Optimally Mapping an Iterative Channel Decoding Algorithm to a Wireless Sensor Network

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***Abstract* –Retransmission based schemes are not suitable for energy constrained wireless sensor networks. Hence, there is an interest in including parity bits in each packet for error control. From an information-theoretic perspective the most efficient usage of network capacity can be achieved by performing full encoding/decoding at each node and using a variable rate in accordance with the link-quality. However, such an approach represents a major burden on power-constrained sensors. In this paper, we propose a more practical approach that is based on optimally distributing iterative channel decoding over sensor networks. In such a paradigm, the guarantee with which the base station, or *collector*, gets the data from a sensor is a function of the processing within the intermediate nodes between source and destination (in-network processing). There are two extreme cases: a) Complete channel decoding at each hop and b) decoding only at the final destination. In this paper, we present a novel scheme in which intermediate nodes conduct partial decoding of LDPC coded packets. In this scheme each node is assigned some number of decoding iterations. The relay node conducts LPDC decoding for that number of iterations and forwards the packet, without ensuring a complete error correction. We show that such partial processing is sufficient to improve the end-to-end reliability significantly. Additionally, we show that it is feasible to tradeoff complexity/energy usage with distortion/reliability by varying the assignment of number of iterations. Finally, we present a low-complexity dynamic programming algorithm that optimally assigns iterations within the network to facilitate operation along an optimal *energy-distortion* curve.**

***Index Terms* – partial processing, LDPC, sensor networks**

I. Introduction

In sensor networks, information passes through multiple hops before reaching the final destination. Further, parity bits can be included with each information packet to introduce robustness against channel induced errors. “Full processing” and “forwarding” represent two extremes of in network processing. *Full processing* implies complete decoding and re-encoding the information sent by the source without considering any complexity or delay constraints, thus achieving the channel capacity. Under *forwarding*, each intermediate node is only allowed to forward the received information without any processing thus significantly reducing the achievable data rate (assuming no path diversity). Most of the network applications have complexity or delay constraints and full processing may not be feasible. *Partial processing* bridges the gap between the two schemes**,** where intermediate nodes conduct finite processing before forwarding the incoming data. Allowing intermediate link nodes to perform finite complexity processing achieves a significant portion of the ultimate capacity in fairly noisy networks [21].

In this paper, we consider the following scenario. Sensors transmit information to a final receiver (base station or collector) by routing packets over a sensor network, represented by a graph, and examine optimally increasing the overall throughput that some finite-complexity processing at intermediate nodes may offer. In particular, we propose a novel scheme in which intermediate nodes do partial decoding of incoming packets, and then forward them to a subsequent hop. This leads to a significant throughput enhancement at the destination. We also present a dynamic programming algorithm to optimally assign decoding iterations for iterative decoding over the multi hop network that trades off complexity/energy usage with distortion/reliability. We use fixed rate Low Density Parity Check codes to demonstrate our algorithm. The algorithm is specifically useful for wireless sensor networks where nodes do not have sufficient resources to completely decode and re-encode the messages, and retransmission based schemes prove to be too expensive.

We refer to our scheme as Embedded Partial Decoding (EPD). Under EPD, an intermediate relay node partially decodes the incoming channel-coded data using lesser number of iterations than required for complete decoding. Hence, at each sensor node, a received packet is partially decoded and sent over the next hop without addition of further parity. At the final destination, a complete decoding takes place by the relatively powerful central processor.

Systems with Forward Error Correction (FEC) can provide objective reliability with lesser transmission power than those without FEC [1]. Due to resource limitation of the sensor nodes, only few works have been done on channel coding in wireless sensor networks. Shih et al propose a scheme based on convolutional codes for FEC in sensor network [7] whereas Sankarasubramaniam et al [2] propose use of BCH codes. Mina et. al [1] presented a framework in which they consider combined source and channel coding with LDPC codes for sensor networks. All these works consider *end-to-end* error correction and thus cater to the worse case scenarios at intermediate forwarding links, adding significant burden over channels with higher signal to noise ratio. Ideally, from an information theoretical point-of-view, the most efficient use of network resources can be achieved with variation of channel coding rate in accordance with the link-quality; however, due to practical considerations associated with puncturing of LDPC codes [15], the channel coding rate in our work is maintained at a fixed value. In terms of power consumption, transmitting a single bit of data is equivalent to 800 instructions in a sensor mote [17]. Thus, energy tradeoff between communication and computation makes a case for processing the data inside the network rather than simply transmitting the sensor readings. Therefore, for improved reliability of data from a source node to the collector and conservation of energy, in-network processing can be highly beneficial. The proposed EPD scheme ensures this by partial decoding of packets and hence enhancing the reliability at the destination with introduction of minimal complexity.

