SOURCE AND CHANNEL CODING STRATEGIES FOR

WIRELESS SENSOR NETWORKS

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In this dissertation, I focus on source coding techniques as well as channel coding techniques. I addressed the challenges in WSN by developing (1) a new source coding strategy for erasure channels that has better distortion performance compared to MDC; (2) a new cooperative channel coding strategy for multiple access channels that has better channel outage performances compared to MIMO; (3) a new source-channel cooperation strategy to accomplish source-to-fusion center communication that reduces system distortion and improves outage performance.

First, I draw a parallel between the 2x2 MDC scheme and the Alamouti's space time block coding (STBC) scheme and observe the commonality in their mathematical models. This commonality allows us to observe the duality between the two diversity techniques. Making use of this duality, I develop an MDC scheme with pairwise complex correlating transform. Theoretically, I show that MDC scheme results in: 1) complete elimination of the estimation error when only one descriptor is received; 2) greater efficiency in recovering the stronger descriptor (with larger variance) from the weaker descriptor; and 3) improved performance in terms of minimized distortion as the quantization error gets reduced. Experiments are also performed on real images to demonstrate these benefits.

Second, I present a two-phase cooperative communication strategy and an optimal power allocation strategy to transmit sensor observations to a fusion center in a large-scale sensor network. Outage probability is used to evaluate the performance of the proposed system. Simulation results demonstrate that: 1) when signal-to-noise ratio is low, the

performance of the proposed system is better than that of the MIMO system over uncorrelated slow fading Rayleigh channels; 2) given the transmission rate and the total transmission SNR, there exists an optimal power allocation that minimizes the outage probability; 3) on correlated slow fading Rayleigh channels, channel correlation will degrade the system performance in linear proportion to the correlation level.

Third, I combine the statistical ranking of sensor observations with cooperative communication strategy in a cluster-based wireless sensor network. This strategy involves two steps: 1) ranking the sensor observations based on their test statistics; 2) building a two-phase cooperative communication model with an optimal power allocation strategy. The result is an optimal system performance that considers both sources and channels. I optimize the proposed model through analyses of the system distortion, and show that the cooperating nodes achieve maximum channel capacity. I also simulate the system distortion and outage to show the benefits of the proposed strategies.

## ACKNOWLEDGEMENTS

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# CHAPTER 1

# INTRODUCTION

Wireless sensor networks (WSN) received a lot of attention in recent years in the research community due to their applications in numerous areas such as environmental monitoring, medical, military surveillance, crisis management, and transportation. WSNs typically consist of a large number of sensing devices organized into a cooperative network that is capable of monitoring an environment and reporting the collected data to a fusion center (FC). Fig.5.1 shows an example of cluster based sensor network.

One major advantage of WSNs is that they can be used for unattended operations in remote or hostile locations. Wireless sensors can be randomly distributed over the area of interest to form a decentralized network that does not rely on a preexisting infrastructure. A FC, used for collecting data from each wireless sensor, can be located at a place farther from the sensor cluster. Besides these advantages, WSN also has few challenges.

## 1.1. Major Challenges

Due to the nature of wireless sensors, many factors could affect the performance of a WSN, such as energy and bandwidth constraints and channel impairments. These are major challenges that need to be addressed before I develop practical applications.

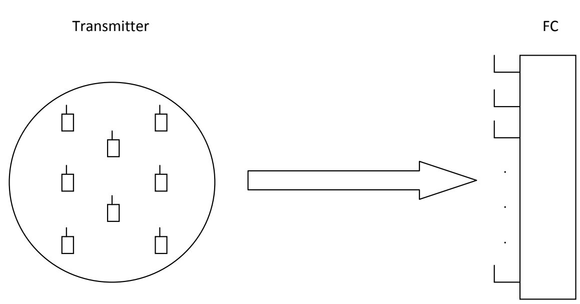



Figure 1.1. Cluster based sensor network model

### 1.1.1. Energy Constraint

The first major challenge faced by WSN is energy constraint. In fact, each sensing device and thus the entire network has a lifetime that depends heavily on limited energy resources usually provided by batteries. It is therefore vital to minimize the energy consumption of sensor networks in order to prolong their lifetime. The problem seeks to find out an optimal approach to maximize the energy efficiency of WSN under the total power constraint.

In WSN, energy savings are influenced by the design of optimal sensor deployment strategies [**1**]. Distributed cooperative communication strategies achieve energy savings through spatial diversity [**2**]. Thus, wireless sensor nodes have to organize themselves into a cooperative network in order to monitor the events of interest efficiently. Energy efficiency of whole WSN can be improved through cooperation among the wireless sensors. The use of cooperative transmission and/or reception of data among sensors minimizes the per-node energy consumption and thus increases the overall WSN's lifetime [**3**].

### 1.1.2. Channel Impairments

Another major challenge faced by WSN is the channel impairments characterized by fading, path loss, and interference among others. One important strategy to combat channel fading is the use of diversity [**4**, **5**], which can be created over time, frequency, and space. The basic idea of obtaining diversity as well as improving the system performance is to create several independent signal paths between the transmitter and the receiver.

In most scattering environments, antenna diversity is practical, effective and, hence, a widely applied technique for reducing the effects of multipath fading. The classical approach is to use multiple antennas at the receiver and perform combining [**6**] or selection and switching [**7**] in order to improve the quality of the received signal. Spatial diversity can also be achieved using space-time coding techniques [**8**, **9**]. Compared with the low capacity and low reliability of single input and single output (SISO) system, multiple input and multiple output (MIMO) system provides higher capacity, better transmission quality, and larger coverage without increasing the total transmission energy.

In addition to channel diversity techniques, one can also make use of source diversity techniques such as multiple description coding (MDC) to improve the overall performance of a communication system [**10**]. In MDC, the source data is separated into multiple correlated streams. The received streams are combined to reconstruct the source at a high-quality. In situations when some of the streams are not received, the source can still be reconstructed although at a lower quality. Typically, source diversity techniques are only used on erasure (on-off) channels [**10**].

## 1.2. Proposed Solutions

In this research, I focus on source coding techniques as well as channel coding techniques. I intend to address the challenges in WSN research discussed above by developing (1) a new source coding strategy for erasure channels that has better distortion performance compared to MDC; (2) a new cooperative channel coding strategy for multiple access channels that has better channel outage performances compared to MIMO; (3) a new source-channel cooperation strategy to accomplish source-to-fusion center communication that reduces system distortion and improves outage performance.

First, I draw a parallel between the 2x2 MDC scheme and the Alamouti's space time block coding (STBC) scheme and observe the commonality in their mathematical models. This commonality allows us to observe the duality between the two diversity techniques. Making use of this duality, I develop an MDC scheme with pairwise complex correlating transform. Theoretically, I show that MDC scheme results in: 1) complete elimination of the estimation error when only one descriptor is received; 2) greater efficiency in recovering the stronger descriptor (with larger variance) from the weaker descriptor; and 3) improved performance in terms of minimized distortion as the quantization error gets reduced. Experiments are also preformed on real images to demonstrate these benefits.

Second, I present a two-phase cooperative communication strategy and an optimal power allocation strategy to transmit sensor observations to a fusion center in a large-scale sensor network. Outage probability is used to evaluate the performance of the proposed system. Simulation results demonstrate that: 1) when signal-to-noise ratio is low, the performance of the proposed system is better than that of the MIMO system over uncorrelated slow fading Rayleigh channels; 2) given the transmission rate and the total transmission SNR, there exists an optimal power allocation that minimizes the outage probability; 3) on correlated slow fading Rayleigh channels, channel correlation will degrade the system performance in linear proportion to the correlation level.

Third, I combine the statistical ranking of sensor observations with cooperative communication strategy in a cluster-based wireless sensor network. This strategy involves two steps: 1) ranking the sensor observations based on their test statistics; 2) building a two-phase cooperative communication model with an optimal power allocation strategy. The result is an optimal system performance that considers both sources and channels. I optimize the proposed model through analyses of the system distortion, and show that the cooperating nodes achieve maximum channel capacity. I also simulate the system distortion and outage to show the benefits of the proposed strategies. The simulation results demonstrate that: 1) by selecting the nodes with smallest observation variances as source nodes, the system distortion can be dramatically reduced; 2) through optimal power allocation between intra-cluster phase and inter-cluster phase, the system can have a better outage performance.

## 1.3. Organization of the Dissertation

The organization of this dissertation is as follows. Chapter 2 presents the literature review. Chapter 3 outlines pairwise MDC scheme using complex transform. Chapter 4 describes cooperative communication based on random beamforming strategy in wireless sensor networks. Chapter 5 combines statistical ranking with cooperative communication strategy in a cluster-based wireless sensor network. Summary and conclusions are discussed in Chapter 6.

# CHAPTER 2

# LITERATURE REVIEW

In a typical wireless sensor networks (WSN) application such as target detection, several sensors are deployed in the field. These sensors observe events of interest and report them to a fusion center (FC) which may be located far from the observation area. A great deal of early works focus on finding a better source and channel coding techniques that improve the WSN system performance.

