Cooperative Transmission of Measurements in WSN for Monitoring Applications

Nikola Bogdanović, Dimitris Ampeliotis, Kostas Berberidis
Department of Computer Engineering and Informatics
University of Patras & C.T.I RU-8, 26500, Rio - Patra, Greece
Emails:{bogdanovic, ampeliot, berberid}@ceid.upatras.gr

***Abstract*—Wireless Sensor Networks (WSNs) have recently received great attention from the scientific community, because they hold the key to revolutionize many aspects of the industry and our life. The process of collecting the measurements, acquired by a sensor network into a central sink node, constitutes one of the main challenges in this area of research and is often referred to as the sensor reachback problem. In this work, we extend a recently proposed power and rate allocation algorithm so as to be able to take into account possible cooperation between the nodes in the WSN. The derived power and rate allocation algorithm considers Distributed Source Coding (DSC), in order to reduce the amount of information that must be transmitted to the sink. Under the assumption that there are several very bad channels between nodes and the sink, our method achieves both a lower peak power threshold, as well as reduced total power consumption.**

I. Introduction

Recent advances in microelectronics and wireless communications have enabled the development of low cost, low power devices that integrate sensing, processing and wireless communication capabilities. A collection of a large number of such devices deployed over some territory of interest, constitutes a so-called Wireless Sensor Network (WSN). Typical applications of WSNs range from medical to military, and from home to industry. The application of our interest is Structural Health Monitoring (SHM), which aims at detecting and localizing the damage in civil structures. One of the most fundamental problems, arising in such a network, is related to the transmission of the acquired observations to a data-collecting node, often termed to as the sink node, which has increased processing capabilities and more available power as compared to the sensor nodes. Our main aim is to minimize the power required to transmit data to the sink, thus saving energy which is a precious resource for the sensor nodes.

In a typical application scenario for Structural Health Monitoring, nearby sensor nodes would have highly correlated measurements, and this fact can be exploited in order to reduce the power consumption. Some of the protocols that have appeared in the literature, concerning the problem at hand, are the so-called Spatial Sampling protocols and Group Testing ones [3]. However, they either impose some distortion or require too strong correlation among the nodes in order to be beneficial.

Another approach which could exploit the spatial data correlation is Distributed Source Coding (DSC). A DSC technique achieves lossless compression of multiple correlated sensor outputs [6] without establishing any communication links between the nodes. A DSC algorithm for the reachback problem, based on pair matching of the nodes, was proposed in [4]. A significantly improved algorithm was proposed in [5], based on application of DSC strategy in a sequential manner.

In contrast to the work in [5], where each sensor node uses a direct communication channel with the sink node, in this work we additionally allow cooperation among the nodes. Under the assumption that there exist unreliable channels between the sensor nodes and the sink, it can be shown that this approach achieves less total power consumption as well as reduced maximum power per sensor node required for a feasible power allocation to exist. Furthermore, these performance improvements are obtained at the cost of only a slight increase in computational complexity as compared to the complexity of the scheme in [5].

The rest of this paper is organized as follows. In Section II, we briefly discuss Structural Health Monitoring. In Section III, we formulate the problem and introduce the background and related work. Also, we present the channel-aware extension of recently proposed data gathering algorithm. In Section IV, we address some of the implementation-related issues. The paper concludes with Section V.

II. Structural Health Monitoring

Structural Health Monitoring (SHM) systems are widely adopted to monitor the behavior of structures during forced vibration testing or natural excitation (e.g. earthquakes, winds, live loading). Structural monitoring systems are applicable to a number of common structures including buildings, bridges, aircrafts and ships. The monitoring system is primarily responsible for collecting the measurement output from sensors installed in the structure and gathering the measurement data at the central sink node [1]. Wireless sensor networks offer tremendous promise for accurate and continuous structural monitoring using a dense array of inexpensive sensors. In fact, there are already commercially available sensor platforms that can meet the demands of SHM, such as Imote2 [2]. The structural response measurements are usually generated at relatively high data rates (e.g. sampling rates up to 500 Hz). The measured data should be compressed in a lossless manner and sent to the sink. This may be achieved by exploiting the