The remainder of the paper is organized as follows. We formulate the EPD problem in Section II. Section III presents LDPC codes and associated concentration theorem that are relevant to the proposed EPD approach. Section IV describes the proposed dynamic programming algorithm for mapping in-network iterative decoding. Section V provides simulation results and discussion, with conclusion and further directions in Section VI.

II. Problem Formulation

A multi-hop wireless channel can be represented as a cascade of channels. Consider a line network with N nodes in cascade. All nodes are considered equally important with every node capable of decoding the received packets. The links between the nodes are assumed to be BSC with each node transmitting at power level P_T per bit.

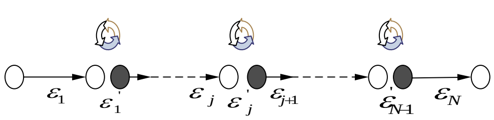

Figure 1. A Multi hop network with in-node processing

Relay nodes are allowed not only to forward the incoming information, but also to process it.

In order to obtain channel error probability for a binary symmetric channel (BSC), the general expression for Signal to Interference Noise Ratio (SINR) can be given as in (1):

$$SINR = \frac{P_T}{P_A + \sum P_{\text{int}}} \qquad (1)$$

where P_A is the ambient noise power, and P_{int} is the interference power of any concurrent transmissions elsewhere in the network. Sources of ambient noise may include other devices operating in the same frequency band or other networks co-located with the WSN. Let $\{n_t; t \in T_x\}$ be the subset of nodes simultaneously transmitting over a certain subchannel, with transmit power P_t for each node. Then the SINR at node n_j for a transmission from node n_i, $i \in T_x$ can be calculated as in [9]:

$$SINR = \frac{\dfrac{P_i}{d(n_i, n_j)^{\alpha}}}{P_A + \sum\limits_{\substack{t \in T_x \\ t \neq i}} \dfrac{P_t}{d(n_t, n_j)^{\alpha}}} \qquad (2)$$

Where $d(n_i, n_j)$ is the separation between n_i and n_j, and $\alpha > 2$.

If $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{-\frac{u}{2}} du$, then the channel error probability ε as described in [18] is:

$$\varepsilon(n_i) = Q(\sqrt{2(SINR(n_i)})) \qquad (3)$$

The source node n_0 generates k message bits which are encoded using a rate R code. The resulting codeword is transmitted over the first link with error probability ε_1. Node n_1 performs l_1 LDPC decoding iterations and the bit error rate in the resulting packet is a function of ε_1 and l_1:

$$\varepsilon_1^{'} = f(\varepsilon_1, l_1) \qquad (4)$$

After partial processing at the second node, the error rate in the resultant packet is:

$$\varepsilon_2^{'} = f(\varepsilon_2, l_2) * \varepsilon_1^{'} \qquad (5)$$

where $\varepsilon_1 * \varepsilon_2 = \varepsilon_2(1-\varepsilon_1) + \varepsilon_1(1-\varepsilon_2)$. (6)

For the cascade line network, we define the total number of decoding iterations $\Gamma(\overline{l})$ in the entire network as:

$$\Gamma(\overline{l}) = \sum_{j=1}^{N-1} l_j \qquad (7)$$

where l_j is the number of decoding iterations at node n_j.