## 2.1. Source and Channel Coding Techniques

Consider the case of transmitting a source through independent channels with random states (e.g. slow fading channels). The goal is to minimize the average distortion between transmitted and received data under a certain power constraint. I focus on two commonly used coding algorithms, Multiple description coding (MDC) and space time block coding (STBC). MDC exploits diversity at the application layer through multiple description coding, and STBC exploits diversity at the physical layer through parallel channel coding.

### 2.1.1. Multiple Description Coding

MDC has been proposed in packet audio and video transmission systems as a means of combating both packet loss and link failure, in a variety of application scenarios [**11**]. MDC is an effective framework for robust transmission over channels with transient shutdown characteristics.

The basic idea in MD coding is to generate multiple independent descriptions of the source such that each description independently describes the source with certain fidelity, and when more than one description is available, they can be synergistically combined to enhance the quality [**12**]. The generalized (n-channel) MD system can decode the delivered signal with different quality levels depending on how many descriptions are correctly received as opposed to a traditional multi-resolution (MR) system for which the quality of decoded signal depends only on the received signal.

Given the average channel rate across both channels $R$, an MDC coder attempts to minimize two kinds of distortion: average distortion of the two-channel reconstruction $D_0(R)$ and average distortion of the one-channel reconstruction given equal-probable loss of either channel $D_1(R)$.

If I consider a standard single description coder (SDC) that is designed for minimizing the distortion $D(\bar{R})$ with the rate $\bar{R}$, where $D(R)$ is the operational rate-distortion, in order to implement the multiple description coder, there are two approaches. The first one is splitting the SDC's output bitstream into two equal-sized bitstreams. Then, when both descriptions are received at the decoder, a high quality signal is reconstructed with the distortion $D_0 = D(\bar{R})$. However, if only one description is received at the decoder, even though it is the one that contains the most important information of the source, the final distortion $D_1$ is still high and not acceptable. The second approach also splits the SDC's output bitstream into two bitstreams, but with correlation, instead of equal-sized. In this case, if both descriptions are received at the decoder, the distortion is also $D_0 = D(\bar{R})$. However, since correlation is added to the two bitstreams, which are transmitted on two independent channels, if only one bitstream is received at the decoder, no matter which one, there will be an acceptable distortion. The tradeoff by using the second method is some additional bits are used to describe the correlation between the two bitstreams. I call these extra bits redundancy $\rho$. Then the question of how to improve the efficiency of MDC converts into how to control the relationship between redundancy, rate, and distortion (RRD).

Transform-based MDC has advantage in coding sources at variable bit rates. By using transform, the required redundancy can be provided at the source to handle the channel impairments. As mentioned before, the transform introduces correlation between source symbols, which helps to reduce the distortion at the decoder side, when the source symbols

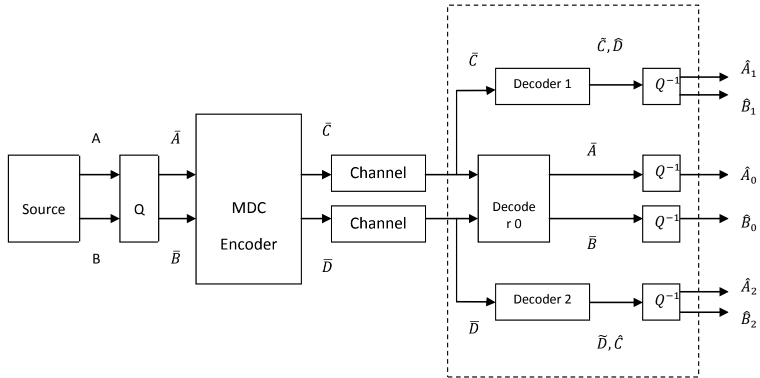



Figure 2.1. Source coding using MDC

are not received.

Given two independent input variables $A$ and $B$, and two output variables $C$, $D$, a pairwise MDC transform with the matrix $T$ is generated.

As shown in Fig 2.1, two source symbol streams after quantization ($\bar{A}$, $\bar{B}$) are sent to the MDC encoder as inputs. The encoder generates two descriptors ($\bar{C}$, $\bar{D}$), which will be sent over two wireless channels. There are there possibilities at the receiver: either first or second descriptor is received or both of them are received. The channel outputs are decoded by one of the three different kinds of decoders. Then, the decoded ($A$, $B$) streams have three different forms.

The quantized versions of $A$ and $B$ with a quantization step-size $Q$ is given by

(1) $$\bar{A} = \left\lfloor \frac{A}{Q} \right\rfloor, \quad \bar{B} = \left\lfloor \frac{B}{Q} \right\rfloor.$$

Basic structure of transform is given by

(2) $$\begin{bmatrix} \bar{C} \\ \bar{D} \end{bmatrix} = T \begin{bmatrix} \bar{A} \\ \bar{B} \end{bmatrix}.$$

The correlation between $\bar{C}$ and $\bar{D}$ is controlled by $T$. The correlation between $\bar{C}$ and $\bar{D}$ defines the redundancy of the MDC coder [**10**]. Then, at the decoder, $\hat{A}$ and $\hat{B}$ can be

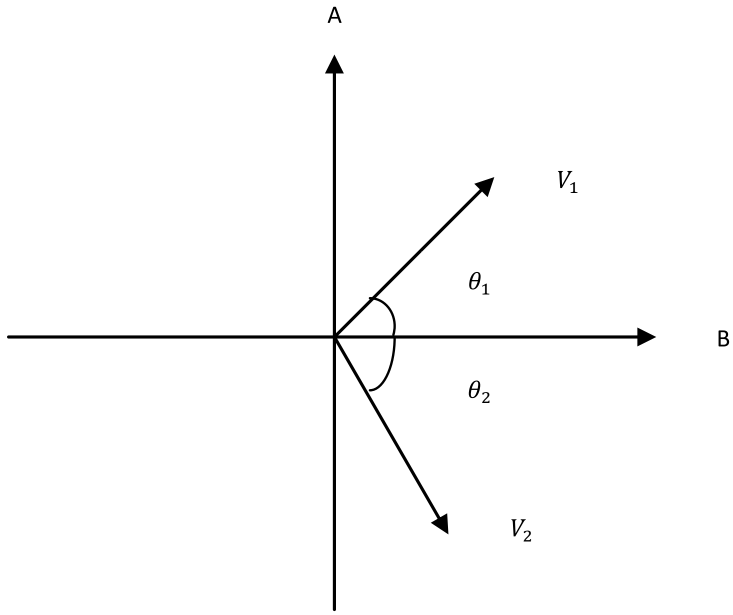



Figure 2.2. Parameterization of the pairing transform

decoded through

(3) $$\begin{bmatrix} \hat{A} \\ \hat{B} \end{bmatrix} = T^{-1} \begin{bmatrix} \bar{C} \\ \bar{D} \end{bmatrix}.$$

If I assume T is linear, the $T^{-1}$ matrix could be

(4) $$T^{-1} = \begin{bmatrix} r_1 sin\theta_1 & r_2 sin\theta_2 \\ r_1 cos\theta_1 & r_2 cos\theta_2 \end{bmatrix} = \begin{bmatrix} v_1 & v_2 \end{bmatrix}.$$

This transform replaces the original variables with two nonorthogonal vectors $v_1$ and $v_2$. The parameters $r_1$, $r_2$ control the length of the vectors and $\theta_1$ and $\theta_2$ control the directions of the vectors.

If one descriptor is received, for example $C$, then the quantized $C$ is $\tilde{C} = \bar{C}Q$. The lost descriptor $D$ can be recovered from $\tilde{C}$ using

(5) $$\hat{D}(\tilde{C}) = \gamma_{D\tilde{C}} \tilde{C},$$

where $\boldsymbol{\gamma}_{D\tilde{C}}$ is a linear estimator [**10**].

### 2.1.2. Space Time Block Coding

Modern wireless systems have more features, such as large coverage, better quality, more power and bandwidth, and can be deployed in diverse environments, to meet the market requirements.

The basic problem that makes reliable wireless transmission difficult is time-varying multipath fading [**13**]. Because of this, it is very hard to increase the quality or reduce the error rate of a wireless system. Compared with wired communication system, wireless communication system needs to increase SNR significantly to get a better performance in error rate. Increasing the SNR is equivalent to increasing the signal transmission power or using additional bandwidth.

In most scattering environments, antenna diversity is a practical, effective and, hence, a widely applied technique for reducing the effect of multipath fading [**13**]. Antenna diversity, which will increase the reliability of the wireless system, can be created by using multiple antennas at both transmitter and receiver side. The diversity technique effectively reduces the sensitivity of the transmitted signal to the fading environments, and uses high level modulation schemes at the transmitter to improve the data rate and decrease the distortion. In STBC algorithm, source signal can be transmitted in an effective way without increasing the total transmission power or expanding the transmission bandwidth.

In Figure 2.3, the top half shows the transmitter and the bottom half shows the receiver of a 2-by-2 STBC system.

For the transmitter, at given time $t$, symbol $S_1$ is transmitted through antenna $a_1$, and $S_2$ is transmitted from antenna $a_2$ simultaneously. In the next time slot $(t + T_s)$, symbol $-S_2^*$ is transmitted through antenna $a_1$, and $S_1^*$ transmitted from antenna $a_2$ simultaneously, where $*$ represents complex conjugate. Here, the channel is slow Rayleigh fading channel with independent complex multiplicative fading coefficients $[h_1 \ h_2]$ for time $t$, and $[h_2^* \ -h_1^*]$ for time $(t + T_s)$.

