Enhancing the Performance of Wireless Sensor Networks with MIMO Communications

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ABSTRACT

Wireless sensor networks are an enabling technology for many future surveillance-oriented applications. Before a practical wireless sensor network is realized, however, significant challenges must be overcome. Chief among the obstacles to netted sensors is providing low power, robust communications between sensor nodes. Multiple Input, Multiple Output (MIMO) communication promises performance enhancements over conventional single input, single output (SISO) technology for the same radiated power. If leveraged in a sensor network, MIMO may be able to provide significant network performance improvements in power consumption, latency, and network robustness. This paper investigates the benefit of MIMO implementations in multihop wireless sensor networks in terms of the mean path length. We find that MIMO provides improvement to wireless sensor networks, particularly those that have low to midrange node densities.

INTRODUCTION

Many applications have been envisioned for sensor networks, including surveillance, intrusion detection, and environmental monitoring [1], [2]. These and other objectives will be accomplished by the cooperation of sensor networks' many small, battery-powered nodes. As a consequence of the small size desired for wireless sensor network nodes, sensor nodes will have limited power storage capabilities. In addition, because sensor nodes will be deployed in remote and oftentimes dangerous locations, their maintenance (in particular, battery replacement) will be unlikely [1]. As a result, there is great interest in optimizing and reducing the power consumption of sensor nodes' basic functions.

Research has been conducted into protocols for obtaining and transferring data that minimize the power consumed by wireless sensor network nodes. In [3] Zou and Chakrabarty propose a protocol for target reporting and a procedure for target localization which conserve energy. In [4] Jiang and Manivannan summarize and compare several routing protocols proposed for sensor networks based on their power consumption, among other things. Krishnamachari, Mourtada, and Wicker compare multipath and singlepath routing based on robustness and energy-efficiency in [5].

Despite this and other research into a broad spectrum of wireless sensor network issues, reliable, power efficient communication remains an open problem in networked sensors [1]. Multiple Input, Multiple Output (MIMO) technology, however, may be a solution as it has several beneficial characteristics that have been exhibited in recent research. MIMO communication has been shown to provide performance gains over traditional Single Input, Single Output (SISO) communication without increasing the bandwidth consumed by the system or the total power radiated from a transmitter [6], [7]. Capacity gains have been shown to be achievable, under certain conditions, when MIMO is used in a spatial multiplexing fashion [6], [8], [9], [10]. Signal processing techniques that utilize multiple transmit and receive antennas, such as space-time coding (STC), have been shown to increase transmission reliability [7], [11]. Because of these features, MIMO has been proposed and incorporated into several standards [9].

Additionally, preliminary research has begun exploring MIMO as a solution technology for netted sensors. In [12] the authors investigate the energy consumption of transmission circuitry for SISO and MIMO systems for links of various lengths. The throughput of MIMO over a slotted Aloha channel is calculated by the authors of [13]. However, to our knowledge, no one has investigated the network-wide benefit of MIMO to sensor networks.

In this paper we compare the mean path length between pairs of nodes in networks formed by SISO-equipped nodes and those formed by nodes implementing 2×2 Alamouti space time coded MIMO. We define *mean path length* as the average of the shortest paths between every pair of nodes in the network. We find, through simulations, that MIMO networks have a shorter mean path length than SISO networks over a range of node densities. However, the magnitude of the mean path length improvement varies with the node density.

In the following sections we describe the simulation framework and methodology employed in obtaining results, and the results that were obtained.

THE SIMULATION FRAMEWORK

A simulation framework has been developed that provides a means for measuring the relative benefit of applying MIMO technology to sensor nodes in a multihop wireless sensor network. In the simulation framework we model multihop SISO and MIMO networks as a set of N nodes randomly placed (independent uniform horizontal and vertical displacement) in the unit square. Each node has an identical transmission radius, r, such that the channel mean for successful SISO communication is located at the radius. We measure the wireless sensor network-wide performance of the two communication technologies by examining the networks they are able to create in various node deployments. The networks each technology is capable of creating are found by determining between which pairs of nodes links exist using a link model.

Link Model

The link model utilized in our simulations represents a multipath environment. It is expected that wireless sensor nodes will be deployed in rich scattering multipath environments. Examples of rich scattering environments include indoor wireless environments, urban areas, and dense forests. For small wireless sensor nodes, rocky ground could provide a rich scattering environment. In a multipath environment, the received signal x resulting from a transmitted symbol y is given by

$$x = \mathbf{H}y + n \tag{1}$$

in which $\mathbf{H}$ is the channel matrix and n is additive noise. Each element of $\mathbf{H}$ has a magnitude and phase ($\alpha e^{j\theta}$).