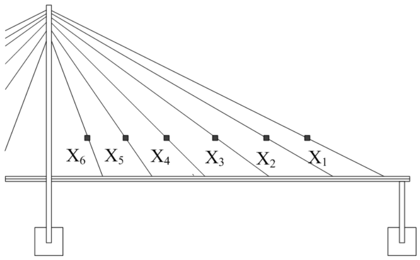


Fig. 1. A span on a bridge.

spatial correlation among the nodes which is present in this type of monitoring.

For instance, the data collected by the sensors on each span of a bridge are correlated since they are measuring the vibration of the same part of the physical structure (Fig. 1). In addition, in some cases of bridge design, two adjacent spans are connected to a common anchorage, resulting in the data across the two spans to be correlated. Similarly, in the case of large buildings, it is natural to group the sensors of the several distinct parts of the building (e.g. floors) and exploit their correlation.

We should also note that the assumption that all sensors have direct, line-of-sight link to the sink does not hold in the case of these structures, due to their massive size and shape. As a result, not all sensors may always have a channel to the sink of good enough quality.

In the following section, we are going to discuss how the spatial correlation among the sensors may be exploited to significantly reduce the data traffic and also present a channel-aware extension of a recently proposed data gathering algorithm.

III. From information theory to real communication practice

In general, we consider a network of sensors acquiring data from a civil structure in order to reproduce a physical phenomenon at the sink. The natural analog signals are first quantized and then compressed in order to minimize the total number of bits which will be sent to the sink.

Let us now formulate the problem more precisely. We consider a dense wireless sensor network consisting of N nodes, deployed in a civil structure that we wish to monitor. Each sensor node acquires a measurement X_n ($n \in \mathcal{N} = \{1, \ldots, N\}$) of some physical variable of its environment and transmits it to a single sink node, for further processing. We model each such measurement as an instance of a discrete random variable $\mathcal{X}_n$ whose number of possible values equals the number of quantization levels. Due to the nature of the event being monitored, we assume that the random variables $\mathcal{X}_n$ are correlated. In this setting, our scope is to devise an energy efficient method for the sensor reachback problem. Thus, a proper cost function would be the sum

$$\sum_{n=1}^{N} P_n \ , \tag{1}$$

where P_n denotes the power required for transmitting the data of node n to the sink. The minimization of (1), subject to some proper constraints, shall give an efficient transmission method for our problem. Apart from the power variables P_n, the transmission rates R_n of each sensor node, also constitute a set of variables that need to be defined in an optimal manner.

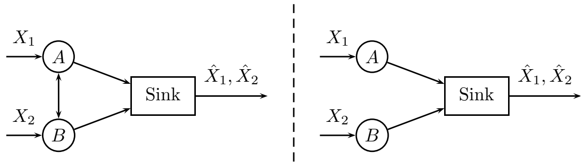
We assume uncorrelated flat fading channels between the sources and the sink, corrupted by additive white Gaussian noise (AWGN). The channel capacity is $C_i(P_i) = log(1 + \gamma_i P_i)$,where the noise power is normalized to one and channel gains γ_i are constants known to the sink. Since the sink is supposed to recover all measurements losslessly, the rate at which each sensor node transmits should satisfy $R_i \leq C_i(P_i)$. For the power which may be transmitted by each sensor node, we also impose a peak power constraint P_{max} due to the fact that every sensor node has limited transmission power in practice.

A. Information Theory background

Recall that the entropy of a discrete random variable X_1, denoted as $H(X_1)$, could be seen as the minimum number of bits required to encode X_1 without any loss of information. Similarly, the joint entropy $H(X_1, X_2)$ of two discrete random variables X_1 and X_2 can be seen as the minimum number of bits required to encode X_1 and X_2 jointly. In case that X_1 contains some information about X_2, the following inequality holds $H(X_1, X_2) < H(X_1) + H(X_2)$.