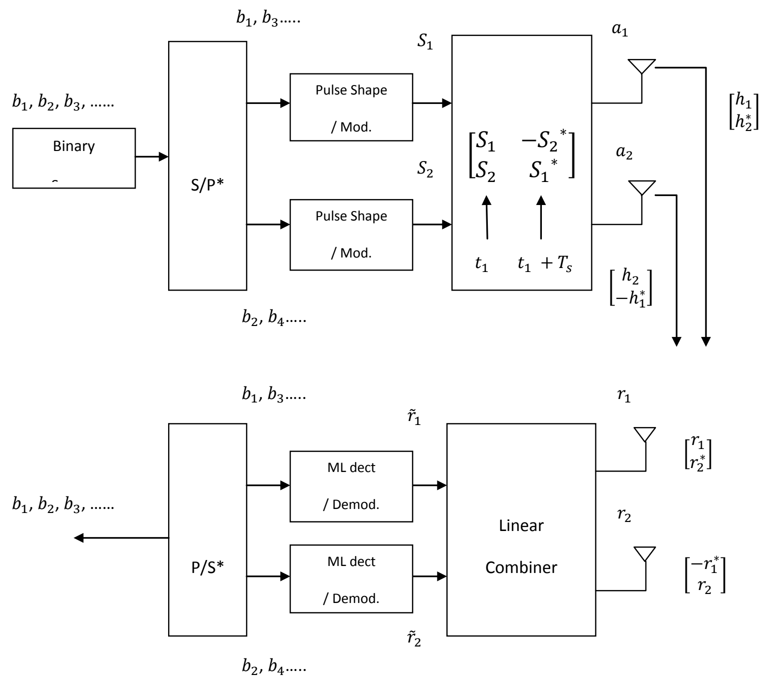



Figure 2.3. Channel coding using STBC (2 X 2) (* S/P means signal to pulse and P/S means pulse to signal)

At the receiver, the received signal is

$$\begin{bmatrix} r_1 \\ r_2^* \end{bmatrix} = \sqrt{E_S} \begin{bmatrix} h_1 & h_2 \\ h_2^* & -h_1^* \end{bmatrix} \begin{bmatrix} S_1 \\ S_2 \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \end{bmatrix}, \tag{6}$$

where $r_1$ is received in the first time slot, and $r_2^*$, which is the complex conjugate of the symbol $r_2$, is received in the second time slot. The parameter $E_S$ is the symbol energy and $[n_1 \ n_2]$ are complex random variables representing channel noise.

At the linear combiner, the received symbols $r_1$ and $r_2^*$ are properly combined to get $\tilde{r}_1$ and $\tilde{r}_2^*$ as follows,

$$\begin{bmatrix} \tilde{r}_1 \\ \tilde{r}_2^* \end{bmatrix} = \rho \begin{bmatrix} S_1 \\ S_2 \end{bmatrix} + \begin{bmatrix} \tilde{n}_1 \\ \tilde{n}_2 \end{bmatrix}, \tag{7}$$

where $\rho = |h_1|^2 + |h_2|^2$.

A lot of other research works focus on using diversity techniques to improve the WSN system performance through combating channel impairments.

## 2.2. Cooperative Diversity

Some early works on cooperation communications [**14**, **15**] introduced a basic communication structure among nodes to exploit cooperative diversity. The results suggested that even in a noisy environment, the diversity created through cooperation between in-cluster nodes can not only increase the overall channel capacity, but also provide a more robust system to combat channel fading.

Laneman and Wornell developed cooperative diversity protocols given consideration of cooperating radio implementing constraint. In this work, the spatial diversity achieved through coordinated transmission was exploit on a distributed antenna system to combat multipath fading [**16**–**18**]. Their previous work assumes the node in the cluster can transmit and receive simultaneously (full-duplex). Since the full-duplex assumption is not applicable in practice, a constraint of half-duplex was employed to the cluster node [**3**]. Also, for a sensor network built in nonergodic scenarios like discrete-time channel models, it is more applicable to use outage probability for the system performance evaluation [**19**].

In addition to cooperative diversity, multiuser diversity can also increase channel capacity. Multiuser diversity focuses on the uplink in a single cell [**20**]. A multiuser diversity system can improve channel capacity by exploiting fading. In this model, multiple users communicate to the base station on time-varying fading channels, and the receiver will track the channel state information and feed back to the transmitters. An efficiency strategy to maximize the total information-theoretic capacity is to schedule at any one time only the user with the best channel to transmit to the base station. Diversity gain is obtained by finding one among all the independent user channels that is near its peak. It can also be considered as another form of selection diversity.

Multiuser diversity is combined with transmit beamforming in [**21**] to achieve *coherent beamforming* capacity. In this model, the transmitter only requires received signal-to-noise ratio (SNR) in the form of feedback. However, this design is based on an assumption of having multiple antennas at the receiving base station. In a cluster based wireless sensor network, however, there are several antennas in each transmitting cluster, which makes opportunistic beamforming method incapable of increasing capacity [**22**]. In order to cope with this situation, multiplexing is used rather than beamforming in [**22**]. In this method, the capacity increases linearly as a function of number of transmit antennas. Thus, there is a need to develop new approachs to increase the channel capacity when using random beamforming.

Given the channel state information (CSI) of all the users is known at FC, through scheduling the best channel status to one user, the overall channel capacity can be increased [**20**]. There are two constraint of this kind of multiuser diversity: all the users are independent to each other and there always exists a user having the best channel conditions. However, Since FC always tries to connect to the user with the best channel, the FC may not be able to guarantee transmission quality to the user [**3**]. In addition, it is not a fair channel assignment for the best user channel always assigned to the FC.

Considering the above drawbacks, a proportional fair scheduling algorithm [**21**] was developed to achieve a fair channel resource allocation. This technique, also known as random beamforming technique, assigns the channel resources based on the user feedback channel quality information, so that the data rate as well as the overall throughput can be maximized. However, random beamforming technique only exploits diversity gain rather than multiplexing gain. Thus, in a given bandwidth, when a higher channel capacity is required, which means the number of transmit antennas needs to be increased, random beamforming technique can not help the capacity to increase linearly. Therefore, some new techniques developed to solve the problem [**22**].

Some researchers focus on combining cooperative diversity and multiuser diversity and exploiting at relay network [**23–25**]. It is been proved that in relay networks, combine two diversity can improve system performance [**26**]. In proposed model, a combined diversity system model has been deployed at a cluster-based decentralized wireless sensor network. I improve the system performance presented in outage probability through optimum power allocation.

Several joint source-channel coding techniques have been developed in the literature to combat the channel fluctuations over multiple parallel channels. For example, the advantages of MDC on erasure channels and the advantages of channel diversity techniques have on continuous channels are combined in [**3**] to achieve better overall performance of the communication system. Other similar techniques include multi-channel multiple description coding [**27**, **28**], resource allocation for broadcast channels [**19**, **29**], and joint source channel coding for Gaussian sources [**30**].

Some other research works focus on improving the energy efficiency of WSN system.

### 2.3. Energy Efficiency in WSN

Some schemes focus on improving energy efficiency of WSN by reducing the data that needs to be transmitted. The mechanisms proposed in [**31**–**34**] achieve energy conservation by either using energy-efficient network protocols or a sleeping scheme where the transceiver module is turned off when there is no data to be received or transmitted: communication being the most energy consuming functionality of sensor nodes. In [**35**], the authors have designed and implemented two lossless data compression algorithms, integrated with the shortest path routing technique in the aim of reducing the raw data size and to accomplish optimal trade-off between rate, energy and accuracy. A closely related solution is compressive sensing [**36**–**39**] where the problem is to accurately reconstruct signal through the collection of a small number of observations at a data gathering point.

One challenge in data reduction strategies is to find the subset of significant observations before they are actually transmitted to the FC. It is possible to achieve this in certain scenarios depending on the observation model. For example, when the sensor observations are uncorrelated, each sensor can decide the value of its observations independently. In fact, in conventional cluster routing protocols, it is not necessary to involve all the sensors due to the redundancy characteristics of the information that they acquire. These observations led to the development of a data reduction strategy in which only sensors with high local SNRs are selected to transmit their observations [**40**].

In addition to improving WSN system energy efficiency through reducing transmitting data, some other schemes focused on reducing the number of transmitting nodes. In [**41**], the authors developed a relative localization geometry to select the right node for transmission. Also, in [**42**], only the sensor provides the maximum information utility is chosen for transmission, which can help with both system stability and tracking accuracy.

A scheme for distributed detection based on a idea of "send/no send" is proposing [**43**]. Each sensor sends only "informative" observation to the FC and those deemed "uninformative" are not transmitted. The problem of interest, therefore, is reduced to an N sensor binary hypothesis testing problem, where the sensors are trying to decide between the null (H0) and alternate (H1) hypotheses. A sensor will transmit its observation if and only if its likelihood ratio is very large or very small. The problem of estimating an unknown parameter in Gaussian noise is considered in [**44**]. The authors proposed an energy-efficient approach in which sensor transmissions are ordered according to the magnitude of their measurements. Only the sensors with high magnitude measurements, greater than a threshold will transmit their observations. When sufficient evidence is accumulated about the data to be estimated, the transmissions are stopped. Similarly, a transmission scheme is proposed in [**45**] in which sensors with more informative observations transmit first. In this approach, the $i^{th}$ sensor will transmit after a time proportional to the inverse of its likelihood ratio $(1/|In(Li)|)$ and once enough evidence is accumulated to decide for one hypothesis or the other, the process is stopped in order to save valuable transmission energy. This assumes, however, the knowledge of prior probabilities of the respective hypotheses, which is not possible in applications such as sonar and radar.

