section II we introduce our system. In Sections III and IV we describe our Cooperative Sensing algorithm and derive WSN power requirements. Simulation results are discussed in Section V and conclusions are drawn in Section 0.

II. Conventional vs Cooperative Sensing

A. Conventional WSN

All sensor nodes sense and transmit/relay data wirelessly, hence the terms sensor and node are used interchangeably. At time t, a node with spatial location x senses a scalar input signal, e.g. temperature or pressure, denoted as $y(x,t)$. Fig. 1 shows the linear sensor arrangement assumed in this paper.

At time t, the sensor network relays to the sink the measurements independently collected by each node; the number of bytes communicated for one measurement is denoted as S^{data}. The data collected from the N_S sensors, $y(x_1,t), y(x_2,t), \ldots, y(x_{N_S},t)$ inform the end-user of the value of

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the sensed signal at each sensor position, as shown in Fig. 1.

B. Cooperative WSN

The core idea is that nodes locally approximate the signal to known models and send model parameters to the sink. The end-user reconstructs the signal using the received model parameters. We consider a piecewise approximation of the signal. Adjacent nodes arrange themselves in groups and cooperatively determine the parameters of a model that approximates the signal over the group location (the local signal segment). Assume the signal is divided into N_M segments; the *j*-th segment comprises group $G_j = \{x_i, \ldots, x_l\}$ containing $G_j^{\text{size}} = l - i + 1$ nodes. At time t, the group computes the model $\mathrm{M}_j(x,t)$.

Upon reception of the model parameters that uniquely identify $\mathrm{M}_j(x,t)$, the end-user locally approximates the signal $y(x,t)$ as:

$$\hat{y}(x,t) = \mathrm{M}_j(x,t), \quad x \in [x_i, x_l] \tag{1}$$

The Cooperative WSN selects the model parameters so as to constrain the approximation error (distortion) incurred by (1):

$$D_j(t) = \frac{1}{G_j^{\text{size}}} \sum_{x_i \in G_j} \left[\hat{y}(x_i,t) - y(x_i,t)\right]^2 \tag{2}$$

The end-user of our system selects an acceptable distortion and nodes determine model parameters so that (2) does not exceed such distortion for any segment. The number of bytes required to represent the model parameters for a group is denoted as S^{model}.

At time t, knowledge of model parameters for all the groups ($G_1, G_2, \ldots, G_{N_M}$) allows the user to approximate the signal over the entire interval $[x_1, x_{N_S}]$, as shown in Fig. 2.

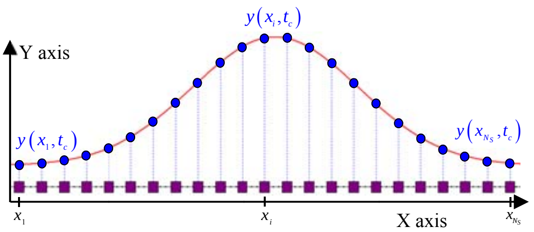


Fig. 1 Conventional sensing based on a set of measurements

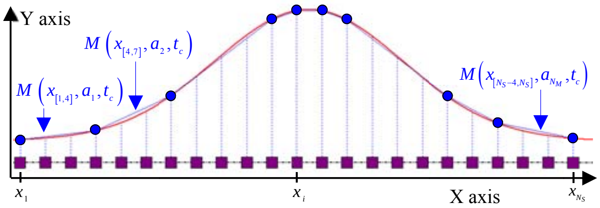


Fig. 2 Cooperative sensing based on a set of models.

III. Cooperative Model Fitting of Signals

We describe how model parameters are derived for a signal that is static over time, hence drop the dependence on *t*. The extension to time-varying signals is outlined later. We employ piecewise signal approximation using polynomials of (up to) degree *K*. The model for group $G_j = \{x_i, \ldots, x_l\}$ is:

$$\mathrm{M}_j(x) = a_0 + a_1 \cdot x + \ldots + a_K \cdot x^K . \tag{3}$$

The *K*+1 coefficients $a_0, a_1, \ldots, a_K$ and the identifier of the first node in the group, x_i, are the *model parameters* that allow the end-user to reconstruct the signal over $[x_i, x_l]$ (the membership of x_l is known when the end-user receives the parameters of the next group $G_{j+1} = \{x_{l+1}, \ldots, x_m\}$). Assuming the number of bytes used to represent one measurement suffice to represent any of the model parameters, we have:

