Cooperative Detection and Communication in Wireless Sensor Networks

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Abstract— We define information theoretic problems in the cooperative detection of targets by a distributed wireless sensor network, and in the cooperative transmission of the results to a remote user. The dominant constraint in both cases is the energy cost of communications, rather than bandwidth or signal processing costs. We show that the detection problem can be cast as a rate distortion problem, and bound the region for Gaussian sources. We describe how the cooperative transmission problem differs from the usual context for space-time codes, and present one practical approach.

I. INTRODUCTION

In wireless sensor networks, potentially a very large number of devices cooperate to detect an event, and report the results of the detection exercise to some end user, who may be remote from the network. A fundamental constraint in sensor networks is the energy of the nodes, which may be limited in their lifetime energy reserves by batteries, and which likely have low peak power available for transmission. Questions then naturally arise as to the most efficient means to make reliable detection decisions, and in achieving longer range communications. In section II we set up the cooperative detection (data fusion) problem as a rate distortion problem, and in section III present the analytic formulation. In section IV we introduce the cooperative communication problem, and present some simple approaches. In section V we present capacity results, and in section VI suggest one simple coding approach that can apply to a large network with varying numbers of cooperating elements. In section VII we present our conclusions.

II. THE DATA FUSION PROBLEM

We now consider the question: what data rates can be supported for data fusion in a sensor network, given a specified tolerable data distortion? Unfortunately, an exact answer to this question is not available in the general case, and thus we have considered the specific case of correlated Gaussian sources in this paper.

The motivation for this problem comes from performing distributed detection of phenomena. It is well known from the theory of distributed detection that higher reliability and lower probability of detection error can be achieved when observation data from multiple, distributed sources is intelligently fused in a decision making algorithm, rather than using a single observation data set [1]. This, coupled with the fact that fabrication technological advances have made low-cost sensors incorporating wireless transceivers, signal processing and sensing in one integrated package a desirable low-cost option, it is inevitable that such devices will be widely used in detection applications such as security, monitoring, diagnostic, remote exploration etc. This has given rise to the development of wireless integrated networked sensors (WINS) [2], Figure 1.

However, the effective deployment of such distributed processing systems introduces some significant design issues, most notably: networking and communication protocols, transmission channel and power constraints, and scalability, among others [2], [3]. It is also evident that some fundamental limits are required to assess the optimality of any system design with regard to the "best design". Thus, an information theoretic analysis of the system is required. Here we assume that the primary constraint is power.

A WINS system invokes a multi-terminal analysis, as diagrammed in Figure 1.

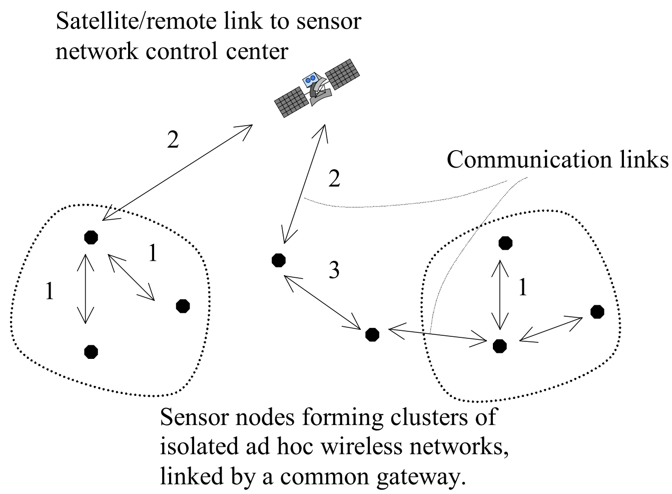

Figure 1: Wireless Integrated Network Sensor System

For this type of a system, all the traditional types of multi-terminal channels considered in information theory appear: the multiple access channel (communication pathways shown in Figure 1 numbered as 1), the broadcast channel (2), the relay and interference channel (3), etc. [4]. Additionally, the channel may be fading or more complex. Unfortunately, in the absence of a general information theory of multi-terminal networks, there is, as yet, no analytical way of evaluating performance bounds for whole systems, for a specific type of task for which the network might be employed, e.g. distributed detection. Our goal is to apply the results known so far to obtain, if not global optimum information limits, at least optimality criteria for each of the individual sub-blocks. In this regard, advances have been made with certain simplifying considerations, most notably the rate-distortion bounds for multiple, correlated nodes. The focus so far has been on pathways 1, inside the local loop.