In the following chapters, I discuss our proposed source and channel coding strategies to deal with the channel fading and energy constraints in WSN. Compared to the techniques that are available in literature, our proposed methods show either better error performance or better outage performance.

# CHAPTER 3

# PAIRWISE MULTIPLE DESCRIPTION CODING USING COMPLEX TRANSFORM

In this chapter, I first draw a parallel between 2x2 multiple description coding (MDC) scheme and Alamouti's space time block coding (STBC) scheme and observe the commonality in their mathematical models. This commonality allows us to observe the duality between the two diversity techniques. Making use of this duality, I develop an MDC scheme with pairwise complex correlating transform. Theoretically, I show that: (1) although the redundancy is doubled, MDC with complex transform can eliminate the estimation error completely when only one descriptor is received; (2) when the stronger descriptor (with larger variance) needs to be recovered from the weaker descriptor, MDC with complex orthogonal transform shows greater efficiency than the real transform; (3) when the quantization error is much smaller compared with the estimation error, MDC with complex transform performs significantly better than MDC with real transform. Results of our experiments on real images also demonstrate the efficiency of the proposed approach.

## 3.1. Channel and Source Diversity

### 3.1.1. Channel Diversity using 2x2 STBC

In the channel diversity scheme illustrated in Fig. 3.1, a pair of source symbols $\mathbf{s}$ is encoded and transmitted through a 2-by-2 multiple input multiple output (MIMO) channel. The decoder reconstructs the source from the channel output $\mathbf{y}$ received in two successive time intervals.

With Alamouti's scheme [**8**] and maximum likelihood (ML) estimation method to decode received symbols, the equivalent MIMO communication system is given by,

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}, \tag{8}$$

where $\mathbf{y}$ stands for the channel output vector $[y_1, y_2]^T$, $\mathbf{x}$ stands for the channel input vector

$[x_1, x_2]^T$, and $\mathbf{n}$ represents the channel noise vector, whose elements are assumed to be zero-mean white Gaussian with variance $\sigma_n^2$, i.e., $n_i \sim N(0, \sigma_{n_i}^2)$ $(i = 1, 2)$. The channel encoding coefficient metric $\mathbf{H}$ is given by,

$$\mathbf{H} = \begin{bmatrix} h_1 & h_2 \\ h_2^* & -h_1^* \end{bmatrix}, \tag{9}$$

which helps in effectively combating the channel fluctuations. It is assumed that the channel states are known at the receiver.

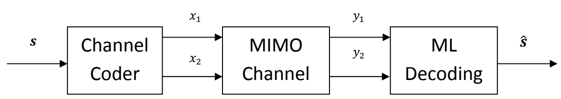



Figure 3.1. Channel diversity technique

### 3.1.2. Source Diversity using 2x2 MDC

In the 2x2 MDC method shown in Fig. 3.2, a pair of source symbols $[A\ B]^T$ is encoded into $[C\ D]^T$ and transmitted on two parallel channels. The decoder receives $[\tilde{C}\ \tilde{D}]^T$ and reconstructs $[\tilde{A}\ \tilde{B}]^T$. If only one of the channel outputs, i.e., either $\tilde{C}$ or $\tilde{D}$ is received, the resulting codeword is used to produce a low fidelity version of the source symbols $[A\ B]^T$. If both $\tilde{C}$ and $\tilde{D}$ are received, they are combined to form a high fidelity version of source symbols.

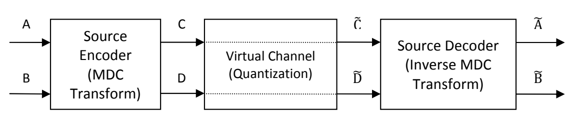



Figure 3.2. MDC transform

The MDC transform represents a source diversity technique and it is described by

$$\begin{aligned} [C\ D]^T &= \mathbf{T}[A\ B]^T \\ [\tilde{C}\ \tilde{D}]^T &= [C\ D]^T + \mathbf{n} \end{aligned} \tag{10}$$

$$[\tilde{A}\ \tilde{B}]^T \;=\; \mathbf{T}^{-1}[\tilde{C}\ \tilde{D}]^T$$

where $[\tilde{C}\ \tilde{D}]^T$ stands for the channel output vector, and the matrix $\mathbf{T}$ controls the correlation between channel inputs [**10**]. The vector $[\tilde{A}\ \tilde{B}]^T$ represents the output obtained from the inverse MDC transform, and $\mathbf{n} = [n_1, n_2]^T$ represents the quantization error vector. The quantization process is modeled as a virtual channel with quantization error representing the noise $\mathbf{n}$ [**46**] whose elements are assumed to be random variables with zero-mean and variance $\sigma^2_{n_i}$ $(i = 1, 2)$. The effect of varying the quantization step size is reflected in the values of noise variance. The vector $[\tilde{C}\ \tilde{D}]^T$, generated by adding the quantization error $\mathbf{n}$ to the source, represents the quantized version of the signal $[C\ D]^T$. The orthogonal transform matrix $\mathbf{T}$ is given by

$$\mathbf{T} = \begin{bmatrix} cos\theta_r & sin\theta_r \\ -sin\theta_r & cos\theta_r \end{bmatrix}. \tag{11}$$

where $\theta_r \in [0, \frac{\pi}{2}]$ controls the redundancy for real transform.

The decoder uses the inverse transform $\mathbf{T}^{-1}$ to reconstruct the source.

## 3.2. MDC with Complex Transform Coefficients

Comparing (8) and (10), one can observe that 2x2 MDC and 2x2 STBC schemes share a common linear model, suggesting that the source diversity technique that implements MDC coding is dual to the channel diversity technique implementing STBC. While this is a simple observation, it provides some interesting insights that lead to the design of an enhanced MDC method. If the quantization error is assumed to be the noise on virtual parallel channels, the use of complex encoding matrix can provide source reconstruction with higher fidelity, combating channel noise analogous to STBC.

3.2.1. Complex Orthogonal Transform

MDC transform typically employs a transform with real coefficients. In this process, two symbols are simultaneously transmitted from two antennas in one time slot. In the proposed scheme with complex transform, each symbol is transmitted with half the power that is used in the former approach, and transmit using two time slots. The MDC transform matrix with complex coefficients ($\mathbf{T}_C$) is shown below:

$$\mathbf{T}_C = \begin{bmatrix} cos\theta_c & -j * sin\theta_c \\ j * sin\theta_c & -cos\theta_c \end{bmatrix}, \tag{12}$$

where $\theta_c \in [0, \frac{\pi}{2}]$. The norm of $\mathbf{T}_C$, represented by $\|\mathbf{T}_C\|$ is equal to 1. Also, the inverse complex transform matrix ($\mathbf{T}_C^{-1}$) can be represented as

$$\mathbf{T}_C^{-1} = \begin{bmatrix} cos\theta_c & -j * sin\theta_c \\ j * sin\theta_c & -cos\theta_c \end{bmatrix}. \tag{13}$$

3.2.2. Performance of the Proposed MDC Scheme on Erasure Channel

Let $A \sim N(0, \sigma_A^2)$ and $B \sim N(0, \sigma_B^2)$ represent the input sources. Let $C$ and $D$ represent complex random variables (R.V.) (not necessarily Gaussian) with zero mean and variances $\sigma_C^2$ and $\sigma_D^2$ respectively. Further, suppose one of the inputs ($C$ or $D$) is lost during transmission. Then, the performance of the proposed MDC scheme over an erasure channel is analyzed below.

