

Information Flow Based Routing Algorithms for Wireless Sensor Networks

Yeling Zhang
Department of Computer
and Information Science
Polytechnic University
Brooklyn, NY 11201
Email: yzhang@cis.poly.edu

Mahalingam Ramkumar
Department of Computer
Science and Engineering
Mississippi State University
Mississippi State, MS 39762
Email: ramkumar@cse.msstate.edu

Nasir Memon
Department of Computer
and Information Science
Polytechnic University
Brooklyn, NY 11201
Email: memon@poly.edu

Abstract— This paper introduces a measure of information as a new criteria for the performance analysis of routing algorithms in wireless sensor networks. We argue that since the objective of a sensor network is to estimate a two dimensional random field, a routing algorithm must maximize information flow about the underlying field over the life time of the sensor network. We develop two novel algorithms, MIR (Maximum Information Routing) and CMIR (Conditional Maximum Information Routing) designed to maximize information flow, and present a comparison of the algorithms to a previously proposed algorithm - MREP (Maximum Residual Energy Path) through simulations. We show that the proposed algorithms give significant improvement in terms of information flow, when compared to MREP.

Index Terms— wireless sensor networks, information flow based routing

I. INTRODUCTION

Advances in microwave devices and digital electronics have enabled the development of low-cost, low-power sensors that can be wirelessly networked together to give rise to a sensor network. Applications of sensor networks range from early forest fire detection and sophisticated earthquake monitoring in dense urban areas, to battlefield surveillance [1] and highly specialized medical diagnostic tasks where tiny sensors may even be ingested or administered into the human body [2]. Given this wide range of applications, wireless sensor networks are poised to become an integral part of our lives.

Though related, wireless sensor networks are very different from mobile ad hoc networks. In wireless sensor networks, the sensor nodes are usually deployed very densely, and each sensor is more prone to failure. Each sensor node, as a micro-electronic device, can only be equipped with a limited power source (< 0.5 Ah, 1.2 V) [1]. For instance, the total stored energy in a *smart dust mote* is on the order of 1J [3]. Furthermore, in most applications, sensor nodes, once placed, do not change their location over their lifetime. Hence, given the difference between the inherent nature of network nodes and topologies in sensor networks and mobile ad-hoc networks, fundamentally different approaches to network design are required.

One area where mobile ad hoc networks and sensor networks differ significantly is in the design of routing protocols. For mobile ad hoc networks, routes are typically computed

based on minimizing *hop count* or *delay*. However as the limit of battery power is one of the most fundamental limitations in sensor networks, routing algorithms for sensor networks generally try to minimize the utilization of this valuable resource. Many researchers have proposed techniques to minimize utilization of energy. For example in Low-Energy Adaptive Clustering Hierarchy (LEACH) [4], Power-Efficient Gathering in Sensor Information Systems (PEGASIS) algorithm [5], and the Geographical and Energy-Aware Routing (GEAR) algorithms [6], the limitation on hop count is replaced by power consumption.

Instead of looking at power consumed by individual nodes, one can also examine energy consumed per bit as one of the obvious metrics for evaluating the efficiency of a sensor network deployment. In this context, the Minimum total Transmission Power Routing (MTPR) algorithm [7] attempts to reduce the total transmission power per bit. The Min-Max Battery Cost Routing (MMBCR) algorithm [8] considers the remaining battery power of nodes to derive efficient routing paths. The Sensor Protocols for Information via Negotiation (SPIN) algorithm [9] attempts to maximize the data disseminated for unit energy consumption. Ref. [10] proposes combining power and delay into a single metric. They developed a scheme for energy \times delay reduction for data gathering in sensor networks.