First, let us consider the explicit communication scenario shown in Fig. 2a. A typical joint encoding of X_1 and X_2 could be achieved by first encoding X_2 to $H(X_2)$ bits (its individual entropy), then communicating these bits to the X_1 node, and finally encoding X_1 to $H(X_1|X_2)$ bits, which is the conditional entropy of X_1 if X_2 is known, and by definition, joint entropy could be achieved $H(X_1, X_2) = H(X_2) + H(X_1|X_2)$. Obviously, exploiting correlation in an efficient way by applying such a joint encoding scheme across the whole WSN is infeasible since it would require all nodes to participate in inter-node communication. Furthermore, the nodes would need to communicate their individual entropies among themselves which would prohibitively increase power consumption.

An alternative strategy, Distributed source coding (DSC), refers to separate compression and joint decompression of two or more physically separated sources. The sources are encoded independently (hence distributed) at the encoders and decompressed jointly at the decoder [6]. In other words, it is enough to use $H(X_1|X_2)$ bits to encode X_1 instead of $H(X_1)$, even without communication between two nodes, given that the decoder has full knowledge of X_2 (Fig. 2b). This was shown for the first time by Slepian and Wolf in 1973 [7]. They showed that two discrete sources X_1 and X_2 can be losslessly decoded as long as the rates of two sources are in



(a) (b)

Fig. 2. (a) Explicit Communication. (b) Distributed Source Coding.

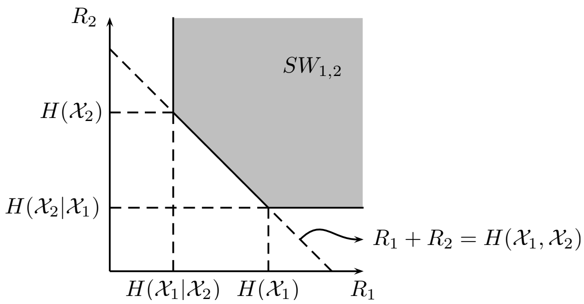


Fig. 3. The Slepian-Wolf region $SW_{1,2}$ for two sources $\mathcal{X}_1$ and $\mathcal{X}_2$, defines the feasible rate pairs (R_1, R_2) for which joint lossless decoding can be performed at the destination.

the so-called Slepian-Wolf region (Fig. 3), which is defined by the following inequalities:

$$R_1 \geq H(X_1|X_2)$$

$$R_2 \geq H(X_2|X_1)$$

$$R = R_1 + R_2 \geq H(X_1, X_2).$$

To understand the concept of DSC and how correlation may be exploited let us consider a simple example in which the most significant bits in both sequences are the same, while some last bits, the least significant ones, differ. In fact, in this example the conditional entropy corresponds to these (different) least significant bits.

B. DSC in a network case

DSC-based optimal strategies for WSNs were proposed in [8], [9]. Despite the attempts to design codes for multiple sources [10], this problem still remains open due to the fact that these codes achieve suboptimal rates. Thus, in practice Slepian-Wolf (S-W) codes only for two sources are considered. These codes can operate at any rate in the S-W region and may adapt to any change in correlation between the sources [11].

Roumy and Gesbert [4] formulated the pairwise distributed source coding problem in the network setting. They presented algorithms for rate and power allocation for two scenarios while assuming the existence of the direct channels between each source node and the terminal.

In the first scenario, by assuming noiseless channels between nodes and the sink, they considered the problem of deciding which particular nodes should be jointly decoded at the sink and which rates should be allocated in order the total sum rate to be minimized. In the second scenario, they assumed orthogonal noisy channels between the nodes and the sink and considered minimization of total power consumption.

Also, it was assumed that the sink possesses full knowledge of the individual and the joint entropies as well as the channel capacities for each possible pair of nodes.

In short, the resource allocation problem is to determine the optimal pairing combinations of the nodes in the network and the corresponding rates for them such that the sum rate or the sum power is minimized. As a result, the problem was mapped onto the graph-theoretic problem of choosing the minimum weight matching of an appropriately defined weighted undirected graph.