For the individual local network loops, the problem is one of efficient communication and data fusion for detection. Associated problems such as network boot-strap, algorithms determining the minimum number of nodes necessary for reliable detection of a phenomenon, etc. have been studied and are not discussed here [3], [5]. Instead the coding problem is considered. The multi-terminal coding theory problem for two correlated memoryless sources with separate encoders has been solved by Slepian and Wolf [5]. The correlated sources assumption is valid in the WINS case, since for nodes observing the same target, the data generated for each sensor is expected to be correlated. Also, in the WINS case, it is apparent that power efficiency can be incorporated by allowing a distortion criteria, since there may be several data fusion centers, and since local processing provides a far higher power gain than RF transmissions. Thus, what becomes of interest then is how much distortion can be tolerated if the sensor network is to achieve some measure of efficiency in distributed detection – in other words, the rate-distortion bound.

Previous work in this area by Wyner and Ziv [7], Han and Kobayashi [9], [10] and Csizar [11] have all focused on special extensions of Slepian and Wolf, but the general rate-distortion regions characterization problem has remained unsolved. We have extended the special case for two correlated memoryless Gaussian sources (Oohama, [7]) to the *n*- sources case (with partial side information). In what follows, the notation is adopted from Oohama, [7]. The next section presents the analytic formulation of the problem and the main result.

III. Analytic Formulation

Consider the multi-sensor system as shown below (Figure 2).

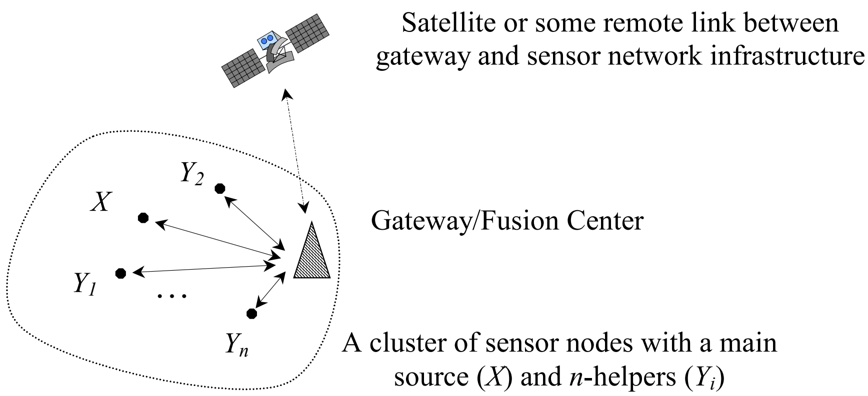

Figure 2: Data Fusion for a Wireless Networked Sensor System

A portion of a distributed cluster of sensor nodes (perhaps mobile) is observing a phenomenon and generating source data. Algorithms exist which can determine which nodes in the proximity of the phenomenon need to be activated and which can remain dormant [4]. Once this boot-up process is completed, the node observation data is assumed to be Gaussian (for analytical simplicity), with one data node acting as the main data source (e.g. that which is closest to the phenomenon), and the remaining nodes generating correlated data. The coding challenge is then to determine appropriate codes and data rates such that the gateway/data-fusion center can reproduce the data from the main node using the remaining nodes as sources of partial side information, subject to some distortion criteria.