It was also realized by the sensor network research community that improving the ratio of information transmitted to power consumed by the network is by itself not a good measure of the efficiency of the network. For example, if such an approach causes fragmentation of the network, where some nodes exhaust their power completely while leaving many nodes with significant amounts of unused power (which may be useless if they also do not have neighbors with power left to relay their messages), then energy efficiency does not translate to efficiency of the entire deployment. Recognizing this issue, some researchers have also proposed methods to utilize to the fullest possible extent, the energy of all nodes. Ref. [11] for instance tries to minimize variation in node power levels. The intuition behind this is that all nodes in network are equally important and no one node must be penalized more than any of the others. This metric ensures that all the nodes

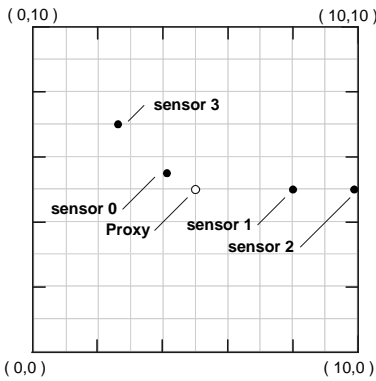


Fig. 1. Example network configuration that illustrates difference in information flow to the proxy over lifetime of network for two different routing strategies.

in the network remain up and running together for as long as possible. In MREP (Maximum Residual Energy Path) [12], which we shall review later, the authors try to achieve this by calculating routing paths that postpone the time of death (running out of battery power) of the first node.

However, the fact that the routing paths are chosen in such a way that all nodes die at the same time does not automatically imply that the energy utilization is optimal. As an extreme case, we can easily see that if appropriately selected subset of nodes are forced to be part of the route for every transmission, it may cause the nodes to “die simultaneously.” But obviously this does not amount to efficient utilization of resources. Therefore, neither a large ratio of transmitted bits to the total energy utilized nor the “uniformity” of expending every node’s resource, by themselves, indicate optimality of the network. This clearly calls for an alternate metric for the evaluation of the performance of sensor networks.

To illustrate our point further, consider the example of Figure 1, where four sensors are deployed on a 10×10 grid at points Node 0 – (4.14, 5.5), Node 1 – (8.0, 5.0), Node 2 – (9.99, 5.0) and Node 3 – (2.54, 7.00). The four sensors measure and relay the information to a “proxy” in the center of the grid at location (5.0, 5.0). Two obvious ways to achieve transfer of information from the sensors to the proxy are:

- 1) Direct path transmission, where each node directly transmits information to the proxy, and
- 2) Shortest path algorithm, by relaying through shortest paths.

If each node is equipped with 500 units of power at the beginning, and each node transmits one unit of information every unit time, and each unit of transmission through a distance d requires d^2 units of power, the direct path algorithm would result in the death of node 2 at 20 units of time, node 3 at 31 units, node 1 at 55 units and node 0 at 500 units. The shortest path algorithm on the other hand would cause node 1 to die at time 28, node 2 at 43, node 3 at 55 and node 0 at time 444. It is not immediately obvious as to which scenario is preferable. The direct path results in the nodes 2 and 3 dying

faster. But the scenario is not bad even after the two nodes die as nodes 0 and 1 on either side of the proxy are still alive. It is therefore still possible to gather some meaningful information from these remaining nodes. On the other hand, even though the shortest path algorithm prolongs the time it takes for two nodes to die (nodes 1 and 2 in the example), the death of these results in a situation where the proxy is not able to get any measurements from one side (as both 1 and 2 are dead). It is intuitive that after the death of nodes 2, 3 (direct path) the network retains the capability to provide more meaningful information as compared to after the death of nodes 1 and 2. This indicates the need for a suitable metric to evaluate the performance of sensor networks.

One of the main motivations of this paper is therefore the choice of a new metric for evaluation of the performance of sensor networks. We propose the use of *total information* delivered by a network, under the constraint of expendable battery power available to each node. It is very important to realize here that total information delivered is not the same as the total number of bits that are transmitted. This is due to two reasons. The obvious reason is that the number of bits transmitted also depend on the number of hops. A bit sent by a sensor node to the proxy may travel through multiple intermediate nodes and hence get re-transmitted multiple times. The second, and from our point of view the more important, reason is that not all bits are equal. Some bits carry more “information” than others. This fact can be understood if one recalls that any deployment of wireless sensors is expected to provide the user with intelligence and a better understanding of the environment in which they have been deployed. The sensors for instance may be measuring some field which may be thermal, acoustic, visual, or infrared. The measurements would then be relayed to a central proxy, which would then relay the information to the end user. What the user cares about is the total information the network delivers *about the underlying random field that is being measured (sensed)* (under a given constraint of battery power in each node). Hence information is a natural evaluation metric for the performance of a wireless sensor network. The question arises as to how can we suitably quantify this metric.