It is of interest to underline that in general the chosen optimal pairs are not the same for both scenarios considered (i.e. sum rate or sum power minimization).

Although this approach has significantly smaller cost than the one which does not apply DSC (all nodes send the measurements at $H(X_n)$, regardless of their correlation), it is still far from the theoretically optimal case (DSC for N sources), especially in cases the correlation among the nodes is high. This is the result of considering only the correlation of the nodes in the pairs, and not among the pairs. Motivated by this, let us examine possible ways to exploit the correlation further.

C. Hierarchical and Sequential structures

Let us assume a hierarchical transmission structure (Fig.4). Without loss of generality, let us assume that only 1^{st} level nodes observe a phenomenon and take the measurements $X_1, X_2, X_3, X_4, ..., X_N$ and that these measurements are correlated. Since we are restricted to practical codes for pairwise DSC, let us examine whether hierarchical organization of these pairs could provide us with any benefit.

Let us assume that each pair applies pairwise DSC sending total bits equal to the joint entropy, e.g. $H(X_1, X_2) = H(X_1) + H(X_2|X_1)$. The question is whether the received sequences at the 2^{nd} level nodes could be further compressed. From the information-theoretic perspective, if $H(X_1, X_2) + H(X_3, X_4) > H(X_1, X_2, X_3, X_4)$ holds, then it is possible to have further gain. However, in the general case, it is not easy to find the correlation pattern of already coded sequences by S-W codes. Therefore, in order to further exploit the spatial correlation of X_1, X_2, X_3, X_4..., the nodes at 2^{nd} level would have to decode the received sequences. In other words, the sequences (X_1, X_2) and (X_3, X_4) should be recovered at the respective nodes at 2^{nd} level.

Let us now consider how the correlation model affects our possible strategies. If the correlation between the joint sequences (X_1, X_2) and (X_3, X_4) was known, then even with pairwise DSC codes (which we are practically restricted to), it would be possible to achieve the optimum overall joint entropy for four sources, $H(X_1, X_2, X_3, X_4) = H(X_1, X_2) + H(X_3, X_4|X_1, X_2)$. However, for a hierarchical structure of $N = 2^i$ sources, in order to achieve the optimum, the correlation between $(X_1, X_2, ..., X_{2^i/2})$ and $(X_{(2^i/2)+1}, ..., X_N)$

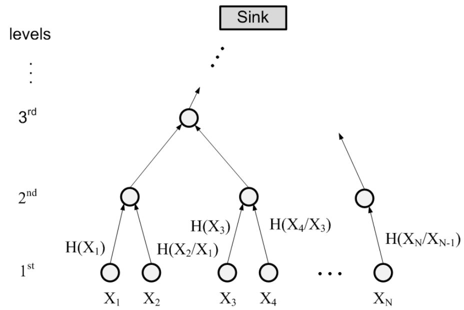


Fig. 4. A hierarchical structure

should be known for each i. This is too difficult to have in practice and thus we restrict ourselves to the pairwise correlation model $(X_1|X_2)$,$(X_2|X_3)$,...,$(X_{k-1}|X_k)$, where $k = 2, \ldots, N$. In this case, for a structure given in Fig. 4, the best achievable rate at 3^{rd} level could be, for instance, $H(X_1|X_2) + H(X_2) + H(X_3|X_2) + H(X_4|X_3)$. Similarly, for N sources, the best achievable rate at the sink would be $H(X_1) + H(X_2|X_1) + \ldots + H(X_N|X_{N-1})$.

Alternatively, the previous rate could be obtained by applying the so-called sequential DSC [12] which is a non-hierarchical, 1-level structure (Fig. 5). The main idea is to use previously decoded data as side information for other sources. For instance, using X_1 as side information, and after receiving $H(X_2|X_1)$, the sink could decode X_2. Next, it could use X_2 as side information for decoding X_3, after receiving $H(X_3|X_2)$, and so on. Consequently, the transmission of only one node at the rate of the individual entropy is required, while all other nodes could transmit at the rates of conditional entropies resulting in the significant reduction of overall transmitted bits.