*Redundancy*: According to (10) and (12), $C$ and $D$ can be represented as follows

$$[C\ D]^T = \begin{bmatrix} cos\theta_c & -j*sin\theta_c \\ j*sin\theta_c & -cos\theta_c \end{bmatrix} \times [A\ B]^T$$

(14)

$$= \begin{bmatrix} Acos\theta_c - j*Bsin\theta_c \\ -Bcos\theta_c + j*Asin\theta_c \end{bmatrix},$$

so the variances of $C$ and $D$ can be estimated as,

$$\sigma_C^2 = \sigma_A^2 cos^2\theta_c + \sigma_B^2 sin^2\theta_c$$

(15)

$$\sigma_D^2 = \sigma_A^2 sin^2\theta_c + \sigma_B^2 cos^2\theta_c.$$

The redundancy is defined as the extra bits required for sending correlated $C$ and $D$ compared to sending uncorrelated $A$ and $B$. The rates (in bits per variable) required for coding ($A$, $B$) and ($C$, $D$), based on optimal bit rate allocation, are [**10**]

$$R_{AB} = \tfrac{1}{2}log_2\tfrac{\sigma_A\sigma_B}{D_0} + K$$

(16)

$$R_{CD} = \tfrac{1}{2}log_2\tfrac{\sigma_C\sigma_D}{D_0} + K,$$

for some constant K. Therefore, by definition, the redundancy ($\rho_c$) is given by,

(17) $$\rho_c = R_{CD} - R_{AB} = \frac{1}{2}log_2\frac{\sigma_C\sigma_D}{D_0} - \frac{1}{2}log_2\frac{\sigma_A\sigma_B}{D_0} = \frac{1}{2}log_2\frac{\sigma_C\sigma_D}{\sigma_A\sigma_B}.$$

The redundancy bring by complex transform ($\mathbf{T}_C$) can be derived through substituting (16) into (17), and it can be shown as,

(18) $$\rho_c = \frac{1}{2}log_2\frac{\sigma_C\sigma_D}{\sigma_A\sigma_B} = \frac{1}{2}log_2\frac{\sqrt{(\sigma_A^2-\sigma_B^2)^2sin^2 2\theta_c + 4\sigma_A^2\sigma_B^2}}{2\sigma_A\sigma_B}.$$

where $\rho_c$ is controlled by angle $\theta_c$ (details are shown in Appendix ). According to (18), it is obvious that when $\theta_c = \frac{\pi}{4}$, the complex transform redundancy reaches maximum, which is $\rho_{c,max} = \frac{1}{2}log_2\frac{\sigma_A^2+\sigma_B^2}{2\sigma_A\sigma_B}$, when $\theta_c = 0$, the complex transform redundancy reaches minimum, which is $\rho_{c,min} = 0$. Since $\rho_c$ can vary from $\rho_{c,min}$ to $\rho_{c,max}$, the range of $\rho_c$ is $[0, \frac{1}{2}log_2\frac{\sigma_A^2+\sigma_B^2}{2\sigma_A\sigma_B}]$.

*Quantization Error*: The channel noise (quantization error) on the channel $C$ to $\tilde{C}$ is assumed to be $n_1$, a complex R.V. with zero mean and variance $\sigma_{n_1}^2$; and the channel noise on the channel $D$ to $\tilde{D}$ is assumed to be $n_2$, another R.V. with zero mean and variance $\sigma_{n_2}^2$. According to (10), the channel outputs can be represented as,

(19) $$[\tilde{C}\ \tilde{D}]^T = \mathbf{T}_C[A\ B]^T + [n_1\ n_2]^T.$$

Since $\mathbf{T}_C$ is an orthogonal matrix and $A$ and $B$ are Gaussian, the quantization error ($D_{qc}$) on erasure channel in the absence of estimation error can be represented as: 1) $D_{qc} = E[(\tilde{C}-C)^2] = \sigma_{n_1}^2$, if only $C$ is received; 2) $D_{qc} = E[(\tilde{D}-D)^2] = \sigma_{n_2}^2$, if only $D$ is received.

*Estimation Error*: When MDC transform with complex matrix coefficients described in (12) is used, I can observe that $C$ and $D$ are orthogonal to each other. Hence, if one of the descriptors (say $\tilde{C}$) is lost, it can be computed from the other descriptor using their relationship:

(20) $$\tilde{C} = j * \tilde{D}^*.$$

Also, $\tilde{D}$ can be recovered from $\tilde{C}$ using $\tilde{D} = j * \tilde{C}^*$.

The modeling of the quantization error as additive noise makes the estimation error independent of the quantization error. Then, the estimation error in the absence of quantization error ($E[(\tilde{C}-\hat{C}(\tilde{D}))^2]$) is given by (say $\tilde{C}$ lost)

$$E[(\tilde{C}-\hat{C}(\tilde{D}))^2] = E[(\tilde{C}-j*\tilde{D}^*)^2] = (cos\theta_c - sin\theta_c)^2(\sigma_A^2+\sigma_B^2). \tag{21}$$

It is obvious that only angle $\theta_c$ can affect the estimation error. When $cos\theta_c = sin\theta_c$, that is $\theta_c = \frac{\pi}{4}$, estimation error $E[(\tilde{C}-\hat{C}(\tilde{D}))^2]$ reaches minimum, which is 0. When $cos\theta_c = 1$ and $sin\theta_c = 0$, that is $\theta_c = 0$, estimation error $E[(\tilde{C}-\hat{C}(\tilde{D}))^2]$ reaches maximum, which is $\sigma_A^2+\sigma_B^2$.

*Reconstruction Error*: In real orthogonal transform, the one-channel reconstruction error per variable reconstruction error ($D_r$) can be represented as **[10]**,

$$\begin{aligned} D_r &= \tfrac{1}{4}(E[(A-\tilde{A})^2+(B-\tilde{B})^2|\tilde{C}] + E[(A-\tilde{A})^2+(B-\tilde{B})^2|\tilde{D}]) \\ &= D_{er}+D_{qr}, \end{aligned} \tag{22}$$

where $D_{er} = \frac{\sigma_A^2+\sigma_B^2}{4}2^{-4\rho_r}$ and $D_{qr} = \frac{\sigma_{n_1}^2+\sigma_{n_2}^2}{2}$ are the estimation error and quantization error respectively with the real transform. When $\rho_r = \rho_{r,min} = 0$, $D_{er}$ reaches maximum, $D_{er,max} = \frac{\sigma_A^2+\sigma_B^2}{4}$. When $\rho_r = \rho_{r,max}$, $D_{er}$ reaches minimum, $D_{er,min} = \frac{\sigma_A^2\sigma_B^2}{\sigma_A^2+\sigma_B^2}$.

In complex orthogonal transform, the one-channel reconstruction error per variable reconstruction error ($D_{qc}$) can be represented as,

$$\begin{aligned} D_c &= \tfrac{1}{4}(E[(A-\tilde{A})^2+(B-\tilde{B})^2|\tilde{C}] + E[(A-\tilde{A})^2+(B-\tilde{B})^2|\tilde{D}]) \\ &= D_{ec}+D_{qc}, \end{aligned} \tag{23}$$

where $D_{ec} = \frac{\sigma_A^2+\sigma_B^2}{4}(cos\theta_c - sin\theta_c)^2$ and $D_{qc} = \frac{\sigma_{n_1}^2+\sigma_{n_2}^2}{2}$ are the estimation error and quantization error respectively with the complex transform. Consider the relation between the estimation error and redundancy, $D_{ec}$ can be represented as a function of the complex redundancy $\rho_c$,

$$D_{ec} = \frac{\sigma_A^2 + \sigma_B^2}{4}(1 - \frac{2\sigma_A\sigma_B\sqrt{2^{4\rho_c} - 1}}{|\sigma_A^2 - \sigma_B^2|}), \qquad when\, 0 \le \rho_c \le \rho_{cmax}. \tag{24}$$

When $\rho_c = \rho_{c,min} = 0$, $D_{ec}$ reaches maximum, $D_{ec,max} = \frac{\sigma_A^2+\sigma_B^2}{4}$. When $\rho_c = \rho_{c,max}$, $D_{ec}$ reaches minimum, $D_{ec,min} = 0$.

3.3. Simulations

I modeled the input as two zero mean Gaussian sources and studied the performance of the proposed MDC scheme on erasure channels. The two MDC schemes with real and complex transform matrices are simulated in MATLAB. For this simulation, I set $\sigma_A$ to 1 and $\sigma_B$ to 0.5. I also define a parameter ($SNR$) as,

$$SNR = 10log_{10}\frac{\sigma_A^2}{\sigma_n^2}, \tag{25}$$

where $\sigma_n^2 = \frac{\sigma_{n_1}^2+\sigma_{n_2}^2}{2}$.

3.3.1. Rate-Redundancy Efficiency

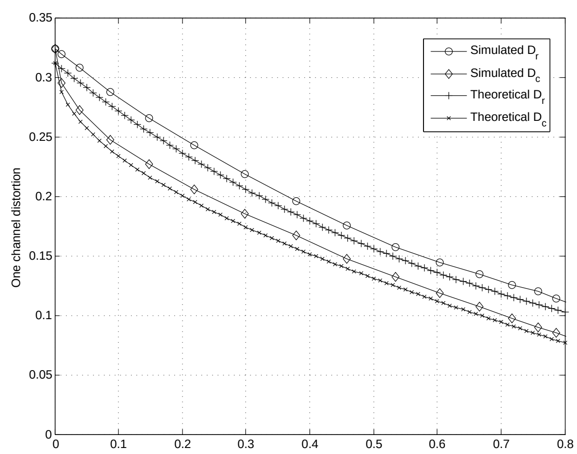



Figure 3.3. Rate redundancy distortion curves for the proposed complex MDC transform compared to the real MDC transform under different values of $\rho$

Fig. 3.3 shows the plots corresponding to the the theoretical and simulated rate-redundancy distortion of complex orthogonal transform described in (12) relative to the real orthogonal transform described in (11). Using the same amount of redundancy ($\rho = \rho_r = \rho_c$), the real and complex transform are compared in terms of one channel distortion. In this simulation, $SNR$ is fixed to $3dB$. The plots demonstrate that the one channel distortion (both $D_r$ and $D_c$) decreases as $\rho$ is increased. The one channel distortion of complex transform $D_c$ decreases faster than the real one $D_r$ as the redundancy increases.