For N hops in cascade, the overall distortion measure D can be expressed as:

$$D = f(f(f(f(\varepsilon_1, l_1)*\varepsilon_2, l_2)*...\varepsilon_j, l_j)*...\varepsilon_{N-1}, l_{N-1})*\varepsilon_N \qquad (8)$$

For $\Gamma(\bar{l}) \le \Gamma(\bar{l})_{budget}$, we intend to find an iteration assignment vector $\bar{l}$ in such a way that the net throughput is maximized at the final destination. Conversely, $D(\Gamma)$ is minimized. We refer the tuple $\left[D, \Gamma(\bar{l}), \bar{\varepsilon}\right]$ as Network Throughput Measure (NTM).

The problem can be seen as a budget constrained allocation problem, such that D is minimized subject to constraint $\Gamma(\bar{l}) \le \Gamma(\bar{l})_{budget}$. From the constraint highlighted above, our problem becomes similar to minimizing a distortion measure given a budget constraint under a rate distortion framework. Therefore, an algorithm providing NTM operating point with minimum distortion D while remaining within budget constraint is needed.

III. LDPC Codes for Embedded Partial Decoding

Low Density Parity Check Codes have gained considerable attention due to their near capacity performance. Gallager provided an algorithm for decoding of LDPC codes that is near optimal [5]. The algorithm iteratively computes the distribution of variables in graph-based models, and comes under different names/variations including Sum Product Algorithm (SPA), Belief Propagation Algorithm (BP), or more generally, Message Passing Algorithm (MPA). Urbanke et.al, in [8] give a concentration theorem for LDPC codes for a wide variety of channels stated below.

LDPC Concentration Theorem

Let $P_e^n(l)$ be the expected fraction of incorrect messages which are passed in the l th iteration of LDPC decoding, where expectation is over all instances of the code, the choice of the message and realization of the noise. For any $\delta > 0$, the probability that the actual fraction of incorrect messages which are passed in the l th iteration for any particular such instance lies outside the range $(P_e^n(l) - \delta, P_e^n(l) + \delta)$ converges to zero exponentially fast in n.

The theorem asserts that (almost) all LDPC codes behave alike and so the determination of the average behavior of the ensemble suffices to characterize the individual behavior of (almost) all codes [8]. Any code from the LDPC ensemble would have performance approaching exponentially fast in n to the mean of the ensemble. For t simulations, we employ a rate ½, (3, 6)-regular Progressive Edge Growth [11] based LDPC code for message length $k = 1024$ bits and the results achieved would have small deviation from the ensemble mean. We use a log-domain Sum Product Algorithm (LSPA) [5] for iterative decoding of the code which has advantages in terms of implementation, computational complexity and numerical stability [12] which is critical in the context of sensor networks. Figure 1 shows the expected bit error rate with variation in number of decoding iterations for different channel error probabilities averaged over 1000 runs.

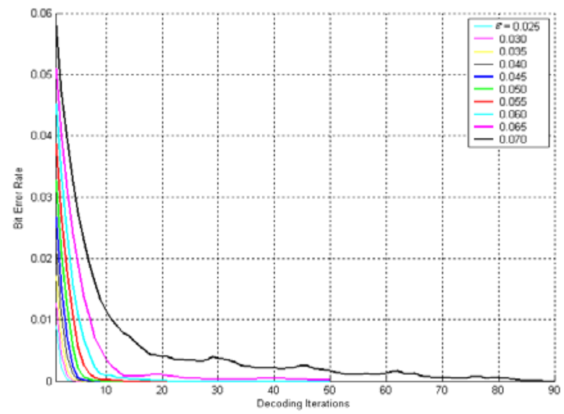

Figure 2. Bit Error Rate as a function of Decoding iterations and Channel Error probability for a rate ½ PEG LDPC code

Based on the above observations, we develop an exponentially decaying statistical model for the variation of bit error rate with decoding iterations. Equation (9) expresses the relationship between the estimated bit error rate $\hat{f}$ for a given channel error probability ε and the number of decoding iterations l for our code as

$$\hat{f}(\varepsilon_{ind}, l) = \alpha(\varepsilon_{ind}) e^{\beta(\varepsilon_{ind}) l} + \gamma(\varepsilon_{ind}) e^{\psi(\varepsilon_{ind}) l} \qquad (9)$$

Where $\varepsilon_{\min} \le \varepsilon \le \varepsilon_{\max}$, $0 < l \le l_{\max}$, ε_{ind} is the corresponding index value with respect to $\varepsilon_{\min}$ and the coefficients $\alpha(\varepsilon_{ind})$, $\beta(\varepsilon_{ind})$, $\gamma(\varepsilon_{ind})$ and $\psi(\varepsilon_{ind})$ attain the values listed in Table 1.

