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| Description | |



Estimation of Observation Error Probability in Wireless Sensor Networks

Xin He, Xiaobo Zhou, Khoirul Anwar and Tad Matsumoto

Abstract—In this letter, we first of all propose for a parallel wireless sensor network (WSN) a decoding technique that well exploits the correlation knowledge of the sensing data to be transmitted from each sensor to the fusion center (FC). This letter then derives an algorithm to estimate the observation error probabilities, representing the correlation, of the links between the sensing object and sensors. The convergence of the algorithm is also evaluated. Furthermore, the comparison of bit-error-rate (BER) performance between two cases, one uses estimated observation error probabilities, the other assumes the full knowledge of the observation error probabilities, is made. The simulation results show that the difference is only around 0.3 – 0.5 dB in per-link signal-to-noise power ratio (SNR), depending on the number of sensors.

Index Terms—Error Probability, Estimation, CEO problem, wireless sensor networks, LLR updating function

I. INTRODUCTION

WIRELESS sensor networks (WSNs) composed of a large number of sensors, deployed in a geographic area to perform distributed tasks, have been recognized as an important technology, since WSNs have significant impacts on the society. In WSNs, each sensor node is required to work under very low power consumption restrictions when it performs specified tasks. Therefore, the sensor nodes have to transmit their data without requiring high transmission power, and the WSN itself has to be highly energy efficient. A technique which is effective in reducing the power consumption is to design the system so that the fusion center (FC) can well exploit the correlation knowledge among the observed data, as supported by the Slepian-Wolf theorem [1]. In fact, the Slepian-Wolf theorem can be used to compress the data or to reduce the transmission power, assuming the source-channel separation [2]. Therefore, in this letter, no specific source encoding technique is assumed.

Distributed source coding schemes for sensor networks based on the Slepian-Wolf theorem are investigated in a tutorial article [3]. In practice, most of WSNs aim to observe the same sensing object, e.g., the sensors monitor the same

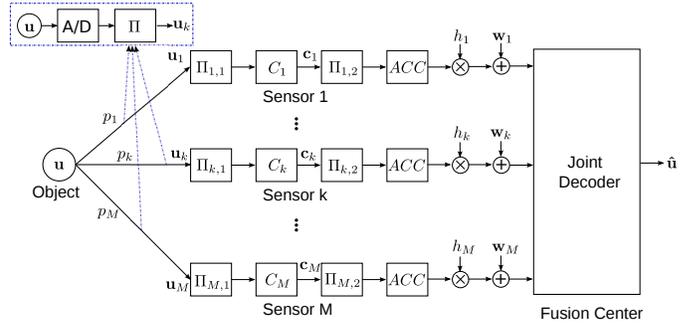


Fig. 1. Structure of the proposed system model.

physical phenomenon. In network information theory, the problem of estimating the correct data emitted from the target over noisy observation link can be modeled by the chief executive officer (CEO) problem [4], as defined in [5]. The quadratic Gaussian CEO problem is studied in [6], where it is assumed that the observed data samples are correlated Gaussian random variables. Rate-distortion function for a parallel Gaussian CEO model is investigated in [7], where also successive coding/decoding strategy is briefly introduced.

In [8], a source type identification technique at the FC using dumb sensors is investigated from the viewpoint of hypothesis testing. Instead, this letter focus on the coding/decoding techniques of analog-to-digital (A/D)-converted binary sequence; the k -th sensor's observation results are A/D-converted with m -bit resolution, interleaved by interleaver Π , and then transmitted to the FC by using binary-phased-shift-keying (BPSK). It should be emphasized that the same Π is commonly used by the M sensors, and the size is equivalent to the $m \times K$, where K is number of the samples. It plays a crucial role in making the length mK bit sequence random so that the observation error can well be represented by the random bit-flipping model after the interleaver Π . Both static Additive White Gaussian Noise (AWGN) and Rayleigh fading channels are assumed for the channels from sensors to the FC.