3.3.2. One Channel Distortion over SNR

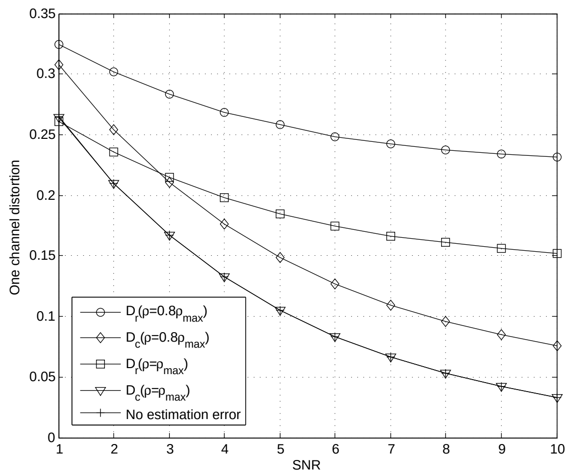



Figure 3.4. Performance of MDC scheme with real and complex transform coefficients on virtual erasure channel for different values of $SNR$

Fig. 3.4 displays the one channel distortion ($D_r$ and $D_c$) between the source $[A\ B]^T$ and its estimate $[\tilde{A}\ \tilde{B}]^T$ for different channel SNR values. Having the same quantization error ($D_{qr} = D_{qc}$), the real and complex transform are compared in terms of one channel distortion.

Fig. 3.4 demonstrates three important points which are described below.

(1) The plots for MDC with real and complex transforms demonstrate that when SNR increases, that is when $D_{qr}$ and $D_{qc}$ decrease, both $D_r$ and $D_c$ decrease regardless of redundancy.

(2) Since MDC with complex transform has an lower estimation error compared to the real transform under same redundancy, MDC with complex transform reduces the

on channel distortion significantly faster than the real transform.

(3) Furthermore, the plots indicate that when $\rho = \rho_{max}$, the complex orthogonal transform can eliminate estimation error and match the curve that only contains quantization error.

### 3.3.3. Image Coding

For comparison purposes, I implemented the multiple description transform coder (MDTC) introduced in [**10**], in which the run-length plus Huffman coding method is deployed to code all Discrete Cosine Transform (DCT) coefficients together in a block, and the resulting bit stream is separated into two streams: stream one (even indexed blocks) and stream two (odd indexed blocks). The two bit streams along with separate Huffman tables are assigned to two symmetric descriptions.

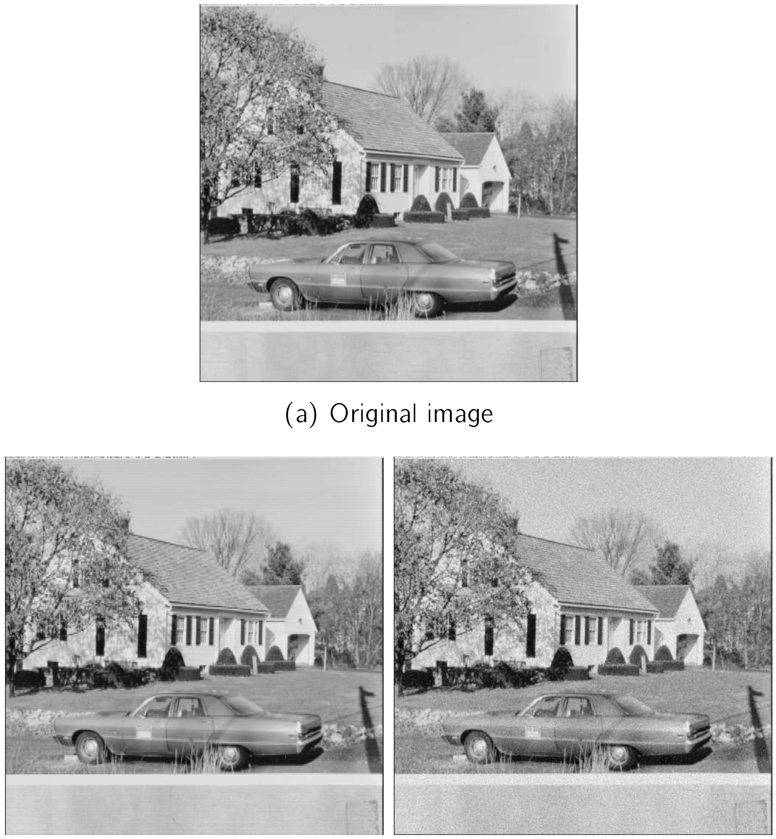
In our image coder, the quantization error is estimated through adding quantization error vector as shown in (19). The distortion caused by the quantization error is controlled through changing the value of $SNR$, which is given by the ratio of variances of the received descriptor and quantization error $\frac{\sigma_D^2}{\sigma_{n_2}^2}$.

The test images are assumed to be transmitted on an erasure channel, which means that only one descriptor is received. The lost descriptor is recovered using the received descriptor using (20) for the complex transform. I used the estimation method described in [**10**] for the real transform. An inverse transform matrix ($T^{-1}$ for the real transform and $T_C^{-1}$ for the complex transform) is applied to $[\tilde{C}\ \tilde{D}]^T$ in order to recover $[\tilde{A}\ \tilde{B}]^T$.

Fig. 3.5 and Fig. 3.6 show the results of our experiments on two different images of size $512 \times 512$. The images are coded using both real and complex orthogonal transform coders.

Fig. 3.5 shows the original and reconstructed images when $SNR = 3$dB. Fig. 3.6 shows the original and reconstructed images when $SNR = 5$dB.

The reconstructed images demonstrate that: 1) when $SNR$ gets higher (lower quan-



(a) Original image

(b) Reconstructed image from single description using real transform

(c) Reconstructed image from single description using complex transform

Figure 3.5. Reconstructed image when SNR = 3dB

tization error) the complex transform coder provides a close to perfect reconstruction of the image compared to the real transform coder; 2) compared to Fig. 3.5, the image reconstructed from the real transform coder does not show significant quality improvement, while the image reconstructed from the complex transform coder does. The same observations can be made from the plots shown in Fig. 3.4. Note that these observations are very clearly visible on the display screen. However, on paper, they may not be clearly visible.

## 3.4. Conclusions

In this paper, I proposed a 2x2 MDC scheme with complex transform by observing the duality between the source and channel diversity schemes. By analyzing the relationship between the MDC transforms in terms of the redundancy-rate distortion, I find the factors that

(a) Original image

(b) Reconstructed image from single description using real transform

(c) Reconstructed image from single description using complex transform

Figure 3.6. Reconstructed image when SNR = 5dB

could affect both transforms. The simulation results demonstrate that MDC with complex transform can effectively reduced the estimation error when the lost descriptor needs to be recovered from the received one, with the same redundancy. When the redundancy reaches maximum for both complex and real transforms, MDC with complex transform can eliminate the estimation error.

I also demonstrate that as the quantization error is reduced, the complex transform performs better than the real transform in terms of minimizing the distortion. Experiments are also preformed on real images to demonstrate these benefits.

# CHAPTER 4

# COOPERATIVE COMMUNICATION BASED ON RANDOM BEAMFORMING STRATEGY IN WIRELESS SENSOR NETWORKS

In this chapter, I propose a cluster based cooperative transmission strategy to achieve multiuser diversity using *random beamforming*. I consider a wireless sensor network with a clustered topology with each cluster consisting of several number of sensors. Each sensor in the transmitting cluster is capable of processing the collecting data and transmitting it through its embedded antenna. The receiving cluster is modeled as a single unit with multiple receiving antennas, and is referred to as virtual fusion center (VFC).

The proposed data transmission involves two phases: (1) intra-cluster phase in which sensors within a cluster communicate with each other over a broadcast channel (each node using one time unit to broadcast), and (2) cluster to VFC phase in which all sensors in the transmitting cluster communicate with the VFC using beamforming. If I consider VFC as a receiving cluster, then, the idea is similar to transmitting data from one cluster to another [**3**]. The VFC combines the received data using maximal ratio combining (MRC) technique, and thus achieves full diversity.

## 4.1. Communication Channel Model

In this section, the channel models for the two phases of communication are discussed. Fig. 4.1 and Fig. 4.2 illustrate the broadcasting and random beamforming phases of transmission.

### 4.1.1. Transmitter Side

Assume that there are $K$ nodes each with one transceiver transmitting data to the VFC. Also, assume that the VFC is equipped with $M$ antennas. Further, since sensor network is power-constrained, a reasonable assumption is that the total power allocated for all nodes

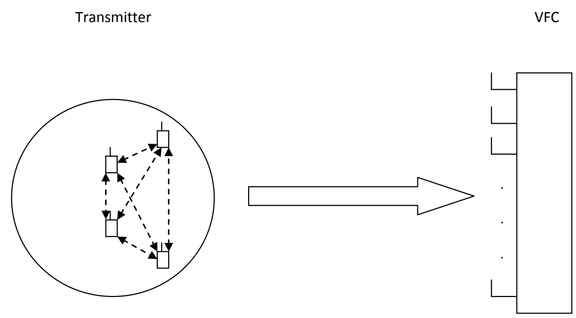



Figure 4.1. Phase I: Intra-cluster broadcasting

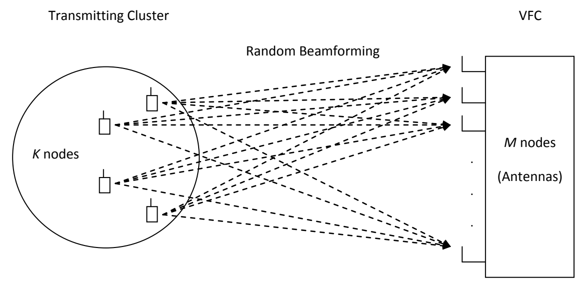



Figure 4.2. Phase II: Random beamforming between a cluster and VFC

for communicating their observations to the VFC is $P_{total}$. The transmission occurs in two phases as described below.