A representation of the received symbol can be obtained by coherent detection with accurate channel state information. The representation for the SISO case is given below.

$$\begin{aligned}\tilde{y} &= \mathbf{H}^* x \\ &= \alpha^2 y + \mathbf{H}^* n\end{aligned} \tag{2}$$

In our simulations, we determine that a link exists between two nodes based on the received E_b/N_0 for transmissions between the nodes. We assume that the links are symmetric, and that coherent detection is used at the receivers.

To determine the nodes between which links exist, we model a lossy communications channel between every pair of nodes in the set. In a set of N nodes there are $\binom{N}{2}$ distinct pairs of nodes.

Consider two nodes separated by a distance d, as shown in Figure 1. The model employed to simulate the channel between nodes 1 and 2 is composed of path loss and multipath components. The path loss component is modeled using a d^{-4} large scale fading model [14]. The multipath component is modeled with zero mean, circularly symmetric, complex Gaussian random variables having unit variance [14]. Random variables of this type effectively models a rich scattering environment [14].

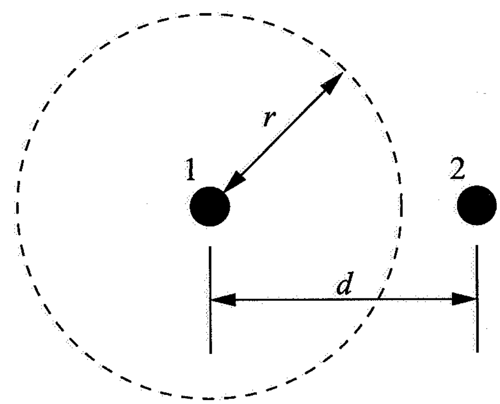

Fig. 1: Two wireless sensor network nodes separated by a distance d

We also assume the transmit and receive antenna gain are unity. To simplify calculations, we fix the SISO transmit power to 1. While we neglect additive noise at the receiver due to interferers and other noise sources, spatially white Gaussian noise is captured by the $\mathcal{CN}(0,1)$ random variables [14].

The channel model we use, which takes into account our assumptions, is given by

$$\gamma = |\mathbf{H}|^2 \times \frac{r^4}{d^4} \tag{3}$$

in which $\mathbf{H}$ is the channel matrix, r is the effective radius of SISO communications, d is the distance between the nodes, and γ is the received E_b/N_0 for communication between the pair of nodes. Each entry in $\mathbf{H}$ is the outcome of an independent trial of the $\mathcal{CN}(0,1)$ random variable. The received E_b/N_0 is normalized by the effective radius of the nodes, r, which we chose. The normalization is such that beyond the effective radius the received E_b/N_0 is attenuated; the E_b/N_0 is amplified closer to the nodes.

A link is considered to be present when γ is greater than or equal to 1. In SISO communication $\mathbf{H}$ reduces to a single complex normal random variable, h. Therefore, to determine whether a link exists between two SISO-equipped nodes, we simply compare the outcome of $|h|^2 \times \frac{r^4}{d^4}$ to 1.

To facilitate the determination of whether a link exists between two MIMO-equipped nodes, we assume Alamouti coding [11] and maximal ratio receive combining (MRRC) at the transceivers [7], [11]. Alamouti coding exploits space and time diversity to improve communications performance between the transmitter and receiver. In Alamouti coding, two symbols are transmitted over two symbol periods. Table I illustrates the transmission sequence. In an initial symbol period, each transmitter broadcasts one of the symbols. In the subsequent symbol period, each transmitter sends the complex conjugate of the symbol transmitted by the other in the previous symbol period; one of the two transmitters additionally inverts the symbol before transmission.

TABLE I: Transmitter behavior in 2×2 Alamouti coding

	Transmitter 1	Transmitter 2
Symbol Period 1	y_1	y_2
Symbol Period 2	$-y_2^*$	y_1^*

In each symbol period, each receiver antenna receives a symbol altered by the channel and corrupted by noise on two diversity channels. Figure 2 illustrates the diversity channels between two MIMO nodes. The coherently detected symbols, $x_{r,\tau}$, where r indicates the receive antenna and τ indicates the symbol period are given below.

$$\begin{aligned} x_{1,1} &= h_{1,1}y_1 + h_{2,1}y_2 + n_1 \\ x_{2,1} &= h_{1,2}y_1 + h_{2,2}y_2 + n_2 \\ x_{1,2} &= -h_{1,1}y_2^* + h_{2,1}y_1^* + n_3 \\ x_{2,2} &= -h_{1,2}y_2^* + h_{2,2}y_1^* + n_4 \end{aligned} \tag{4}$$

The diversity channels are represented above by $h_{t,r}$, where t and r respectively indicate the transmit and receive antennas as well as the row and column in the channel matrix, $\mathbf{H}$. We assume that the channel coherence time is longer than two symbol periods so that each $h_{t,r}$ remains the same between the two symbol periods.