Now, it is clear that the total information received by the proxy depends on the information originating from each node, and the life of each node. Also, the information originating from a node at any point in time also depends on the number of nodes that are “alive” at that point in time, and the spatial location of the nodes. For instance if two nodes are very close to each other (and the field that is being measured is continuous), then there exists a high correlation between the data originating from the two nodes. The total information from both nodes in this case may be very close to the information originating from just one node. As a more concrete example, in the example of four nodes we investigated earlier, the information from node 1 becomes more important after the death of node 2.

In this paper, we present a measure for the information originating from each sensor node based on the differential entropy of a random field model. This gives us a metric to

evaluate the performance of a sensor network in terms of the total information received by the proxy over the lifetime of the network. Note that we define “lifetime” as the time until some fraction of the nodes in the network die (completely deplete their power), which may be more practical than earlier definitions that used time to first node death as lifetime. We then present two information flow based routing algorithms, Maximum Information routing (MIR) and Conditional Information routing (CMIR), that focus on maximizing the proposed metric, i.e., total information flow from the wireless sensor network during its lifetime.

The rest of the paper is organized as follows. Section 2 introduces an information measure based on differential entropy of the sensor measurements and provides a description of the problem and our objectives. Section 3 presents the two novel routing algorithms (MIR and CMIR) and a brief overview of the MREP algorithm [12], against which the two novel algorithms are compared in Section 4. Conclusions are offered in Section 5.

II. PROBLEM SETTING

Consider a square field of wireless sensors, measuring samples of a first-order Gauss-Markov process with correlation ρ , which is widely used to model spatially smooth measurements [13] (e.g. the atmospheric sensing system for wind analysis near major aircraft by Federal Aviation Administration(FAA) [14]). A proxy is located at the center of the field, which has significantly more processing power for further processing of the information it receives from various nodes, and energy to guarantee transmission range large enough for the delivery of the information to a possibly larger network for retrieval by the end user. A certain number of sensors are assumed to be randomly dropped in the field. The sensors measure a sample of the Gauss-Markov field (which may be acoustic, magnetic, or seismic information) and send the information to the proxy. Each sensor is constrained by the same limitation on available battery power and has power control to expend the minimum required energy to reach the intended recipients and to be turned off to avoid receiving unintended transmissions. The energy expenditure for transmission from node i to j is proportional to d_{ij}^α , where d_{ij} is the distance between node i and j , and α is between 2 and 4 [15]. We choose $\alpha = 2$ as the path loss exponent for free space propagation in the paper. When one node breaks down due to exhaustion of its battery, we assume the node is “dead” for the entire remaining lifetime of the network. An example of such a scenario is shown in Figure 2.

In sensor network literature, several different definitions have been proposed for the “lifetime” of a network. Ref. [16] defines “lifetime” as the time till the first sensor “dies”. Ref. [17] considers lifetime as the time till all sensors die. The definition of “lifetime” should obviously depend on the nature of the application. For instance, for applications like surveillance, it may be crucial that all sensors be alive. So even the death of one sensor may end the “useful” life of the network. In practice, as nodes keep dying, at some point,

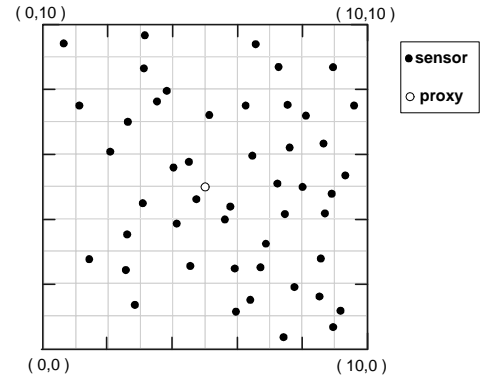


Fig. 2. Example sensor network of randomly scattered sensors in a square and proxy in the center of the field.