Thus for a main source, X, and n correlated sources, Y_i, with $\{X_t, Y_{1t}, \cdots Y_{nt}\}_{t=1}^{\infty}$ being stationary Gaussian memoryless sources, for each observation time, t=1, 2, 3, ..., we let the random *(n+1)*-tuplet $(X_t, Y_{1t}, \cdots Y_{nt})$ take values in $X \times Y_1 \times \cdots Y_n$. The joint probability density function is given by the usual expression for the multi-dimensional Gaussian probability density function, where the covariance matrix can be denoted as:

$$\Lambda = \begin{bmatrix} \sigma_X^2 & \rho_{XY_1}\sigma_X\sigma_{Y_1} & \cdots & \rho_{XY_n}\sigma_X\sigma_{Y_n} \\ \rho_{XY_1}\sigma_X\sigma_{Y_1} & \sigma_{Y_1}^2 & \cdots & \rho_{Y_1Y_n}\sigma_{Y_1}\sigma_{Y_n} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{XY_n}\sigma_X\sigma_{Y_n} & \rho_{Y_1Y_n}\sigma_X\sigma_{Y_1} & \cdots & \sigma_{Y_n}^2 \end{bmatrix} \quad (1)$$

We can write independent copies of $\{X_t\}_{t=1}^{\infty}$ as $X^m = X_1, X_2, \cdots, X_m$ and similarly for $\{Y_{kt}\}_{t=1}^{\infty}$, *k=1,2,…,n*. Next, we consider a coding system where data sequences $X^m, \cdots Y_k^m$ are

separately encoded to $\varphi_1(X^m), \varphi_1(Y_k^m)$ and sent to the information processing / data fusion center. The decoder function, $\Psi = (\psi_X, \psi_1, \cdots, \psi_n)$, observes the *(n+1)*-tuplet $\left\{\varphi_1(X^m), \varphi_1(Y_1^m), \cdots, \varphi_1(Y_n^m)\right\}$ and estimates $\left(\hat{X}^n, \hat{Y}_1^m, \cdots, \hat{Y}_n^m\right)$. We let $\Im_{n,\delta}(R_X, R_1, \cdots, R_n)$ denote the set of all such coding and decoding schemes, $(\varphi_X, \varphi_1, \cdots, \varphi_n, \Psi)$, which can exist with the properties mentioned above. We take :
$d_x : X^2 \to [0,\infty), \quad d_1 : Y_1^2 \to [0,\infty), \cdots, d_n : Y_n^2 \to [0,\infty)$
as the distortion measures, which, in our case, is the squared distortion measure, and we let the average distortions be $\Delta_1 = E\left\{\frac{1}{m}\sum_{t=1}^{m} d_1(X_t, \hat{X}_t)\right\}$ (similar expressions for the other sources).
Then for given positive numbers $D_X, D_1, \ldots, D_n$, a rate *(n+1)*-tuplet $R_X, R_1, \ldots, R_n$, is admissible if for any $\delta > 0, \quad n \ge n_0(\delta)$, there exists a *(n+2)-tuplet* $(\varphi_X, \varphi_1, \cdots, \varphi_n, \psi) \in \Im_{n,\delta}(R_x, R_1, \cdots, R_n)$, such that $\Delta_i \le D_i + \delta$.

In our specific case, we do not care about the reproduction of the Y_i's, so the D_i's can be large. Rather, the Y_i's act as helpers to reproduce X by providing side information at the data fusion node. This is the so called *n*-helper case. Then for an encoding system using the Y_i,'s as *n*-helpers, the rate-distortion region given by:
$\Re(D_X, D_1, \cdots D_n) = \{(R_X, R_1, \cdots R_n) : (R_X, R_1, \cdots R_n) \text{ is admissible}\}$ for a given set of rates and distortion measures, is desired.