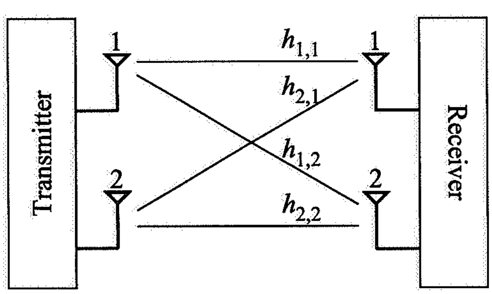

Fig. 2: A 2×2 MIMO system with diversity channels

The receiving node maximal ratio combines the four received symbols in the standard way, producing representations for each of the two information symbols. The representations are given by

$$\begin{aligned} \tilde{y}_1 &= h_{1,1}^* x_{1,1} + h_{2,1} x_{1,2}^* + h_{1,2}^* x_{2,1} + h_{2,2} x_{2,2}^* \\ &= \left(\alpha_{1,1}^2 + \alpha_{2,1}^2 + \alpha_{1,2}^2 + \alpha_{2,2}^2\right) y_1 + h_{1,1}^* n_1 + h_{2,1} n_2^* \\ &\quad + h_{1,2}^* n_3 + h_{2,2} n_4^* \\ \tilde{y}_2 &= h_{2,1}^* x_{1,1} - h_{1,1} x_{1,2}^* + h_{2,2}^* x_{2,1} - h_{1,2} x_{2,2}^* \\ &= \left(\alpha_{1,1}^2 + \alpha_{2,1}^2 + \alpha_{1,2}^2 + \alpha_{2,2}^2\right) y_2 - h_{1,1}^* n_3 + h_{2,1} n_1^* \\ &\quad - h_{1,2}^* n_4 + h_{2,2} n_2^* \end{aligned} \tag{5}$$

In the MIMO simulations we model the radiated power per antenna as one half that of the SISO case to provide an equal transmitted power comparison. In addition, four separate channels, $h_{1,1}$, $h_{2,1}$, $h_{1,2}$, and $h_{2,2}$, the diversity channels between the two transmit antennas and the two receive antennas, are modeled between the nodes. Thus, we can compute $|\mathbf{H}|^2$ as

$$|\mathbf{H}|^2 = \frac{||\mathbf{H}||_F^2}{2} \tag{6}$$

where $||\mathbf{H}||_F^2$ is the Frobenius matrix norm of $\mathbf{H}$, squared. The Frobenius matrix norm is defined as (c.f. [14])

$$||\mathbf{H}||_F = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n} |h_{i,j}|^2}$$

Adjacency Matrices

In our simulations, we exploit adjacency matrices to measure the benefit provided by MIMO to wireless sensor networks. An adjacency matrix, denoted $\mathbf{A}$, is a matrix representation of a simple graph [15]. A simple graph with n vertices is represented by an $n \times n$ adjacency matrix [15]. In an adjacency matrix 1's and 0's indicate the presence and absence, respectively, of edges between vertices in the graph [15]. There are also 1's along the main diagonal of an adjacency matrix to indicate that vertices have notional or virtual edges to themselves.

The nodes in a set, and the links formed between them, are an analogue to a graph, where the nodes are vertices and the links are edges. Based on the linkages in the graph, an adjacency matrix can be derived from the graph. A 1 in the i,j entry of the adjacency matrix indicates an edge or link between nodes i and j, while a 0 indicates the absence of a link. By multiplying the adjacency matrix by itself, and setting to 1 every entry in the resulting matrix that is greater than 1, a two hop adjacency matrix can be calculated. The two hop adjacency matrix indicates which nodes can communicate in two or fewer hops.

The process can be generalized to find the n hop adjacency matrix. That is, by raising the adjacency matrix to the n^{th}

power and setting to 1 of every entry greater than 1 in the resulting matrix, the n hop adjacency matrix is formed. This algorithm can be used to determine whether a path exists between every pair of nodes in the network.