It should be noted that the process of decoding X_n is dependent on whether $H(X_n|X_{n-1})$ and all previous sequences have been correctly received or not. If any of these fails to be received, the chain is broken and X_n is not able to be decoded.

Apart from this reliability issue, it could be concluded that hierarchical decoding/re-encoding scheme with both pairwise S-W codes and correlation model attain the same rate as the 1-level sequential DSC scheme. Moreover, the upper layer nodes could only be seen as simple relay nodes, and there is no benefit of their decoding/re-encoding capabilities. So, it can be concluded that, once properly implemented, DSC strategy is independent of the routing/transmission structure, which was also discussed in [13], in a more general context. The reliability issue, or dependence on receiving previous $H(X_n|X_{n-1})$ sequences correctly, will be tackled in the following subsection by allowing some cooperation between the nodes.

Also, it should be noted that the case in which all nodes in the hierarchical structure of Fig. 4 take measurements (not only at 1^{st} level) is a special case of a 2-D sequential case, which is actually a directed spanning tree problem (Fig. 6), as described in [5]. A more general solution was proposed in [5] which outperforms the one in [4], especially in the

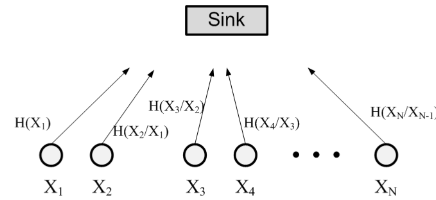


Fig. 5. A sequential structure

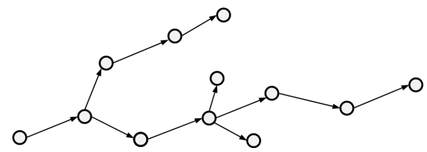


Fig. 6. An example of a directed spanning tree

case of high correlation among the measurements of the nodes. More specifically, the previously explained sequential strategy was applied so that a node may participate in joint decoding more than once, while in [4] it was assumed that each node participates in joint decoding strictly once. They proposed solutions for both noiseless and noisy channel cases. The former case was solved by applying an algorithm based on finding the minimum weight directed spanning tree of an appropriately defined directed graph. The latter case was solved by finding the minimum weight matching forest of an appropriately defined mixed graph.

D. Channel-aware cooperation-based extension of sequential decoding

To begin with, let us discuss the case that two nodes transmit their measurements to the sink as in Fig. 2b. In general, the nodes have to transmit at overall rate which equals to the joint entropy of their measurements $H(X_1, X_2)$.

For the noiseless channels, the nodes may transmit at any rates as long as their rates are on the boundary of Slepian-Wolf region (Fig. 3). However, it should be noted that there are two corner points defining the minimum rate each node may have while the other transmits at its individual entropy (maximum) rate. For noisy AWGN channels which are of similar quality ($\gamma_1 \approx \gamma_2$), in order to minimize the sum of powers, the sink should set the rates to be somewhere in the middle of the slope ($R_1 \approx R_2$). In practice, it may happen that there is a physical obstacle between a node and the sink causing a very small γ in the respective link. In such a case when a node experiences a deeply faded (bad) channel, the sink may compensate for that to a certain extent by allocating the maximum rate to the other node (corner point). Therefore, for a given channel, the minimum transmit power of a node is a function of its conditional entropy.

In a network setting, it is shown in [5] that the sequential scheme achieves optimal overall sum rate under pairwise DSC and pairwise correlation model constraints. Except for the first node, which transmits at the rate of its individual entropy, all other nodes transmit at the conditional entropy rates (corner points). As a result, in the case that a node has a very bad channel, the sink cannot compensate for it any further. Although a first node and one of its first neighbors will be encoded at a rate on the slope (and allocated power proportional to their channels quality), all other nodes will have a corner point rate allocation and corresponding power allocation.