Main Result:

For the special case of the correlated Gaussian source, we can now state the main result that we have obtained. We consider the encoding functions:
$\varphi_X : X^m \to \aleph_1 = \{1, \cdots, C_1\}, \cdots, \varphi_i : Y_i^m \to \aleph_i = \{1, \cdots, C_i\}$ to be such that the rate constraints being satisfied are: $\frac{1}{m}\log C_i \le R_i + \delta$, *i=X,1, 2, ...n.* Extending previous results [4]-[10], we show that for an admissible rate $(R_X, R_1, R_2, \cdots R_n)$, and for some D_i's > 0, the *n*-helper system data rates for correlated Gaussian sources can be fused to yield an effective date rate (with respect to source X) satisfying the following lower bound:

$$R_X \ge \frac{1}{2}\log\left\{\frac{\sigma_X^2}{D_X} \cdot \left[\prod_{k=1}^{n}\left(1 - \rho_{XY_k}^2 + \rho_{XY_k}^2 \cdot 2^{-2R_k}\right)\right]^{\frac{1}{n}}\right\}$$

This is the desired rate distortion region.

Proof:

In the interests of brevity, an outline of the main steps of the proof is given. The method of employing joint weakly δ-typical tuplet, based on typical sequences, is used in the proofs of the characterization, rather than a measure-theoretic approach [11].

We assume that an admissible set of rates exists, and we let $W_x = \varphi_X\left(X^n\right), W_i = \varphi_i\left(Y^n\right)$. Then:
$n\left(R_x + \delta\right) \ge \log\left(C_1\right) \ge H\left(W_1\right) \ge I\left(X^n; \hat{X}^n\right) - \frac{1}{n}\sum_{k=1}^{n} I\left(X^n; W_k\right)$ and $\quad n\left(R_i + \delta\right) \ge \log\left(C_i\right) \ge H\left(W_i\right) \ge I\left(Y_i^n; W_i\right)$.
Note that $W_i \to Y_i^n \to X^n$ forms a Markov Chain, thus defining:

$F_n(D) = \inf_{\hat{X}^n:\Delta_1 \le D} \frac{1}{n} I(X^n;\hat{X}^n)$, $G_i(R) = \sup_{\substack{W_i: \frac{1}{n} I(Y_i^n;W_i) \le R \\ W_i \to Y_i^n \to X^n}} \frac{1}{n} I(X^n;W_i)$ we get:

$$R_X + \delta \ge F_n(D_X + \delta) - \frac{1}{n}\sum_{k=1}^{n} G_k(R_k + \delta)$$

By the Gaussian property of the sources, and concavity of the logarithm function, we get: $\frac{1}{n} I(X^n;\hat{X}^n) \ge \frac{1}{2}\log\left(\frac{\sigma_X^2}{D}\right) \Rightarrow F_n(D) \ge \frac{1}{2}\log\left(\frac{\sigma_X^2}{D}\right)$

Finally, an upper bound of $G_i(R)$ is obtained by an extension of the technique for the two node case (entropy of the power inequality, monotonicity, Jensen's inequality): $\frac{1}{n} I(X^n;W_i) \le \frac{1}{2}\log\left(\frac{1}{1-\rho_{XY_i}^2 + \rho_{XY_i}^2 \cdot 2^{-2R}}\right)$

Substituting the bounds in the expression for $F_n(D)$, we obtain:

$$R_X + \delta \ge F_n(D_X + \delta) - \frac{1}{n}\sum_{k=1}^{n} G_k(R_k + \delta)$$
$$\ge \frac{1}{2}\log\left(\frac{\sigma_X^2}{D_1 + \delta}\right) + \frac{1}{2}\sum_{k=1}^{n}\log\left(1-\rho_{XY_k}^2 + \rho_{XY_k}^2 \cdot 2^{-2(R_k+\delta)}\right)^{\frac{1}{n}}$$

Letting $\delta \to 0$, we obtain the final result:

$$R_X \ge \frac{1}{2}\log\left\{\frac{\sigma_X^2}{D_X} \cdot \left[\prod_{k=1}^{n}\left(1-\rho_{XY_k}^2 + \rho_{XY_k}^2 \cdot 2^{-2R_k}\right)\right]^{\frac{1}{n}}\right\}.$$

IV. THE COOPERATIVE COMMUNICATION PROBLEM

With many low-power and low-cost sensors available, the goal is to achieve more robust and higher rate communications. For example, we may again consider the situation in Figure 1, where now communication to the satellite may be accomplished by a cooperating group of nodes to overcome their peak power limitations. This problem is of interest for example in remote planetary exploration, where the cost of providing power generation on the surface of a planet is orders of magnitude greater than for the downlink. The communication schemes to accomplish this goal must be insensitive to the number of transmitters and their location, and robust to the transceiver failure or motion. We are also interested in problems where for example clusters of nodes on the surface must cooperate to overcome gaps in the multi-hop network caused by infelicitous node placement, or node failures. Thus multiple transmitters and receivers may cooperate.