the total information that is delivered from the network to the proxy keeps reducing. At some point when the total information delivered by the network is below some threshold, it may, for instance, not be worthwhile for the proxy to keep operating. So a network with only few sensors alive may be useless. To avoid the two extreme definitions of lifetime, we use lifetime as the time until β of the total sensors die, where $0 < \beta < 1$.

Now that we have defined the framework under consideration, let us examine the total information originating from a wireless sensor network as the one shown in Figure 2. We consider the measurement x_i of the i 'th node as a Gaussian random variable. We shall assume further, without any loss of generality, that the measurements constitute samples of a unit variance Gaussian distribution. The covariance matrix $|\mathbf{K}|$ of the n measurements x_0, x_1, \dots, x_{n-1} is then

$$\begin{pmatrix} E[x_0, x_0] & \dots & E[x_0, x_{n-1}] \\ \vdots & \ddots & \vdots \\ E[x_{n-1}, x_0] & \dots & E[x_{n-1}, x_{n-1}] \end{pmatrix} \quad (1)$$

If the field is isotropic and Gauss-Markov with a correlation coefficient of ρ , the covariance matrix \mathbf{K} can be written as

$$\begin{pmatrix} \rho^{d_{0,0}} & \dots & \rho^{d_{0,n-1}} \\ \vdots & \ddots & \vdots \\ \rho^{d_{n-1,0}} & \dots & \rho^{d_{n-1,n-1}} \end{pmatrix} \quad (2)$$

where $d_{i,j}$ is the distance between x_i and x_j .

A measure of the total information delivered by the sensors in the field is then given by the differential entropy of the multivariate Gaussian distribution, or,

$$h(X) = \frac{1}{2} \log((2\pi e)^n |\mathbf{K}|) \quad (3)$$

Now, if one node x_j dies, then the information provided by the remaining nodes is

$$I_1 = h(X_1) = \frac{1}{2} \log((2\pi e)^{n-1} |\mathbf{K}_1|) \quad (4)$$

where $|\mathbf{K}_1|$ is the covariance matrix of the random variables $x_0, \dots, x_{j-1}, x_{j+1}, \dots, x_{n-1}$ - which is the matrix $|\mathbf{K}|$ with the j 'th row and column deleted.

Say that the first node dies at time t_1 , and the second at time t_2 and so on. In general, if we represent as t_i as the time at which the i 'th node dies ($t_0 = 0$) and $h(X_i)$ as the differential entropy (or the total information flow) of the network when i out of n nodes are dead, then

$$I_i = h(X_i) = \frac{1}{2} \log((2\pi e)^{n-i} |\mathbf{K}_i|), \quad (5)$$

where \mathbf{K}_i is a $(n-i) \times (n-i)$ covariance matrix obtained by removing the rows and columns of \mathbf{K} corresponding to the i dead nodes. The total information provided by the network during its "lifetime" (or till β of the total nodes die) is given by

$$I_{total} = \sum_{i=1}^{\lfloor \beta n \rfloor} I_{i-1}(t_i - t_{i-1}). \quad (6)$$

The objective therefore is to maximize I_{total} . That is, given a random deployment of n sensors in the grid, to develop a strategy for routing the measurements from each sensor to the proxy such that I_{total} is maximized. We try to achieve this by the routing algorithms proposed in the next section.

III. ROUTING ALGORITHMS FOR MAXIMIZING INFORMATION

In this section we present two routing algorithms, MIR and CMIR, that focus on maximizing the information flow metric we have defined above. Before we explain our proposed routing algorithms, we first quickly review the MREP algorithm [12] as it serves as the basis of our constructions.