TABLE I

Coefficients $\alpha(\varepsilon_{ind})$, $\beta(\varepsilon_{ind})$, $\gamma(\varepsilon_{ind})$ and $\psi(\varepsilon_{ind})$ With $\varepsilon_{\min} = 0.025$, $\varepsilon_{\max} = 0.07$, $l_{\max} = 150$

ε_{ind}	$\alpha(\varepsilon_{ind})$	$\beta(\varepsilon_{ind})$	$\gamma(\varepsilon_{ind})$	$\psi(\varepsilon_{ind})$
1	-0.694600	-0.376200	0.712600	-0.384100
2	-0.971500	-0.471100	0.998500	-0.478300
3	-1.170000	-0.481300	1.206000	-0.488300
4	-1.126000	-0.415400	1.167000	-0.422300
5	0.311300	-1.090000	-0.307900	-1.377000
6	0.175600	-0.921000	-0.266100	-1.963000
7	0.435400	-0.668200	-0.389400	-0.748000
8	0.050130	-0.365200	0.017250	-0.368100
9	0.068400	-0.271100	0.000198	0.000539
10	0.009578	-0.040290	0.063590	-0.245600

The Root Mean Square Error in our statistical model is shown in figure 3.

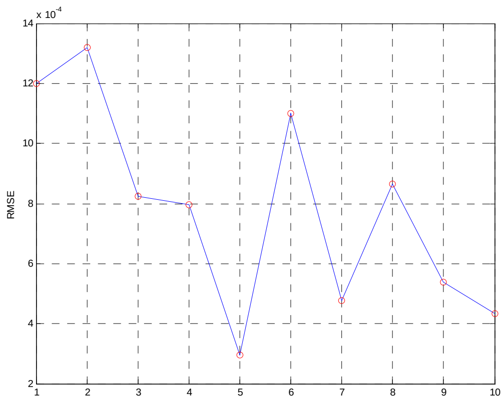

Figure 3. Root Mean Square Error for $f(\varepsilon, l)$ and $\hat{f}(\varepsilon_{ind}, l)$

Therefore, significant enhancements in performance can be achieved as the number of LDPC decoding iterations are increased at the receiver provided the channel error probability is below the achievable performance bound [14] for the ensemble of codes. This result can be used to formulate an in-network processing framework to maximize the achievable reliability at the destination.

IV. Optimal Mapping of an Iterative Channel decoding Algorithm to a wireless sensor network

For the proposed EPP scheme, we are looking for an optimal tuple $\left[D, \Gamma(\bar{l}), \bar{\varepsilon}\right]$ such that $\Gamma(\bar{l}) \leq \Gamma(\bar{l})_{budget}$ i.e. a minimal overall bit error rate that meets the budget constraint. The problem can be viewed as one that allocates the overall iteration budget $\Gamma(\bar{l})_{budget}$ among all nodes in the network such that distortion is minimum.

The computational complexity of optimally mapping the iterations to the network is high, as NTM region consists of all possible operating points obtained by choosing all possible combinations of iteration assignments within the budget constraint. The hull of the NTM region would provide the desired optimal solution.

We first solve the problem for a single path line network, which can then be mapped to the entire network.

A. Dynamic Programming Approach

To find out the optimal hull of NTM region, we employ a dynamic programming approach similar to the method used in determination of the RD region for optimal quantizer design [6]. The algorithm stated is greedy in nature and it is possible that it may not find the optimum tuple $\left[D, \Gamma(\bar{l}), \bar{\varepsilon}\right]$, though it does provide optimal solution under various practical scenarios ([3], [10],[6]).