A technique that utilizes the knowledge of the observation error probabilities at the FC is proposed in [9]; each sensor uses parallel concatenated convolutional codes (PCCC) for the data transmission to the FC, and the extrinsic log-likelihood ratio (LLR) from the each decoder is combined; and after they are combined, the extrinsic information of the combiner is fed back to the each PCCC decoder, weighted by the observation error probabilities p_k , $k = 1, \dots, M$. In [10], we propose a technique to more efficiently utilize the knowledge about p_k than in [9], where the combined output extrinsic LLR is updated by using so-called f_c -function [10]; it is assumed that

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where following [2],

$$\hat{q}_{ij} = \frac{1}{N} \sum_1^N \frac{\exp(\mathbf{L}_{\mathbf{u}_i}^{\mathbf{p}}) + \exp(\mathbf{L}_{\mathbf{u}_j}^{\mathbf{p}})}{[1 + \exp(\mathbf{L}_{\mathbf{u}_i}^{\mathbf{p}})] \cdot [1 + \exp(\mathbf{L}_{\mathbf{u}_j}^{\mathbf{p}})]}. \quad (5)$$

N represents the number of the *a posteriori* LLR pairs from the two decoders with their absolute values larger than a given threshold T . Since the reliability of \hat{q}_{ij} is influenced by N , it is very important to choose an appropriate T value. However, how to determine the optimal T is out of the scope of this letter.

We can reformulate (4) by introducing the identity matrix \mathbf{I} of size M and a matrix \mathbf{J} defined by (7), into the following form:

$$[(\mathbf{I} + \mathbf{J}) - 2 \cdot \text{diag}(\hat{\mathbf{P}}) \cdot \mathbf{J}] \cdot \hat{\mathbf{P}} = \hat{\mathbf{q}}, \quad (6)$$

where, $\hat{\mathbf{P}} = [\hat{p}_1, \hat{p}_2, \dots, \hat{p}_M]^T$, and $\hat{\mathbf{q}} = [\hat{q}_{12}, \hat{q}_{23}, \dots, \hat{q}_{M1}]^T$. The $\text{diag}(\cdot)$ is the operator that forms a diagonal matrix from its argument vector, and \mathbf{J} is denoted as follows:

$$\mathbf{J} = \begin{bmatrix} 0 & 1 & 0 & 0 & \dots & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & 0 & \dots & 0 \end{bmatrix}. \quad (7)$$

Now, our objective is to find a nonnegative vector $\hat{\mathbf{P}}$ that minimizes $\|\mathbf{A}\hat{\mathbf{P}} - \hat{\mathbf{q}}\|^2$, which is formulated as follows:

$$\begin{aligned} \min \quad & \|\mathbf{A}\hat{\mathbf{P}} - \hat{\mathbf{q}}\|^2 \\ \text{s.t.} \quad & \hat{\mathbf{P}} \succeq \mathbf{0}, \end{aligned} \quad (8)$$

where, $\mathbf{A} = [(\mathbf{I} + \mathbf{J}) - 2 \cdot \text{diag}(\hat{\mathbf{P}}) \cdot \mathbf{J}]$.

To solve (8), this letter proposes an iterative algorithm summarized in Algorithm 1. In this algorithm, we use the standard Nonnegative Least Squares (*lsqnonneg*) described in [12], proposed by Lawson and Hanson.

Algorithm 1: $\hat{\mathbf{P}}$ Estimator

Input: $\hat{\mathbf{q}}$, ϵ , Pre-defined maximum iterations IT_m

Output: $\hat{\mathbf{P}} \succeq \mathbf{0}$ such that $\|\mathbf{A}\hat{\mathbf{P}} - \hat{\mathbf{q}}\|^2$ is minimized.