The simplest way to achieve cooperative communication is by multiplexing. Frequency, time, code division multiple access (FDMA, TDMA, CDMA), and multiuser orthogonal frequency division multiplex (multiuser OFDM) are all feasible approaches. Using these methods, channels starting from different transmitters can work in parallel and independently.

Different transmitters could cooperate with each other or process information independently. For FDMA, TDMA, if they process information independently, obviously, the improvement on the performance over the single transmitter system is that information data rate increases by a factor of the number of transmitters. Meanwhile, the bandwidth expands by the same factor. Even if coding is used across transmitters, the data rate increases by the same factor because the received symbol rate increases by the same factor. Although the analyses for CDMA and multiuser OFDM are not so straightforward, there is also an increase for the data rate. Thus, in order to deal with a peak power constraint, increased communications range or rate can be achieved if the transmitters first share the message to transmit, and then all send it. Some weighted combining scheme can be used in the receiver array. Using more bandwidth as the number of transmitters is increased is thus a simple way to improve energy efficiency, taking advantage of the absence of competing uses.

For fading channels, optimal combining is simple as well. Because each channel is uncorrelated, the number of received signals are the number of transmitters times the number of receivers. The same optimal combining formula applies to these received signals.

In addition to the bandwidth expansion, it is noted that control signaling overhead is necessary. Its function is to allocate and manage channel resources as well as ensure the messages of the transmitters are coordinated. For FDMA and

CDMA, the receiver complexity grows with the numbber of transmitters linearly. For TDMA, the receiver speed goes up with the number of transmitters. For multiuser OFDM, the number of transmitters doesn't affect the receiver complexity so dramatically. However, time and frequency synchronization [12][13] are critical issues that must be dealt with carefully.

Multiplexing affects the transmitter design as well. For FDMA and CDMA, each transmitter uses a unique frequency band and spreading code, respectively. This uniqueness could be implemented by hardware or by software. TDMA and multiuser

OFDM transmitters are assigned channel resources dynamically, and this results in more complicated hardware design.

No matter whether multiplexing is adopted, it is valuable to investigate communications with multiple transmitters over the same channel. They are orthogonal communication schemes in the sense that multiplexing just deals with how channels are allocated, and doesn't care how each channel is used. So, there could be different coding, modulation, etc. at different multiplex channels. In our study, we address the communications over the same channel. One advantage of this kind of communications is the simplicity of transmitter design. Transmitters using the same channel can be almost identical.

We consider two kinds of channels that may be involved. They are the AWGN channel and the fading channel with unequal path loss. The availability of channel state information affects RF synchronization and the choice of modulation and demodulation schemes. It is easy to appreciate the importance of estimating the channel state information for fading channels. It includes the magnitude and phase of the channel response, both critical quantities in optimal combining. For AWGN channels, there is no path loss. However, due to the different path lengths, transmitted signals arrive at the transmitter with different RF phases. This phase relationship is part of the channel state information. Here, acknowledge of channel state information is characterized into three types, as follows.

We assume channels are not reciprocal. Thus, channel state information must be estimated at the receiver side. One approach is to insert a pilot sequence [14][15] periodically in each transmitted signal sequence. Because more than one transmitter uses the same channel and there is interference between pilot sequences from different transmitters, some properties must be satisfied among these pilot sequences so that the channel state information for each channel can be estimated. Then, the channel state information is feed back to the transmitters explicitly or implicitly. From this channel state information, transmitters can adjust their constellation phase with respect to each other so that their signals arrive at the receiver in phase. This is called RF synchronization.