*Intra-cluster Broadcasting.* During the first phase, each sensor broadcasts its observations to all other nodes in the same cluster with certain power. Assume that all nodes decode the received data simultaneously [**47**]. Half-duplexing transmission is assumed in this phase, where all the nodes in cluster can not send and receive at the same time on the same frequency. The total power used for all nodes to accomplish broadcasting (each node using one time unit to broadcast) is $P_1$. Therefore, the number of cooperative nodes, $K$, in each cluster depends on the selection of $P_1$.

*Random Beamforming between a Cluster and VFC.* During this phase, all nodes in the cluster will transmit the data they aggregated to the VFC using total power $P_2$, and the complete transmission process takes one time unit. I propose a random beamforming technique during this phase with a transmit power for each cooperative node set to be $a_i$. I pre-multiply the input vector with a beamforming matrix $\mathbf{V}_b$ consisting of $K \times K$ number of complex numbers $a_1 exp(j\theta_1)$, $a_2 exp(j\theta_2)$, ... , $a_{K^2} exp(j\theta_{K^2})$, where $\theta_i \in [0, 2\pi]$ for $i = 1, ..., K^2$. Given $a'_i \sim U(0, 1)$ for $i = 1, ..., K^2$, and $a'_i$ can be normalized that $a_i = \frac{a'_i}{\sqrt{\sum_{i=0}^{K^2} a'^2_i}}$, so $a_i \sim U(0, 1)$ and $\sum_{i=0}^{K^2} a_i = 1$.

In order to keep the power consumption of each transmission the same, the following condition must be satisfied:

$$P_{total} = P_1 + P_2. \tag{26}$$

Based on the power constraints specified, $K$ is linearly proportional to $\frac{P_1}{P_{total}}$.

4.1.2. Receiver Side

The VFC receives data from each cluster over $K \times M$ random beamforming channel. In order to obtain full receiver diversity, I propose MRC technique to reconstruct the received data. For evaluating the performance of the random beamforming strategy, I use V-BLAST MIMO channel [**48**] with the same amount of the total power as in proposed method to compare, i.e.,

$$P_{MIMO} = P_{total}, \tag{27}$$

where $P_{MIMO}$ represents the transmit power used for transmission over the MIMO channel. Since V-BLAST MIMO is a technique applied on MIMO channels as in Phase 2 of the proposed algorithm, I actually compare the performance of Phase 2 of the proposed algorithm with that of V-BLAST MIMO with the same power constraint and time duration.

## 4.2. System Model and Error Probability

Before transmitting, the input is premultiplied by a random beamforming matrix $\mathbf{V}_b$. The system model I proposed is shown in Fig. 5.6. The random beamforming communication model can be described by

$$\mathbf{y} = \mathbf{H}\mathbf{V}_b\mathbf{x} + \mathbf{n}, \tag{28}$$

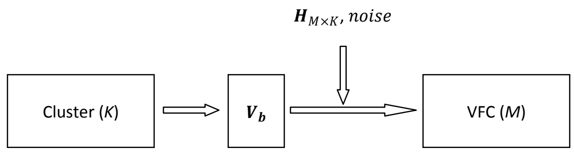



Figure 4.3. Proposed system model: Communicating aggregated sensor observations over $M \times K$ random beamforming channel

where $\mathbf{y}$ stands for the channel output vector $[y_1, y_2, ..., y_M]^T$, $\mathbf{x}$ stands for the channel input vector $[x_1, x_2, ..., x_K]^T$, $\mathbf{n}$ represents the channel noise vector, whose elements are assumed to be zero-mean white Gaussian with variance $\sigma_n^2$, i.e., $n_i \sim N(0, \sigma_n^2)$ $(i = 1, 2, ..., m)$, $\mathbf{H}$ represents the channel fading coefficient matrix, and $\mathbf{V}_\mathrm{b}$ represents random beamforming matrix. In comparison, a V-BLAST communication is assumed for MIMO model which is described by [**48**]:

$$\mathbf{y} = \mathbf{H}_{\mathrm{MIMO}}\mathbf{x} + \mathbf{n}. \tag{29}$$

At VFC, the decoder implements MRC method to reconstruct the source, which is described by

$$\hat{\mathbf{x}} = \mathbf{x} + (\mathbf{H}\mathbf{V}_\mathrm{b})^\mathrm{H}\mathbf{n}, \tag{30}$$

where $\hat{\mathbf{x}}$ represents the reconstructed source and $(\mathbf{H}\mathbf{V}_\mathrm{b})^H$ represents the conjugate transpose of $\mathbf{H}\mathbf{V}_\mathrm{b}$.

The signal-to-noise ratio (SNR) for the received signal can be described as [**21**]

$$SNR = \frac{P_2}{\sigma_n^2}||\mathbf{H}\mathbf{V}_\mathrm{b}||^2, \tag{31}$$

where $\sigma_n^2$ represents the variance of the channel noise.

Let us assume that the transmission rate between a cluster and VFC is $R_{tr}$. Then, according to Shannon's limit, when

$$R_{tr} \leq log_2(1 + \frac{P_2}{\sigma_n^2}||\mathbf{HV}_{\mathrm{b}}||^2), \tag{32}$$

the receiver is expected to decode the received data correctly. Unsatisfactory reception or outage occurs when this condition is not met.

I focus on random beamforming phase. The system outage probability is given by

$$P_{out} = P(||\mathbf{HV}_{\mathrm{b}}||^2 < \frac{2^{R_{tr}} - 1}{\frac{P_2}{\sigma_n^2}}), \tag{33}$$

which I use to as a performance measure for the proposed system. System optimization requires us to find the optimum power allocation strategy for the system to minimize this outage probability. The system performance depends on the number of transmitting nodes.

## 4.3. Optimum Power Allocation Strategy

In this section, I discuss an optimum power allocation strategy for the proposed system. The discussion is split into two parts: broadcasting and random beamforming.

### 4.3.1. Broadcasting

Assume that broadcast rate for all the nodes in the cluster are the same and can be represented as $R_{br}$. Each node will broadcast its data to all other nodes. According to Shannon limit, when

$$R_{br} \leq log_2(1 + \frac{P_1}{K\sigma_{nbr}^2}), \tag{34}$$

the receiver is expected to reconstruct the source correctly, where $\sigma_{nbr}^2$ represents noise on the broadcast channel. Eq (57) can also be written as,

$$P_1 \geq K(2^{R_{br}} - 1)\sigma_{nbr}^2, \tag{35}$$

which shows the lower bound on power used for broadcasting ($P_1$) for reliable transmission. I choose $P_1$ and $R_{br}$ such that they satisfying 58. Therefore, there is no outage during broadcasting.

4.3.2. Random Beamforming

Given two statistically independent random variables X and Y, the distribution of the random variable Z that is formed as the product $Z = XY$ [**49**]. Therefore, given that $\mathbf{H} \sim N(0, I)$ and $\mathbf{V}_{\mathrm{b}} \sim U(0, I)$, $\mathbf{HV}_{\mathrm{b}} \sim PDF\ of\ H \times PDF\ of\ V_b = PDF\ of\ H$, thus, $\mathbf{HV}_{\mathrm{b}} \sim N(0, I)$, and $||\mathbf{HV}_{\mathrm{b}}||^2 \sim \chi^2_{n_t}$ (Chi-Square distributed random variable with $n_t$ degrees of freedom), where $n_t = M \times K$ [**50**]. Since the CDF of $\chi^2_{n_t}$ is the regularized lower incomplete Gamma function $\gamma(.,.)$, the outage probability ($P_{out}$) can be described as [**51**]

$$P_{out} = \frac{\gamma(\frac{MK}{2}, \frac{2^{R_{tr}}-1}{\frac{2P_2}{\sigma_n^2}})}{\Gamma(\frac{MK}{2})}, \tag{36}$$

where $\Gamma(.)$ is the Gamma function. A closed form expression for $P_{out}$ is too complex to derive. I used simulations for our optimization analysis.

4.3.3. Optimization Problem

The optimization problem is to minimize $P_{out}$ subject to the total power ($P_{total}$) constraint. Let us assume that $P_1 = \alpha P_{total}$ such that $P_2 = (1-\alpha)P_{total}$. Then, the optimization problem can be expressed as follows:

$$P^*_{out} = \begin{matrix} min \\ \alpha, K \end{matrix}\ P_{out}, \tag{37}$$

$$s.t.\ P_1 + P_2 = P_{total}, P_1 = \alpha P_{total}, P_2 = (1-\alpha)P_{total}$$

where $P^*_{out}$ is the minimum outage probability. Assume the broadcast power for each node to maintain error-free broadcasting is $P_s$ and $M$ is a fixed number, then $P_1 = KP_s = \alpha P_{total}$.