The use of adjacency matrices to analyze wireless networks is known. Li explores different characteristics of wireless networks, including node degree, diameter, and connectivity, with matrices, in [16]. In [17] Zhang and Seah formulate algorithms that utilize adjacency matrices to calculate the maximum number of simultaneous sessions in an ad hoc network, as well as the lengths and average hop count of shortest paths between pairs of nodes in the network.

THE IMPACT OF MIMO

We determine the impact of MIMO on wireless sensor networks through simulation. The simulations measure the performance of SISO and MIMO sensor networks in terms of network robustness, probability of cohesion, mean path length, and power consumption. The simulations were performed using MATLAB® by The MathWorks.

Independent simulations were performed on sets of nodes ranging in size from 5 to 100 nodes. Each node was randomly located (independently uniform in horizontal and vertical) in a square 1 unit of length across by 1 unit of length tall, commonly known as the unit square. For each set of N nodes, the N nodes were randomly placed 200 times. We define a *node placement* or *node topology* as an arrangement of nodes. Thus, for each N, 200 node topologies are generated.

While random distributions of nodes are interesting, they are just one possible node deployment—one that is not very likely in actual applications of sensor networks. A more likely deployment is one in which the nodes are arranged around an object or area of interest, for example, a road or building. To model this type of network we maintain the uniform random variable to determine the node locations, but scale the horizontal coordinate by a factor of 4 and constrict the vertical coordinate by the same factor to elongate the target area (as in the case of a road) but retain the unit size of the area. We call these trials *elongated region scenarios*. The node topologies generated for the elongated region scenario simulation trials are generated independently of those for the unit square scenarios.

In all of the simulation trials, each node had an effective transmission radius of 0.3 units. The channels between the nodes were calculated 10 times for SISO and 10 times for MIMO for each of the node topologies. Each channel calculation produced a set of links between the nodes. The resulting networks were analyzed using adjacency matrices to measure the performance of the SISO and MIMO networks.

We assume an optimal routing protocol. That is, each node behaves as a router with complete knowledge of the network topology. As a result, each node forwards traffic along a path that is "best" in some sense. Unless otherwise noted, we consider the best path to be that with the minimum number of hops.

Mean path length

Mean path length provides a measurement of the impact of MIMO communications on a wireless sensor network. Mean path length provides a rough estimate of the amount of time and energy expended in a data transmission from one node to another in the network. A lower mean path length implies less energy and (generally) less time is used in the communication of sensed data through the network, and a higher mean path length implies the opposite. Since the lifetime of a wireless sensor network is connected to power consumption, mean path length is an important measure of network performance for netted sensors. In addition, the expeditious transfer of data may improve a sensor network's ability to fuse and consolidate data and perform other crucial tasks; mean path length is a useful metric of network performance for these reasons, as well.

We measure mean path length, $\bar{l}$, in the number of hops in the shortest path between a traffic source and destination. Our method is similar to that of [17]. For a given node density, we maintain a count of the number of paths and a sum of the lengths of the shortest paths between nodes over all the simulation trials for that N. $\bar{l}$ for that N is simply the quotient of those two quantities.

To obtain the lengths of the shortest paths between every pair of nodes in a network, a shortest path length matrix is constructed in accordance with

$$\mathbf{L} = \left| \left(\sum_{i=1}^{N} \left[\mathbf{A}^i \geq 1 \right] \right) - \left(\mathbf{N}^{+1} - \mathbf{I}_N \right) \right| \tag{7}$$

where $\left[\mathbf{A}^i \geq 1\right]$ is an $N \times N$ matrix having entries equal to one where the corresponding entries of $\mathbf{A}^i$ are greater than or equal to one, and entries of zero everywhere else. Also, $\mathbf{N}^{+1}$ is the $N \times N$ matrix with all of its entries equal to $N+1$, and $\mathbf{I}_N$ is the $N \times N$ identity matrix. The i, j entry of $\mathbf{L}$, $l_{i,j}$, is the shortest path available from node i to node j. If there is no path from node i to node j (i.e. nodes i and j reside in separate clusters), $l_{i,j}$ is $N+1$.

To ensure a fair comparison, the shortest path lengths of only those paths that exist in both the SISO and MIMO networks are used to compute the mean path lengths.