Moreover, in [5] it is assumed that $P < P_{max}$. However, it should be noted it is required that all previous sequences have been correctly received in order to decode X_n, thus P_{max} threshold should be set really high to account for any possible very bad links in the network. This is not desirable since the sensor nodes are of limited power in practice.

To remedy this problem, we propose a cooperation scheme where a neighboring node could be used as a relay.

Let us first give a relation between the rate variables R_n and the respective power variables P_n. This relation will be given in terms of some functions $f_n(R_n)$ that are defined as the minimum powers required by the nodes of the network in order to transmit data at a rate R_n from node n to the sink node:

$$f_n(R_n) = \text{Minimum } P_n \text{ for rate } R_n \ . \qquad (2)$$

In the case where the nodes of the network are only allowed to transmit to the sink node using a direct Additive White Gaussian Noise (AWGN) channel with Signal to Noise Ratio (SNR) equal to $\gamma_n = |h_n|^2/\sigma_n^2$ we have that

$$f_n(R_n) = \frac{2^{R_n} - 1}{\gamma_n} \ , \qquad (3)$$

which is the inverse of the capacity function of the respective AWGN channel.

Let us assume that the sink performs all calculations regarding the rate and power allocation to the nodes. It possesses the full knowledge of the correlation between each possible pair of nodes, the individual entropies of the sources as well as the channel gains for all node-sink links. In addition, in our strategy, the sink should also know the internode channels among the nodes. Therefore, the sink may locate those nodes which have very bad channels according to some criteria. A criterion might be a threshold channel gain $\gamma_{threshold}$ below which a channel can be considered as a bad one. Another possibility would be to compare the power allocated to a node to a maximum power allowed (peak power constraint). We assume that there are several nodes with bad channels in the network, sparsely distributed. Next, for a node which has been denoted as a large power consumer, a test whether to cooperate with the best of its neighbors is performed as explained below.

Firstly, the sink chooses the best cooperating node from the subset of neighboring nodes, $\mathcal{S}_n$, which includes the predecessor and all successors of the node with a bad channel. In fact, in a sequential scheme where the rate allocation is computed by the directed spanning tree method, each node usually has one node as predecessor and one or more as successors. The exceptions are: i) the first node, which represents the root of the tree and do not have any predecessor ii) last nodes, which represent the leaves of the tree and do not have any successors. However, the method can be still applied since they have at least one neighbor.

Finally, the sink performs a test to decide whether it is beneficial to cooperate in terms of power consumption.

So, each node may transmit either through the direct channel to the sink, or use a relay (cooperate), so the decision will be made between these two available protocols:

1) Direct sink access: Each node n is given the option to communicate with the sink, via an AWGN channel with complex gain h_n and noise variance σ_n^2. Thus, using $\gamma_n = |h_n|^2/\sigma_n^2$, the capacity of this link is given by

$$C_n^{\text{Direct}}(P_n) = \log_2(1 + \gamma_n P_n) \ . \qquad (4)$$

2) Cooperative decode and forward: Each node n is given the option to send all its data to a relay node, which will then forward it to the sink, in a two time-slot protocol. Let us assume that the channel between node n and node m, which will act as a relay, is an AWGN channel with complex gain h_{nm} and noise variance σ_{mn}^2, and define also $\gamma_{nm} = |h_{nm}|^2/\sigma_{nm}^2$. Then, the capacity of this protocol, taking also into account optimal power allocation between the nodes n and m, is given by [3]:

$$C_n^{\text{DF}}(P_n) = \frac{1}{2}\log_2\left(1 + \frac{\gamma_{nm}\gamma_m}{\gamma_{nm} + \gamma_m} P_n\right) \ . \qquad (5)$$

As previously explained, the node transmission performance is tested against the performance of the best relay chosen from the subset $\mathcal{S}_n$. So, the capacity of the second option equals to

$$C_n^{\text{DF}}(P_n) = \frac{1}{2}\log_2(1 + b_n P_n) \ , \qquad (6)$$

where

$$b_n = \max_{m \epsilon \mathcal{S}_n}\left\{\frac{\gamma_{nm}\gamma_m}{\gamma_{nm} + \gamma_m}\right\} \ . \qquad (7)$$