A. MREP Algorithm

MREP has been shown an effective routing scheme for energy conservation [12]. It is assumed that the limited battery energy is the single most important resource. In order to maximize the lifetime, the traffic is routed such that the energy consumption is balanced among the nodes in proportion to their energy reserves, instead of routing to minimize the absolute consumed power (as in [18], [19]). The authors in [12] also showed that ("necessary optimality condition") if the minimum lifetime over all nodes is maximized then the minimum lifetime of each path flow from the origin to the destination with positive flow has the same value as the other paths. For a path $p \in P_i$, where P_i is the set of all paths from sensor i to the proxy as the destination, the path length L_p is defined as a vector whose elements are the reciprocal of the residual energy for each link in the path, after the route has been used for a unit flow. The routing path is therefore calculated for each unit flow. The vector of such link costs is represented by

$$c_{ij} = (\underline{E}_i - e_{ij}\lambda)^{-1}, \quad (7)$$

where $\underline{E}_{i,j}$ is the residual energy at node i , λ is a unit flow, and e_{ij} the transmission cost (per bit) from node i to node j . A lexicographical ordering was used in comparison

of the two length vectors to enable comparison of the largest elements first and so on. The shortest path from each node i to the destination is obtained using a modified version of the distributed Bellman-Ford algorithm [20] using the modified link costs. The flow then occurs via the the shortest path so obtained.

The central idea behind the MREP algorithm is to augment the flow on paths whose minimum residual energy after the flow augmentation will be the largest. In the simulations performed in [12], 20 nodes are randomly distributed in a square of size 5 by 5 among which 5 sensors and 1 proxy are randomly chosen and the transmission range of each node is limited by 2.5. The energy expenditure per bit transmission from node i to j is given by

$$e_{ij} = \max(0.01, \frac{d_{ij}}{2.5})^4 \quad (8)$$

where $d_{ij} \leq 2.5$ is the distance between nodes i and j . The cases where there is no path available between the sensor and the proxy are discarded. Simulation results indicate that the average gain in the system lifetime obtained by MREP is above 90% of the optimal, while that by shortest path algorithm is only about 75%.

B. MIR Algorithm

The crux behind the MIR algorithm is the realization that *not all nodes are equal*. For instance, it is easy to see that two nodes which are very close to each other do not provide twice as much information as a node which is relatively "lonely". This also means that the death of a node where two nodes are close does is not as worrisome as the death of the latter.

If $h(X)$ is the total information emanating from the network, and if ${}_jI = h({}_jX)$ is the total information of the network without the node j , then $h(X) - h({}_jX)$ can be considered as the node j 's "contribution" to the information of the network. Therefore we would ideally like for the nodes that "contribute" more information to stay alive longer. This is achieved in the MIR algorithm by adding an additional penalty related to information contribution of that node for all paths through that node. The "shortest" path is then calculated using Dijkstra's algorithm [20].

More explicitly, we define ${}_jI$ as the information provided by the network in the absence of the node j . So this means that "important" nodes would have smaller values of ${}_jI$. When we determine the weight of a link, the transmission power needed by a link is weighed by a factor proportional to $\frac{1}{{}_jI}$. As the ${}_jI$'s for different nodes are very close, we use $\frac{1}{\exp({}_jI)}$ as the weighting factor to amplify the role of the the elemental information supplied by a node. The penalty for a link from i to j is therefore heuristically proportional to

$$\frac{d_{i,j}^2}{\exp({}_jI)} \quad (9)$$

Though not explicitly shown in the equation above, ${}_jI$ is also a function of time - as nodes keep dying, ${}_jI$ changes. In this way, we direct the data to the sensor according to not only the