Let S and M be the SISO network and MIMO network adjacency matrices, respectively, and $\mathfrak{s}_{i,j}$ and $\mathfrak{m}_{i,j}$ be the i,j entries of the $[\mathbf{S}^{N-1} \geq 1]$ and $[\mathbf{M}^{N-1} \geq 1]$ matrices, respectively. These matrices are defined in the same way as the $[\mathbf{A}^i \geq 1]$ matrix above. The total path length of the shortest paths of a network, consequently, can be expressed as

$$l_T = \frac{1}{2}\sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N} l_{i,j} \times (\mathfrak{s}_{i,j} * \mathfrak{m}_{i,j}) \tag{8}$$

where $*$ is the logical AND operation. The main diagonal is neglected so that nodes' paths to themselves are not included in the calculation, and the sum is divided by two to avoid double counting any paths.

The number of paths observed by (8) is given by

$$\nu_p = \frac{1}{2}\sum_{i=1}^{N}\sum_{\substack{j=1\\ j\neq i}}^{N} (\mathfrak{s}_{i,j} * \mathfrak{m}_{i,j}) \tag{9}$$

Therefore, the mean path length is given by

$$\bar{l} = \frac{l_T}{\nu_p} \tag{10}$$

Figure 3 shows mean path length of MIMO and SISO random networks over a range of node densities.

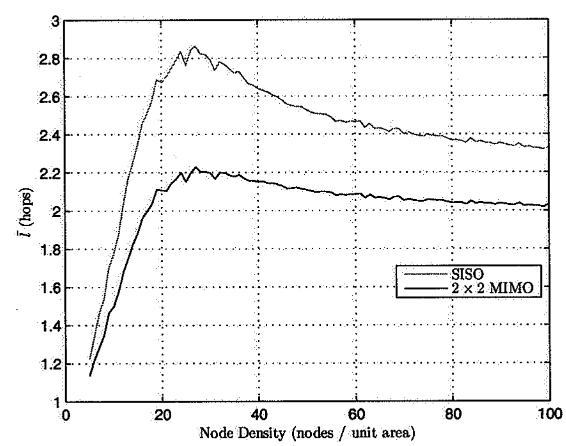

Fig. 3: Mean path length of networks over a range of node densities

The networks of MIMO-equipped nodes always have a shorter average path length than those of SISO-equipped nodes. The magnitude of the improvement provided by MIMO, however, varies with the node density. By visual inspection it can be seen that, at low node densities, the benefit of MIMO increases rapidly with node density. The greatest reduction in mean path length occurs at a node density of 26 nodes per unit area, at which the SISO mean path length is 2.84 hops and the MIMO mean path length is 2.2 hops. Beyond a certain point, the benefit of MIMO is less pronounced. At 100 nodes per unit area, the benefit provided by MIMO is only 0.3 hops; SISO and MIMO networks have mean path lengths of 2.34 and 2.03 hops, respectively.

In the elongated region scenario the largest improvement in mean path length becomes apparent at a greater node densities. The improvement grows more gradually in the elongated region case; however, the magnitude of the improvement does peak and begin to decline with increased node density as in the unit square scenario. The peak is located at 72 nodes per unit area, at which the SISO and MIMO mean path lengths are 5.37 and 4.5 hops, respectively. At 100 nodes per unit area, the SISO and MIMO mean path lengths are 5.29 and 4.56 hops, respectively. The mean path lengths for the elongated region scenario are shown in Figure 4.

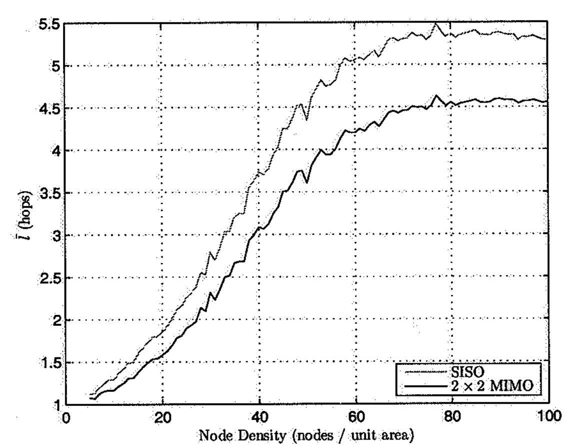

Fig. 4: Mean path length of networks over in an elongated region

CONCLUSION

MIMO provides a reduction in mean path length over all the node densities investigated. At very low node densities the improvement is minimal, because both MIMO and SISO are unable to form links. In dense networks each node has many destination nodes within one hop, and many more destinations within 1 hop of a neighbor. As a result, MIMO provides moderate improvement at high node densities. The most significant mean path length reduction is provided by MIMO in the low or midrange of node densities because the internode spacing is such that MIMO can reliably form some links that SISO cannot. In the elongated region scenario this trend holds, though it is less apparent.

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