Thus, according to the previous, the required functions $f_n(R_n)$ in this case are given by

$$f_n(R_n) = \min\left\{\frac{2^{R_n} - 1}{\gamma_n}, \frac{4 \cdot 2^{R_n} - 1}{b_n}\right\} \ , \qquad (8)$$

and according to the values of γ_n and b_n we have the following two cases:

(a) When $b_n \leq 4\gamma_n$, we have that

$$f_n(R_n) = \frac{2^{R_n} - 1}{\gamma_n} \qquad (9)$$

(b) When $b_n > 4\gamma_n$ (which also implies that $b_n > \gamma_n$), we have that

$$f_n(R_n) = \begin{cases} \frac{2^{R_n}-1}{\gamma_n}, & R_n \leq \log_2\left(\frac{b_n-\gamma_n}{b_n-4\gamma_n}\right) \\ \frac{4 \cdot 2^{R_n}-1}{b_n}, & R_n > \log_2\left(\frac{b_n-\gamma_n}{b_n-4\gamma_n}\right) \end{cases} \qquad (10)$$

Thus, from the above, we can see that energy savings, relative to the scheme in [5], are possible when $b_n > 4\gamma_n$ and $R_n > \log_2\left(\frac{b_n-\gamma_n}{b_n-4\gamma_n}\right)$. Fig. 7 depicts a plot of $f_n(R_n)$ for $\gamma_n = 1$ and $b_n = 5$, thus, since $b_n > 4\gamma_n$ Eq. (10) is used.

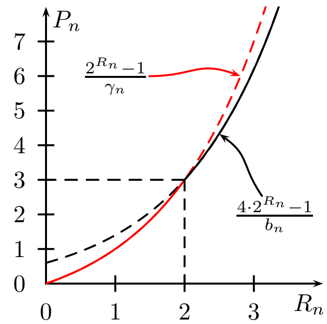


Fig. 7. A demonstration of the function $f_n(R_n)$ for $\gamma_n = 1$ and $b_n = 5$. Function $f_n(R_n)$ appears as a solid line, while the two constituent functions according to (10) appear as dashed lines.

TABLE I
COMPARISON OF SUM POWERS.

	Number of deeply faded channels		
	1	2	3
Non-DSC	2571.40	3751.60	5092.90
Sequential	175.73	245.15	324.05
Proposed	129.02	152.76	179.81

1) Numerical Results: In order to illustrate the gains achieved by applying a DSC approach as well as the proposed extension, let us consider a bridge scenario in which 10 sensors are equidistantly placed along the deck, similarly as in Fig. 1. The joint entropy model for any two sources, also used in [4], is a function of the individual entropy (which equals 8 for all nodes), of a correlation coefficient c = 0.1, and the distances d_{ij} between the sources i.e.,

$$H(X_i, X_j) = H(X_i) + (1 - 1/(1 + d_{ij}/c))H(X_i).$$

The distance between consecutive sensors is 0.1 and their distance to the sink is in the range from 0.5 to 1.0296. The channel gains are in general assumed equal to the inverse square distance. However, in some cases node-to-sink channels are further faded due to e.g. obstacles. Let us take as deeply faded channels those with b_n/γ_n=10. The total sum powers for non-DSC approach, sequential DSC and the proposed technique are presented in Table I. Under the assumption that some nodes experience deeply faded channels comparing to their neighbors, the proposed strategy results in a decreased power consumption by the network as a whole. Under the same assumption, the peak power constraint is lowered as well.