$$S^{\text{model}} = (K+2) S^{\text{data}} . \tag{4}$$

The following sections outline a Model Fitting (MF) algorithm that progressively segments & models the signal, growing groups from initial seeds. The algorithm aims to: (*i*) divide nodes into groups following local signal characteristics; (*ii*) within each group, approximate the signal with a *K*th degree polynomial ensuring that (2) is below a set threshold.

A. Distributed Least-Square Polynomial Fitting

Given a group $G_j = \{x_i, \ldots, x_l\}$ and the node measurements $y(x_i), \ldots, y(x_l)$, the polynomial coefficients (3) are obtained via least-square fitting. Minimizing (2) yields [9]:

$$\underbrace{\begin{bmatrix} \sum_{x_i \in G_j} y(x_i) \\ \sum_{x_i \in G_j} x_i \cdot y(x_i) \\ \vdots \\ \sum_{x_i \in G_j} x_i^K \cdot y(x_i) \end{bmatrix}}_{\mathbf{w}_j} = \underbrace{\begin{bmatrix} G_j^{\text{size}} & \sum_{x_i \in G_j} x_i & \cdots & \sum_{x_i \in G_j} x_i^K \\ \sum_{x_i \in G_j} x_i & \sum_{x_i \in G_j} x_i^2 & \cdots & \sum_{x_i \in G_j} x_i^{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{x_i \in G_j} x_i^K & \sum_{x_i \in G_j} x_i^{K+1} & \cdots & \sum_{x_i \in G_j} x_i^{2K} \end{bmatrix}}_{\mathbf{Z}_j} \underbrace{\begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_K \end{bmatrix}}_{\mathbf{a}_j} \tag{5}$$

The *K*+1 coefficients of (3) are obtained as $\mathbf{a}_j = \mathbf{Z}_j^{-1} \mathbf{w}_j$. Next we define the *expansion model vector* as:

$$\mathrm{EMV}_j \equiv \left[\mathbf{w}_j ; G_j^{\text{size}} ; y_j^{\text{ms}}\right] \tag{6}$$

where $\mathbf{w}_j$ is as in (5) and

$$y_j^{\text{ms}} = \sum_{x_i \in G_j} y^2\left(x_i\right) \big/ G_j^{\text{size}} . \tag{7}$$

EMV_j is a fixed-size vector comprising K+3 coefficients. Representing any coefficient with the same number of bytes used for one-measurement yields:

$$S^{\text{EMV}} = 3\left(K+1\right) S^{\text{data}} \tag{8}$$

EMV_j includes the information required for a node that is not part of a group to determine whether it should join the group. A candidate node receiving EMV_j can compute the model coefficients and the approximation distortion for the expanded group (including the candidate node): if (2) is below the set limit, the node updates EMV_j and passes it to the next node. This is exploited by our MF Algorithm described next.

B. Model Fitting of Static Signals

The proposed MF Algorithm is implemented as follows:

- Step 0 (seeding): Begin with seed segment $G_1 = \left\{x_1\right\}$.
- Step 1 (initial model): The group determines the *model parameters* via $\mathbf{a}_j = \mathbf{Z}_j^{-1}\mathbf{w}_j$.
- Step 2 (test expansion): Transmit EMV_j to a neighboring sensor; The recipient node (current node) determines the model parameters and distortion of the expanded segment.
- Step 3a (expansion allowed): If the set distortion is not exceeded, the current node joins the group and EMV_j is updated accordingly; Continue from Step 2.
- Step 3b (expansion blocked): Conversely, the current node is not included in the group; The node transmits to the sink the model parameters of the group (not including itself); The node then starts a new seed segment and continues from Step 1.

C. Extension to Dynamic Signals

The MF algorithm can be extended to signals $y(x,t)$ that vary slowly over time compared to a node sampling period T. Performing the MF algorithm at each sampling instant t_c yields $\mathrm{M}_j\left(x,t_c\right)$ for every group G_j.