It is also possible that the channel state information is not fed back to the transmitter side. Thus, the constellation phase cannot be controlled, and RF synchronization cannot be achieved. Signals may arrive at the receivers constructively or destructively. Individual transmitted signals must be determined at the receiver with the help of channel state information. Since the constellation and channel state information are known, the possible combined receive signal can be computed, and coherent communication schemes can be used if the phase of the combined receive signal can be tracked as well.

When channel state information cannot be estimated, obviously, there is no way to achieve RF synchronization. Since the possible clean received signal cannot be determined, it would be more feasible to adopt noncoherent communication schemes.

V. CAPACITY RESULTS

The information theoretic capacity for multiple antennas communications has been investigated to by Foschini[16], and Telatar [17] independently. Let us assume there are n_T transmitters and n_R receivers, and there is no feedback link from transmitter to receivers. The n_T transmitted signal components are taken to be statistically independent Gaussians. The virtue of a Gaussian distribution for the transmitted signal is well established, see [18]. Under the assumption of uncorrelated noise on each channel, the capacity takes the form [18-20],

$$C = \log_2 \det(\mathbf{I}_{n_r} + \frac{1}{No}\mathbf{G}\mathbf{A}_s\mathbf{G}^H) \quad (2)$$

where $\mathbf{A}_s$ is the transmitted signal covariance matrix, $\mathbf{G}$ is the channel response matrix that includes path loss and fading, and No is the noise variance. It is observed that capacity is a function of the channel state information $\mathbf{G}$ and the transmitted signal covariance matrix $\mathbf{A}_s$. Furthermore, from Hadamard's inequality [21], in order to maximize the capacity, $\mathbf{G}\mathbf{A}_s\mathbf{G}^H$ must be a diagonal matrix. When channels are independent from each other, $\mathbf{G}$ and $\mathbf{G}^H$ are diagonal, and $\mathbf{A}_s$ has to be diagonal as well.

For Gaussian channels, it is obvious to see the best power allocation policy is the equal power distribution. Several combinations of the numbers of transmitters and receivers are briefly discussed here.

1. Receive Diversity: maximum ratio combining, $n_T=1$, $n_R=n$

For Gaussian channels,

$$C = \log_2[1 + SNR * n] \quad (3)$$

For unequal path loss fading channels,

$$C = \log_2[1 + SNR * ||\mathbf{G}||^2] \quad (4)$$

where $\mathbf{G}$ is a nx1 vector, and SNR is defined as the ratio of transmit power to the receiver noise power.

2. Transmit Diversity $n_T=n$, $n_R=1$.

The capacity can be derived from (2). For Gaussian channels,

$$C = \log_2[1 + \sum_i SNR_i] \quad (5)$$

where SNR_i is defined as the ratio of the i-th transmit power to the receive noise power, assuming the noise power is equal at all receivers. For unequal path loss channels,

$$C = \log_2[1 + \sum_i SNR_i * ||\mathbf{G}_i||^2] \quad (6)$$

where $\mathbf{G}_i$ is the channel response from the i-th transmitter to the single receiver. It has a chi-square distribution with 2 degrees of freedom and a variance that depends on the path loss.

3. Combined Transmit-Receive Diversity.

The capacity can be computed numerically by Monte Carlo simulation. For $n_T \geq n_R$, equal transmit power and equal path loss Rayleigh fading channels, the capacity lower bound was derived in [17]

$$C > \sum_{k=n_T-(n_R-1)}^{n_T} \log_2[1 + \chi^2_{2k} SNR] \quad (7)$$

where χ^2_{2k} is a chi-square distribution with 2k degrees of freedom.