The starting point of our algorithm is the case when no iterations are assigned to any intermediate nodes. Hence, D is maximum and $\Gamma(\bar{l})$ minimum. Thus the tuple $\left[D^0, \Gamma(\bar{l})^0, \bar{\varepsilon}\right]$ has D^0 closest to the D axis. The algorithm then adds a single iteration to intermediate nodes, one by one in a greedy fashion, and selects the node where the minimum D is achieved. This provides the next operating point $\left[D^1, \Gamma(\bar{l})^1, \bar{\varepsilon}\right]$. The procedure is repeated till $\Gamma(\bar{l}) \leq \Gamma(\bar{l})_{budget}$ is satisfied and all the iterations are now assigned.

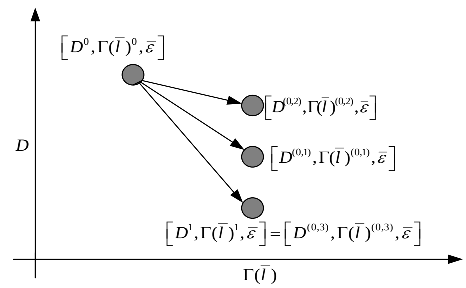

Figure 4. Selection of Next Optimal Point $\left[D^1, \Gamma(\bar{l})^1, \bar{\varepsilon}\right]$ for Dynamic Programming algorithm

Thus, the algorithm maximizes the separation between optimal point achieved in the prior run D^- and the new points D^+ obtained in the current run for all intermediate nodes on the path. This corresponds to maximizing the gradient between the two points.

Mathematically, we have:

$$\bar{l} = \arg\max_{j=1:N-1} \left[\frac{D^- - D^+}{\Gamma(\bar{l}^-) - \Gamma(\bar{l}_j^+)} \right] \qquad (10)$$

Where, we take $\Gamma(\bar{l}^-) - \Gamma(\bar{l}^+) = 1$.

For extension of the algorithm to a multi hop multi path network with all nodes transmitting to a central base station, we conduct optimal iteration assignments on individual paths to obtain assignment vector $\bar{l}$ and distortion D for each path. The distortion is then averaged over all paths, from sources to base station, to obtain cumulative bit error rate.

V. Simulations and Analysis

We consider a wireless sensor network consisting of N nodes spread over a $10m$ x$10m$ square grid according to a random distribution. We place the base station at coordinates (5, 5) and limit the transmission range of individual sensor nodes to a maximum transmission range

$r = 2m$. Figure 6 shows the wireless sensor network topology for $N = 150$ nodes.

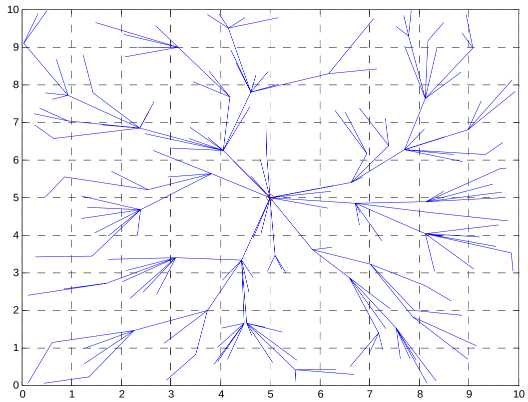

Figure 6. Network Topology for WSN with $N = 150$

Since the most widely used wireless sensor network routing algorithms (DSR, AODV, Directed Diffusion) are different forms of shortest path routing algorithms, we assume that at any given time the routes from individual nodes to the base station form a tree rooted at the base station [20]. We are thus discounting the possibility of using bifurcated routing i.e. multiple paths from source to destination. Hence, we assume that all the network nodes sending traffic back to the base station on shortest paths already established through some routing algorithm. We take per bit transmit power $P_T = 1mW$, per second, for each node.

For the proposed EPD algorithm, we assume that if $\varepsilon < \varepsilon_{\min}$, only one iteration is sufficient to completely decode the LDPC code, which is the behavior of our code on average and is depicted from the trend in figure 2 for the (3,6)-regular LDPC code. The node behaves as a forwarding node if either $\varepsilon > \varepsilon_{\max}$ or no iteration is assigned to it. We set $\varepsilon_{\max} = 0.07$ (See [14] and [8] for tighter bound on $\varepsilon_{\max}$). For each path, we fix $\Gamma(\bar{l})_{budget} = 60$ iterations.