Initialization: $\hat{\mathbf{P}}^{(0)} = \mathbf{0}$, Calculate \mathbf{A} and

$\Delta(0) = \|\mathbf{A}\hat{\mathbf{P}}^{(0)} - \hat{\mathbf{q}}\|^2$

for $l = 1$ **to** IT_m **do**

 Calculate $\hat{\mathbf{P}}^{(l)}$ by using *lsqnonneg* algorithm;

 Update $\mathbf{A} = [(\mathbf{I} + \mathbf{J}) - 2 \cdot \text{diag}(\hat{\mathbf{P}}^{(l)}) \cdot \mathbf{J}]$;

$\Delta(l) = \|\mathbf{A}\hat{\mathbf{P}}^{(l)} - \hat{\mathbf{q}}\|^2$;

if $\Delta(l) \geq \Delta(l-1)$ **then**

 | Exit For;

end

if $\|\hat{\mathbf{P}}^{(l)} - \hat{\mathbf{P}}^{(l-1)}\|^2 \leq \epsilon$ **then**

 | Exit For;

end

end

$\hat{\mathbf{P}} = \hat{\mathbf{P}}^{(l)}$;

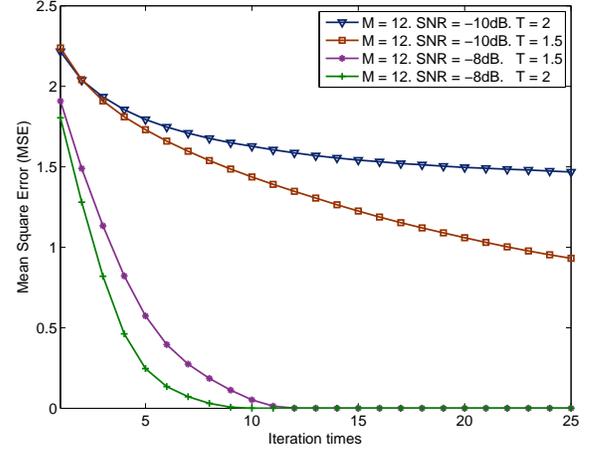


Fig. 3. Mean square errors of estimation versus decoding iteration times.

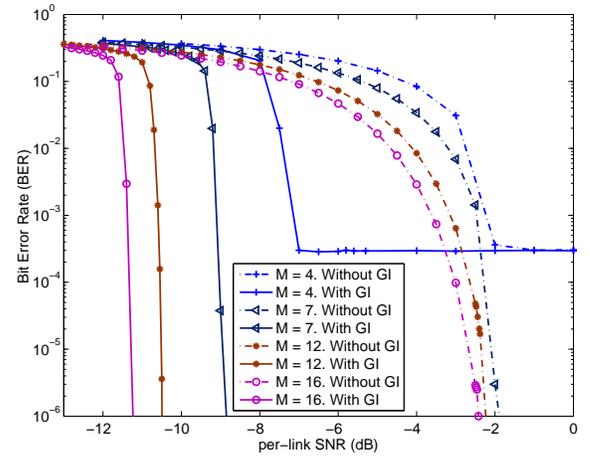


Fig. 4. BER performances with and without *GI* in AWGN channels.

V. PERFORMANCE EVALUATION

A. Convergence Property

Fig. 3 shows the mean square estimation error of the observation error probability vector \mathbf{P} versus the *GI* times where one *LI* was followed by one *GI*. The code parameters are the same as in the case of Fig. 4 described in the next subsection. The results are plotted for sensor number 12 with per-link SNR and LLR threshold T as parameters.

As shown in Fig. 3, the mean square estimation error $\|\hat{\mathbf{P}} - \mathbf{P}\|^2$ decreases as iteration times increased, indicating that the more *GIs* performed, the more accurate the estimate of \mathbf{P} . Furthermore, the rate of convergence depends on the values of per-link SNR and T , because the values of per-link SNR and T affect the reliability of \hat{q}_{ij} given by (5).

B. BER Comparison

Fig. 4 illustrates the difference on BER performances between the case of involving *GIs* and that of not involving *GI*. In this simulation, a half rate memory-1 nonrecursive systematic convolutional code with the polynomial $G = [3, 2]_8$ was used for C_k . The doping ratio P_d was set to 1. The observation error probabilities p_k were all set to 0.01, and block length