The above discussion for transmit diversity is based on the situation when RF phases are not synchronized at the receivers. When their relative phases are adjusted so that they are aligned at the receiver, the amplitude of the combined signal is the sum of the constituent transmit amplitudes. Therefore, for unequal path loss fading channels, the capacity is

$$C = \log_2\left[1 + \left(\sum_{k=1}^{n_T} \sqrt{SNR_i * ||\mathbf{G}_i||^2}\right)^2\right] \quad (8)$$

The capacity for Gaussian channels is obtained by replacing $\mathbf{G}_i$ with 1. For receiver diversity, RF synchronization is not a problem because there is only one transmit signal at any instant of time. For combined transmit-receive diversity, RF synchronization is almost impossible to be achieved simultaneously at all receivers unless transmitters and receivers are deliberately located in the fixed channel environment, and can move to any location in the varying channel environment. The capacity for RF synchronization is much higher than that for RF non-synchronization.

VI. A PRACTICAL APPROACH

In wireless sensor networks, the number of available transmitters may vary with time. Sensor failures or additions are expected to take place. Thus, the communication scheme used in the environment must be adaptive with respect to the number of transmitters. Space-time trellis codes [22] are designed for fixed numbers of transmitters. We propose an approach which is easier to implement and more insensitive to the change of the number of transmitters. In the approach, the relative constellation phases of transmitters change every symbol interval so that signals combined destructively may combine constructively in other symbol intervals. Consequently, the channel behaves like a fast fading channel. We have conducted a computer search for the best relative phase rotation. There are two transmit antennas using BPSK signal constellations and the rate 1/2 repetition code. The channels are AWGN channels. The constellation phase of the first transmit antenna is fixed, while the second transmit antenna increases its constellation phase by the value of relative phase rotation at the second symbol interval. It turns out that the best phase is 180 degrees. In other words, the second transmit antenna flips its constellation phase every symbol interval. It is interesting that the BER at this point is equal to the BER for one transmit antenna with the same total transmit power. If the constraint is on the individual transmit power, which is the usual case in wireless sensor network, we will obtain 3dB gain in performance. For three transmit antennas, the minimum appears at three points, $(0,\pi)$, (π,π) and $(\pi,0)$. These three points can be obtained with the same operation. Two constellations change by the same phase, while the other changes 180 degree more. When 2 and 3 transmit antenna cases are considered together, we can observe the robustness to the number of transmit antennas. When one transmit antenna is added to the 2 transmit antenna scenario, the original two antennas work in the same way, while the third antenna can choose to flip every symbol interval, as the second antenna, or not, as the first antenna. Therefore, the system scales up without changing the operation of the existing transmitters.

VII. CONCLUSION

In this work, we have considered the rate distortion problem for a sensor network employing data fusion at a node. The main assumption has been that the n-helper nodes are all producing correlated Gaussian data, which has then enabled us to obtain an analytic form for the rate distortion bound. The primary utility of this result is to compare practical data fusion schemes with the predicted bounds—in particular, to determine which are the most critical and sensitive parameters affecting rate and performance of a data fusion scheme in a network sensor system.

The main limitation of the work is that currently, extensions to the more 'real-world' scenario of non-Gaussian sources and channels are not obvious. However, efforts are underway to formulate numerically solvable versions for the more realistic scenarios. Our ultimate goal is, in the absence of any tractable analytical expression, to obtain at least an iterative algorithm, or a convex optimization form. Ideally, this would allow us to accurately predict maximum rate/ minimum distortion pairs for a wide variety of channels and sources for random arrangements of sensors. We would also like to be able to investigate various 'what-if" scenarios in simulation set-ups for particular types of configurations and coding implementations. Thus, we hope eventually to be able to use these bounds to definitively compare various data fusion and network communication schemes for wireless sensor networks, with regards to their performance and efficiency.

We have also presented a simple phase rotation scheme that enables a variable number of transmitters without a common phase reference to achieve gains over simple non-coherent combining, assuming the same channel must be used. However, much work remains to be done in devising schemes with superior performance. Simple capacity calculations indicate that substantial gains can be obtained by providing a coherent phase reference, and thus it is likely that approaches which devote a significant fraction of the energy to beacons may be fruitful.

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