A more efficient approach is to allow individual groups to detect local changes in the signal and update group models where these changes exceed a set threshold. In this paper we restrict our attention to the simpler method outlined above, used as a proof of concept for our cooperative system.

IV. WSN Power Performance

In Conventional Sensing, every node transmits a message of S^{data} bytes via relay to the sink. Averaging transmissions costs for every node in the system, the power spent by a node is:

$$P^{\text{conv}} = \frac{E^{\text{transm}}}{T} S^{\text{data}} \bar{N}^{\text{msg}} \tag{9}$$

where E^{transm} is the energy required to transmit one byte (directly from node to node) and $\bar{N}^{\text{msg}}$ is the average number of messages transmitted when a node communicates to the sink via relays. As expected, the power requirements of a Conventional Sensing node solely depend on system settings.

In Cooperative Sensing, the MF algorithm requires node-to-node communication of EMV_j to grow groups from initial seeds. In addition, for each group, a message of S^{model} bytes is transmitted (via relay) to the sink. This leads to:

$$P^{\text{coop}} = \frac{E^{\text{transm}} S^{\text{data}}}{T}\left(\left(K+3\right) + \frac{\left(K+2\right)\bar{N}^{\text{msg}}}{\bar{G}^{\text{size}}}\right) \tag{10}$$

where $\bar{G}^{\text{size}} = \sum_{j=1}^{N_M} G_j^{\text{size}}$ is the average group size G_j^{size} across the network. Besides communication settings (via $\bar{N}^{\text{msg}}$), P^{coop} also depends on the chosen polynomial degree (via K).

V. Experimental Results

A. Wireless Sensor Network Configuration

The WSN in Fig. 1 monitors temperature along a pipeline and includes 400 nodes, grouped into equal-sized clusters. The cluster closest to the sink (placed in the middle of the linear arrangement), requires zero hops to reach it and is termed *cluster-zero*. WSN settings are listed in Table I. We compare WSNs performing Conventional and Cooperative Sensing; for the latter, the polynomial interpolation degree choices are: K=1, K=2 and K=3. All WSNs operate with the same settings and input signals. To ensure the Cooperative WSN delivers similar accuracy as the Conventional WSN, the approximation distortion (2) is limited to 2.5% of the average input value.

The temperature signal is generated from the template:

$$y\left(x\right) = A_x \sin\left(2\pi f_x x\right) \tag{11}$$

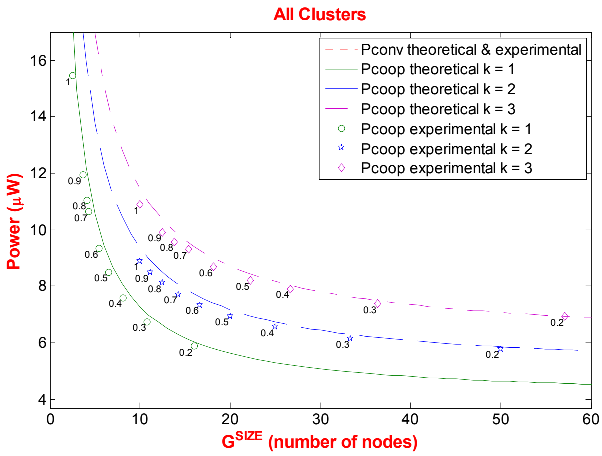
where we set the spatial frequency $f_x \in [0.2\,,1]$ with a step of 0.1 cycles/km. Increasing values of f_x progressively shrink signal features across space. Thus we experimentally trace the way a Cooperative system adapts to spatial frequencies: we expect large groups to form at low frequencies and smaller ones for progressively higher frequencies. For the chosen inter-node separation of 50 m, the highest frequency considered here is suitably within the Shannon-Nyquist limit. Operating with higher frequency signals is not advisable for this sensor arrangement, irrespective of the sensing strategy. A time-varying signal is obtained from the template (11) as:

$$y\left(x,t\right) = A_x \sin\left(2\pi f_x x\right) + A_t \sin\left(2\pi f_t t\right) \tag{12}$$