TABLE I

PERFORMANCE GAIN OF THE ALGORITHMS WITH RESPECT TO MREP FOR DIFFERENT NETWORK SCALES ($\beta = 50\%$ AND $\rho = 0.8$)

scale	50 nodes			100 nodes			150 nodes		
algorithm	MIR	CMIR $\gamma = 0.5\beta$	CMIR $\gamma = 0.8\beta$	MIR	CMIR $\gamma = 0.5\beta$	CMIR $\gamma = 0.8\beta$	MIR	CMIR $\gamma = 0.5\beta$	CMIR $\gamma = 0.8\beta$
average(%)	5.22	11.94	7.49	8.32	16.68	15.89	12.62	21.52	21.11
max (%)	10.92	17.45	18.73	14.88	25.10	26.05	21.56	36.45	26.88
min (%)	-0.9	9.41	-7.88	1.04	8.12	3.83	0.27	2.05	12.79

TABLE II

PERFORMANCE GAIN OF THE ALGORITHMS WITH RESPECT TO MREP FOR DIFFERENT LIFETIMES ($n = 100$ NODES AND $\rho = 0.8$)

lifetime (β)	0.3			0.5			0.7		
algorithm	MIR	CMIR $\gamma = 0.5\beta$	CMIR $\gamma = 0.8\beta$	MIR	CMIR $\gamma = 0.5\beta$	CMIR $\gamma = 0.8\beta$	MIR	CMIR $\gamma = 0.5\beta$	CMIR $\gamma = 0.8\beta$
average(%)	-8.33	13.56	11.11	8.32	16.68	15.89	-11.35	16.51	21.19
max (%)	-1.74	21.20	25.16	14.88	25.10	26.05	-5.48	25.87	28.61
min (%)	-14.9	-2.49	-5.65	1.04	8.12	3.83	-16.97	3.42	11.30

power consumed but also based on (the lack of) information in the originating node of the link.

The algorithm proceeds as follows, in n steps. In each step, we use Dijkstra's algorithm to find the shortest path. After this step the weight of the links that have been used are increased by a certain factor (this would indirectly correspond to weighing the path based on expended battery power, as in MREP). The next shortest path is then calculated based on the updated weights, and the weights of the calculated path are increased again. This process is repeated until every sensor's shortest path to the proxy is determined. In our simulations, the factor used was 1.8. Since the algorithm entails at most n iterations of Dijkstra's algorithm, it results in a worst case complexity of $O(n^2 \log n)$, where n is the number of sensors.

C. CMIR Algorithm

The Conditional Maximum Information Routing (CMIR) algorithm, is a hybrid algorithm. CMIR uses MIR till a certain point in time and switches to MREP for the remaining lifetime. The switch occurs at a certain threshold. In this paper the threshold is arbitrarily set as the time at which γ of the nodes die, where $0 < \gamma < \beta$. Simulations show that the hybrid algorithm runs better than both the MIR algorithm and MREP algorithm. During the period before the threshold, the remaining battery life of the nodes is roughly the same. However, as the algorithm progresses, the imbalances in the remaining battery life become significant. As MIR does not amplify the problem of remaining battery life as much as MREP, MIR performs better when the remaining battery life of the nodes is more even. However, as the the remaining battery power becomes highly variant, MREP does better. The CMIR algorithm recognizes this trend, and therefore utilizes MIR initially, and MREP at the later stages.

IV. PERFORMANCE COMPARISON THROUGH SIMULATION

For the simulations, random allocation of the sensors were generated to evaluate the performance of the three algorithms

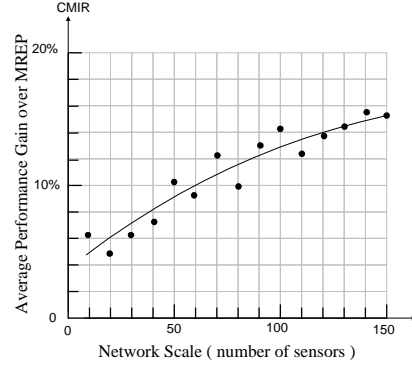


Fig. 3. CMIR's average performance gain over MREP with No. of sensors ($\rho = 0.7$, $\beta = 50\%$ and $\gamma = 0.5\beta$).

- MIR, CMIR and MREP. The metric chosen was the total information flow from the network till the death of some fraction of the nodes in the network.