IV. IMPLEMENTATION-RELATED ISSUES

In our system model, we made several assumptions, such as independence of the channels and full knowledge of network topology, correlation model and the channel gains. There are several practical ways which can assure that the above assumptions come true. Let us outline some of the main ones:

1) Independent channels can be achieved by using multiple access techniques appropriate for WSNs.
2) All the involved channels may be estimated during a training period in which all nodes take part.
3) The sink could estimate the pairwise correlation model and corresponding joint entropies from the system model created during the design phase of a construction. Otherwise, it could be obtained after receiving the real measurements sent by the nodes at the rates of individual entropies (without applying DSC) during the training period.
4) In case that some node fails, the sink would need to establish new relations among the nodes only in the neighborhood of this node, without changing the whole sequential scheme.

Throughout this paper, we consider only spatial correlation. However, temporal correlation can be utilized as well. Developing a strategy which exploits efficiently both types of correlation is of current investigation.

V. CONCLUSION

We studied the sensor reachback problem in wireless sensor network (WSN), where distributed source coding (DSC) is used in order to compress the data. This approach is efficient when there is spatial correlation between the sensor nodes, as in Structural Health Monitoring (SHM) application. The channel-aware extension of sequential decoding, based on cooperation between the nodes, has been proposed to minimize the total sum power.

REFERENCES

[1] Jerome P. Lynch, Kenneth J. Loh. A Summary Review of Wireless Sensors and Sensor Networks for Structural Health Monitoring. *The Shock and Vibration Digest*, March 2006.

[2] Rice, J. A., Mechitov, K. A., Sim, S. H., Spencer, B. F. and Agha, G. A.. Enabling framework for structural health monitoring using smart sensors. *Structural Control and Health Monitoring*, 18: 574587, 2011.

[3] Y-W. Hong, W.-J. Huang, F-H. Chiu, and C.-C.J. Kuo. Cooperative communications in resource-constrained wireless networks. *Signal Processing Magazine, IEEE*, 24(3):47–57, May 2007.

[4] A. Roumy and D. Gesbert. Optimal matching in wireless sensor networks. *IEEE Journal on Selected Topics in Signal Processing, Special issue on Convex Optimization Methods in Signal Processing*, Dec 2007.

[5] S. Li and A. Ramamoorthy. Rate and power allocation under the pairwise distributed source coding constraint. *IEEE Transactions on Communications, vol. 57, no.12*, Dec 2009.

[6] Stankovic, V., Stankovic, L., Cheng, S. Distributed source coding: Theory and applications. *Proc. Eusipco-2010 18th European Signal Processing Conference*, Aalborg, Denmark, August 2010.

[7] D. Slepian and J. K.Wolf. Noiseless coding of correlated information sources. *IEEE Trans. Inform. Theory, vol. IT-19, pp. 471480*, Jul. 1973.

[8] R. Cristescu, B. Beferull-Lozano, and M. Vetterli. Networked Slepian-Wolf: Theory, algorithms, and scaling laws. *IEEE Trans. Inform. Theory, vol. 51, no. 12, pp. 40574073*, Dec. 2005.

[9] A. Ramamoorthy. Minimum cost distributed source coding over a network. *in Proc. IEEE Intl. Symp. Inform. Theory*, 2007.

[10] V. Stankovic, A. Liveris, Z. Xiong, and C. Georghiades. On code design for the Slepian-Wolf problem and lossless multiterminal networks. *IEEE Trans. Inf. Theory, vol. 52, no. 4, pp. 1495-1507*, Apr. 2006.

[11] V. Toto-Zarasoa, A. Roumy, and C. Guillemot. Rate-adaptive codes for the entire Slepian-Wolf region and arbitrarily correlated sources. in *Proc. IEEE Int. Conf. Acoustics, Speech Signal Processing(ICASSP)*, 2008.

[12] D. Marco and D. L. Neuhoff. Reliability vs. efficiency in distributed source coding for field-gathering sensor networks. in *Information Processing in Sensor Networks, Proceedings of the Third International Symposium, Berkeley, CA, USA*, April 26-27, 2004, pp. 161-168.

[13] J. Barros, S. D. Servetto. Network Information Flow with Correlated Sources. *IEEE Trans. on Inform. Theory*, Vol. 52(1), pp. 155-170, 2006.