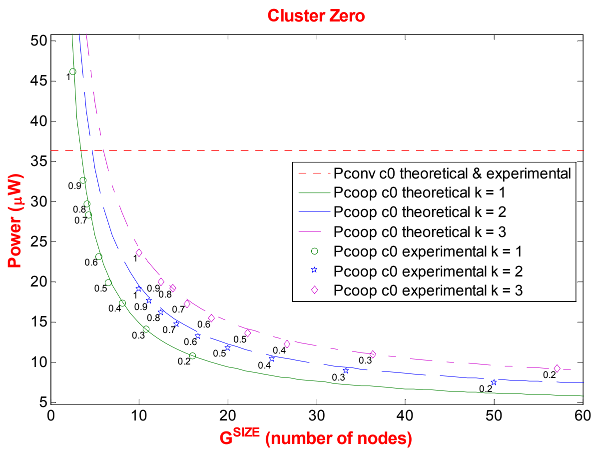
where A_t/A_x ; 0.1 and f_t=0.002 Hz. Signal temporal variations are suitably within the Shannon-Nyquist limit for the given sensor sampling period (1 s).

B. Experimental WSN Power Curves

We consider the average power required by a node in either Cooperative or Conventional Sensing. We also isolate the power required by an average *cluster-zero* node in either system. Cooperative Sensing repeats the MF algorithm of Section III.B every sampling period *T*. We perform 10 simulations using signal (12), each with a different spatial frequency f_x and representing 251s of operation. Results in Fig. 3 report the average power for the entire WSN (a) and for cluster-zero nodes only (b). For the Cooperative WSN, we plot power against $\bar{G}^{size}$ (which stays practically constant during a simulation). The experimental points in the figure are in good agreement with the analytical power curves obtained from (9) and (10) for different values of *K*.



(a)



(b)

Fig. 3 Power consumption of Conventional (Pconv) and Cooperative (Pcoop) Sensing for: (a) all clusters; (b) cluster-zero

The Cooperative Sensing power curves in Fig. 3 are below the one for Conventional Sensing for most of the experimental data considered, thus a WSN performing Cooperative Sensing requires less power. Therefore the average battery-powered node in a Cooperative Sensing WSN can operate longer than an equivalent node in a conventional WSN.

Minimizing power expenditure of cluster-zero nodes further extends the system operational life, even if the average power across the entire WSN increases. Data in Fig. 3 for *K*=1 and $f_x = 0.8$ or $f_x = 0.9$ are practical examples. Cooperative Sensing requires slightly more power than Conventional when all sensors are considered. However, focusing on cluster-zero reveals that Cooperative Sensing is more power-efficient for the nodes that ultimately dictate the system operational life.

TABLE I
WSN EXPERIMENTAL SETTINGS

Symbol	Meaning	Value
N_s	Total number of nodes	400
x_1	Spatial location first node	0 m
x_{N_s}	Spatial location last node	19.95 km
	Spatial location server	9.975 km
$x_{i+1} - x_i$	Inter-node distance	50 m
E^{transm}	Energy to transmit 1 Byte	1 μJ/B
T	Sensing period	1 s
	Number of nodes in each cluster	10
	Total number of clusters	41
$\overline{N}^{msg}$	Average number of messages generated by relay transmission	10.95

VI. CONCLUSION

We presented a novel Cooperative Sensing scheme aimed at increasing WSN operational life. The main tool to achieve this aim is a distributed sensing algorithm that uses piecewise polynomial fitting to represent the sensed signal to a user-set accuracy level. The algorithm discussed in Section III can be applied to most WSNs of interest and is amenable of the analytical study presented in Section IV. The experimental evaluation in Section V demonstrates many cases where the proposed Cooperative Sensing lowers the global WSN power consumption compared to a Conventional approach. We also show cases where, despite not reducing the overall power, Cooperative Sensing extends the WSN operational life by easing the communication burden on cluster-zero nodes.

The benefit of this work on WSN performance and maintenance is twofold. Firstly, it increases the operational life of WSNs for the same battery capacity. Secondly, it reduces the frequency and complexity of maintenance by balancing power consumption across the network, ensuring that all nodes require battery replacement at similar times. This in turn allows scheduling one maintenance operation for all nodes.

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