Fossorier et al. in their work on low complexity LDPC iterative decoding [16], tabulate a comparison of mathematical operations required for one iteration of various LDPC decoding algorithms including MPA. Assuming each node a sensor mote equipped with Atmel Atmega128L processor, and 800:1 ratio between per bit transmit energy and computation energy spent per instruction, the performance curves for EPD scheme against computation energy spent for partial decoding of LDPC coded message at intermediate nodes, averaged over all paths in the network, is shown in figure 7.

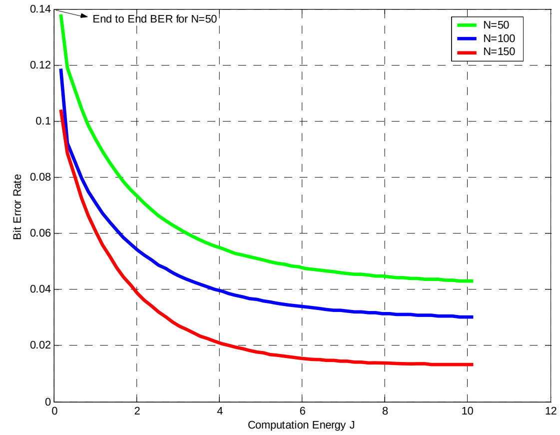

Figure 7. Optimum curves for Average Bit Error Rate vs. Computation Energy spent for the proposed embedded partial decoding of LDPC coded messages at intermediate sensor nodes.

The above plots show that it is feasible to optimally trade-off complexity/energy usage with distortion/reliability by varying the assignment of iterations. The two extremes of the Complexity–Distortion curve in Figure 7 represent the performance that is offered when two extremes of in-network processing is employed. When we do not conduct any decoding at intermediate nodes, the accumulation of errors increases exponentially. In such a scenario a large number of packets eventually received at the collector may have zero or very little information utility. In other extreme when decoding is employed at all or almost all the intermediate nodes, the data reliability can be increased significantly, but the energy consumption is also significant. Thus, in such an operation mode, even though the throughput of a sensor network is improved, the network life-time is decreased significantly. Our proposed approach allows us to fine-granularly operate at a large number of intermediate points. Thus in an actual deployment, the operating point can be chosen in accordance with the current demands of the network. If an important event is being sensed, we may choose to operate at high in-network processing point, as against that if the network is in more passive state, we may prefer saving energy despite getting noisy readings.

The results in Figure 7 show that as the number of nodes increase the amount of in-network processing required to achieve improvement in reliability reduces. This can be explained by highlighting that, as the node density increases, the number of error prone links decrease. Since error recovery is primarily required only due to the presence of noisy links, decrease in the number of noisy links naturally leads to reduced requirement of network processing. The above observation has important implications about adapting the functional usage of a sensor network through its life-time. We illustrate our point by way of an example: Let us say that a network initially composed of 150 sensors demands a functional usage represented by a error probability of 0.04. To support such a demand with in-network processing, we shall have to spend 2 Joules. With time as sensors die the density of sensors reduces, lets say our density drops to 100 sensors. At such point if the functional demand is not reduced the amount of energy that will have to be spent is infact increased to 4 Joules. This increase in energy spending may set-off a chain reaction eventually leading to the death of a *network*. Thus, as the density reduces, it may be essential to adapt the functional demands from a network. The Complexity-Distortion curves obtained by our analysis can provide important guidelines on how these demands should be reduced as sensors start dieing.

VI. Conclusion

We have presented an Embedded Partial Decoding scheme that enhances the decoding reliability at the receiver by processing within the network through partial decoding of data within sensor networks. We provide an algorithm that optimally maps the decoding iterations to the intermediate nodes for enhanced reliability at the destination. We give bounds on the performance of the algorithm for computational energy spent within the network for partial decoding of ensembles of LDPC codes. One extension of the proposed approach is employing similar procedures that can be used with varying code lengths and choice of channel codes. Another extension of our work, in preparation, is introduction of fairness in assignment of iterations such that nodes closer to the base station are not over burdened. This can be achieved through introduction of cost factors that take into consideration the reach-back problem in sensor networks [4].

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