The size of the square field considered was 10 by 10 units. The field itself was assumed to be a first order Gauss-Markov field with unit variance and correlation coefficient ρ . The proxy (with unlimited resources) was assumed to be located at the center of the field. Each sensor node was assigned an initial energy of 1000 units, with random $0 \leq x \leq 10$ and $0 \leq y \leq 10$ coordinates chosen for the simulations.

The performances of the MREP, MIR, CMIR with $\gamma = 0.5\beta$, and CMIR with $\gamma = 0.8\beta$ when $\beta = 50\%$ in different network scales (50, 100 and 150 nodes respectively) is compared in Table I, in terms of percentage improvement over MREP. The comparison shows significant improvement of MIR and CMIR with different switch point over the MREP algorithm, especially for large n , the number of sensors deployed. Also the performances of the MREP, MIR, CMIR with $\gamma = 0.5\beta$, and CMIR with $\gamma = 0.8\beta$ with different β value when $n = 100$ sensors is compared in Table II.

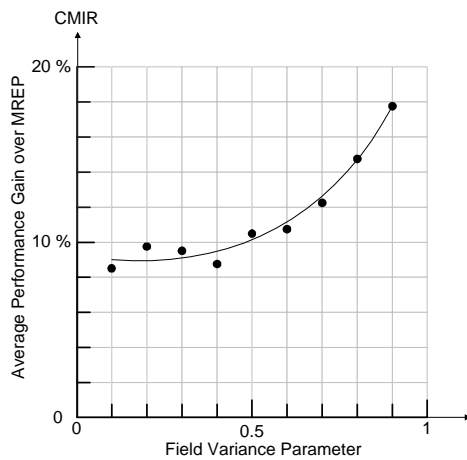


Fig. 4. CMIR's average performance gain over MREP with field variance parameter ($N = 70$, $\beta = 50\%$ and $\gamma = 0.5\beta$)

It indicates the MIR and CMIR perform better than MREP, even with different reasonable lifetime definitions. Figure 3 shows the average performance gain of CMIR over MREP with number of sensors in the field with $\rho = 0.7$, $\beta = 50\%$ and $\gamma = 0.5\beta$ in the system. The average performance gain of CMIR with respect to MREP vs. field variance parameter ρ , while $N = 70$, $\beta = 50\%$ and $\gamma = 0.5\beta$ is shown in Figure 4. It is evident that the average gain of CMIR over MREP increases as the field variance parameter or the number of sensors increases in the system.

The choice of the weighting factors for information $\exp(jI)$ and the factor (1.8) for adjusting the weights of computed paths, although reasonable and intuitive, are primarily arbitrary. However, the results given here are representative of results obtained with different parameters in an average sense.

V. CONCLUSION AND FUTURE WORK

In this paper we proposed a new strategy for routing in wireless sensor networks. The basis of our work is the realization that the primary metric for the performance of a network is the information delivered by the network. The basis translates to the observation that not all nodes are equal, even in a fairly uniform field, due to the (random) spatial locations of the sensors. All nodes do not contribute the same amount of information. Therefore the routing algorithm tries to extend the life of nodes that contribute more information, at the expense of nodes that do not.

We proposed two novel routing algorithms, Maximum Information Routing (MIR) algorithm and the Conditional Maximum Information Routing (CMIR) algorithm. Simulations show that the two novel algorithms perform significantly better than the Maximum Residual Energy Path (MREP) algorithm proposed in [12].

It is still not clear about the fundamental performance bounds or reference to the "optimal" solution for maximizing the information during the "lifetime" of a wireless sensor network. Since the information depends on both the spatial

distribution of the sensors and the energy cost of each sensor, there may not be a single scheme that is optimal for all sizes / distributions of a wireless sensor network. To obtain more insight, our current work is focused on optimal routing schemes for a fixed allocation of wireless sensors, and spatial allocations that are inherently suitable for such applications. Also, in the current work we have assumed a Gauss-Markov random field. Although this is a reasonable assumption for a smoothly varying field, in some applications this may not be the case. Future work will also look at algorithms based on our new metric for other models for the underlying random field being sensed by the network.

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