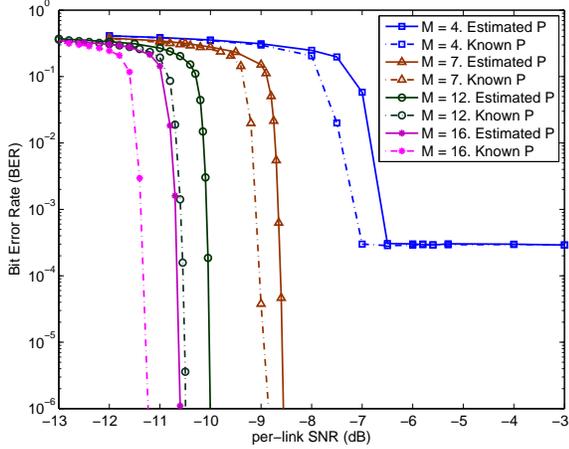


Fig. 5. BER performance comparison for different number of sensors.

was 10^3 bits. We performed 25 *GIs* for \mathbf{P} estimation. The channels between sensors and the FC are independent AWGN channels, where the channel coefficient $h_k = 1$. Fig. 5 shows the BER performances for the cases where $\hat{\mathbf{P}}$ and \mathbf{P} are used at the FC, with the numbers M of sensors as a parameter. The other transmission parameters are the same as for Fig. 4. In the observation error probability estimator, T and ϵ were set to 2 and 10^{-6} , respectively, and the maximum iteration times, IT_m , were set at 20. The channels are assumed to be the same as in Fig. 4.

The BER performances in the case sensors-FC links suffer from block Rayleigh fading are shown in Fig. 6. We also evaluate the gain with *GI* over without *GI* in Rayleigh fading channel. We can still achieve around 4 dB gain when $M = 8$ at 10^{-4} BER range. Furthermore, it is found that the BER curves obtained by using actual \mathbf{P} and its estimate $\hat{\mathbf{P}}$ are very close (around 0.2 dB loss) with each other.

It is found from the figure that the BER performance can be improved by increasing the number of sensors M . With $M = 4$, the error floor can not be reduced to less than 10^{-4} by increasing per-link SNR, however it can be reduced to less than 10^{-6} with $M \geq 7$. Nevertheless, we believe that it is impossible to totally eliminate the error floor, even though it may happen at a very small BER region. The reason is because we can not completely eliminate the distortion due to the observation error, which is common to the CEO problems. Compared with the case where \mathbf{P} is known, only 0.3–0.5 dB loss in per-link SNR is observed when using estimated $\hat{\mathbf{P}}$, where the loss depends on M . Furthermore, our proposed technique has around 1–3 dB improvement in per-link SNR compared with the scheme proposed in [9].

VI. CONCLUSION

In this letter, we have investigated for a parallel wireless sensor network the transmission techniques of data gathered by multiple sensors to the fusion center. We first proposed a new algorithm that, instead of exploiting the correlation knowledge over all the possible combinations of the sensor pairs, combines the local and the global iterations to avoid the necessity of heavy computational complexity. We also

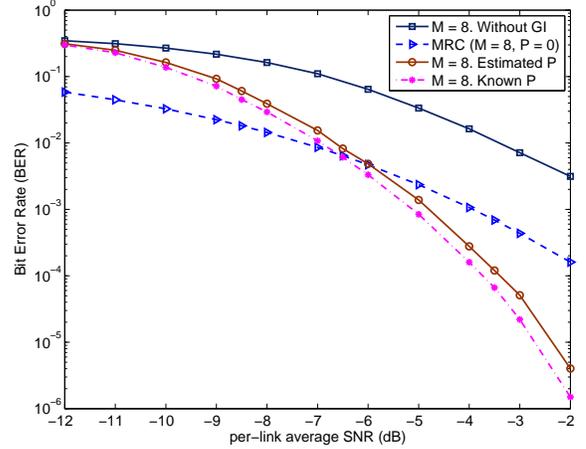


Fig. 6. BER performance in block Rayleigh fading channels.

proposed a nonnegative constrained iterative algorithm to estimate the observation error probabilities. It has been shown through simulations that the algorithm converges only after several iterations. In addition, the results of BER performance show that the proposed technique using $\hat{\mathbf{P}}$ can achieve only roughly 0.3–0.5 dB loss in per-link SNR compared to the case actual \mathbf{P} is used in static AWGN channel, and 0.2 dB loss in Rayleigh fading channel.

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