Therefore, the relation between $\alpha$ and $K$ is given by $K = \alpha \frac{P_{total}}{P_s}$.

According to (59) and (60), outage probability can be reduced by increasing the number of transmitting nodes ($K$), since increased number of transmitting nodes ($K$) will increase the multiuser diversity deployed in the random beamforming phase, which will reducing the outage probability. However, increasing $K$ will result in increased $\alpha$, which in turn, will reduce the power $P_2$ allocated for random beamforming. Reduced transmission power $P_2$ in the random beamforming phase will lead to decreased receiving SNR at FC, and that will degrade the transmission performance in outage probability. Therefore, increasing the power allocation factor ($\alpha$) will introduce more multiuser diversity and deduct transmission power in random beamforming at the same time, and there exists an optimal power allocation that minimizes the outage probability. In the following section, numerical results are provided to illustrate the effect of $\alpha$.

## 4.4. Performance Evaluation

The proposed model is simulated in MATLAB and its performance is evaluated by estimating the outage probability on slow fading correlated and uncorrelated Rayleigh channels. All nodes are assumed to be uniformly distributed in each cluster, so that the broadcast power $P_1$ is directly proportional to the number of cooperating nodes. Also, $\alpha$ is varied within the range (0.2 to 0.8) such that the transmission quality is maintained, and $\frac{P_{total}}{P_s}$ is assumed to be 15, so that $K = 15\alpha$. For all simulations, broadcasting rate $R_{br}$ is set to 2 bits/Hz and random beamforming $R_{tr} = 3$ bits/Hz.

### 4.4.1. Slow Fading Uncorrelated Rayleigh Channel

Consider the case of slow fading uncorrelated Rayleigh channel in which the channel gains remain constant for each use of the channel. The channel fading states are modeled as independent and identically distributed zero mean and unit variance complex Gaussian random variables. In order to implement random beamforming, the base station only needs to know

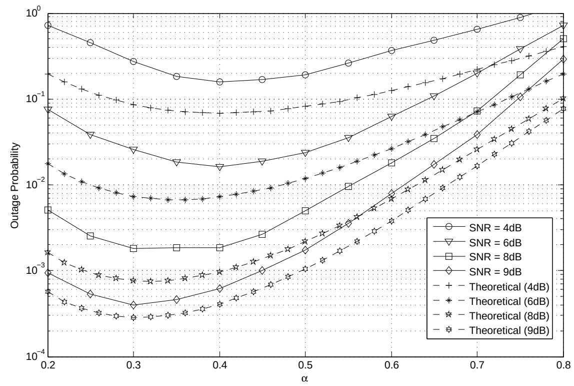



Figure 4.4. Outage probability as a function of the power allocation factors for different channel SNRs

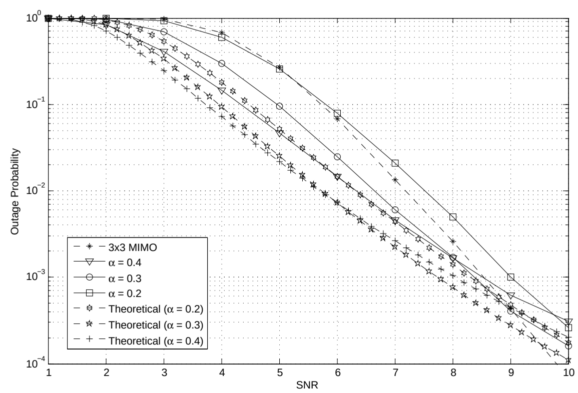



Figure 4.5. Outage probability as a function of the channel SNR for different power allocations

the overall SNR, which is defined as $\frac{P_{total}}{\sigma_n^2}$. To achieve multiuser diversity, I need to add fast time-scale fluctuations on the channel using $\mathbf{V}_{\mathrm{b}}$.

As shown in the Fig. 5.8, when SNR is equal to 4 dB, $P_{out}$ reaches the minimum at $\alpha_\tau = 0.4$. As SNR is increased, the value of $\alpha_\tau$ gets reduced. For instance, when SNR is equal to 9 dB, $P_{out}$ achieves the minimum at $\alpha_\tau = 0.3$. I compare our approach with V-BLAST MIMO under the same total power constraint. The theoretical lower bounds are also plotted. As shown in the Fig. 5.9, when SNR is equal or lower than 9 dB, the proposed system performs better compared with the 3x3 MIMO [**48**] in terms of outage probability, where $K$ equals to 6, 9, and 12.

Fig. 5.9 also demonstrates that when SNR is lower than 8dB, the proposed system exhibits the lowest outage probability when $\alpha_\tau = 0.4$. When SNR is higher than 8dB, $\alpha_\tau$ gets reduced to 0.3.

### 4.4.2. Correlated Rayleigh Fading Channel

To simulate the correlated Rayleigh fading environment, I multiplied the correlation matrix $\mathbf{C}$ with the channel matrix $\mathbf{H}$. The correlation level ($\rho(\mathbf{C})$) is given by

$$\rho(\mathbf{C}) = \frac{||\mathbf{C} - diag(\mathbf{C})||_F}{||diag(\mathbf{C})||_F}, \tag{38}$$

where $||\mathbf{C}||_F$ is the Frobenius norm of $\mathbf{C}$ matrix and $diag(\mathbf{C})$ is the matrix that contains only the diagonal components of $\mathbf{C}$. The correlated Rayleigh fading channel can be described by

$$\mathbf{y} = \mathbf{CHV}_\mathrm{b}\mathbf{x} + \mathbf{n}. \tag{39}$$

Assuming that the eigenvalues of the channel matrix $\mathbf{V}_\mathrm{b}{}^\mathrm{H}\mathbf{H}^\mathrm{H}\mathbf{C}^\mathrm{H}\mathbf{CHV}_\mathrm{b}$ are $\lambda_1, \lambda_2, ...\lambda_n$, the channel capacity is linearly proportional to their product $\lambda_1\lambda_2...\lambda_n$. Channel correlation increases the condition number of the effective channel matrix $\mathbf{V}_\mathrm{b}{}^\mathrm{H}\mathbf{H}^\mathrm{H}\mathbf{C}^\mathrm{H}\mathbf{CHV}_\mathrm{b}$ [**52**] by increasing the difference between the largest and smallest eigenvalues. Hence, the channel capacity decreases with increased $\rho(\mathbf{C})$. This is demonstrated in Fig. 4.6.

## 4.5. Conclusions

In this paper, I proposed a cluster based cooperative communication strategy using random beamforming technique. In the first place, through comparing the outage performance between the proposed system and V-BLAST MIMO, I demonstrated that when the received SNR is low, the outage probability of the proposed system is better compared with that of the multiple-input and multiple-output system on slow fading Rayleigh fading channels.

Through analyzing the optimal power allocation factor ($\alpha$) under different overall SNRs, I find out that: (1) when the overall SNR is low, e.g. lower than 8dB, increased

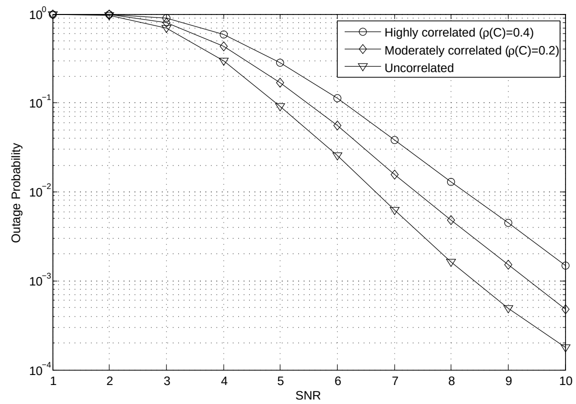



Figure 4.6. Outage probability as a function of the received SNR on correlated and uncorrelated Rayleigh fading channels with 9 transmitting antennas and $\alpha = 30\%$

multiuser diversity ($\alpha = 0.4$, $P_1 = 0.4P_{total}$, $P_2 = 0.6P_{total}$) show greater advantage in combating the channel fading and noise compared with increasing transmission power in random beamforming phase ($\alpha = 0.3$, $P_1 = 0.3P_{total}$, $P_2 = 0.7P_{total}$); (2) when the overall SNR is high, e.g. higher than 8dB, increased transmission power in random beamforming phase ($\alpha = 0.3$) will show more benefits in reducing the outage probability than increased multiuser diversity ($\alpha = 0.4$).

I also compare the performance on correlated and uncorrelated Rayleigh fading channels. Our results demonstrate that since the channel capacity decreases with increased correlation level $\rho(\mathbf{C})$, channel correlation will degrade the proposed system outage performance in linearly proportional to the correlation level.

# CHAPTER 5

# AN EXPLORATION OF SOURCE-CHANNEL COOPERATION IN WIRELESS SENSOR NETWORKS

In this chapter, I would like to combine source-channel cooperation and statistical ranking of sensor observations to provide not only diversity but to also reduce communication costs in order to prolong the lifetime of the network. The objective is to transmit only the most informative observations from the "best" sensors to the fusion center (FC) by cooperating with the sensor nodes whose observations were regarded as "uniformative". Through this procedure, I hope to improve the performance of the network in term of distortion and outage.

In this chapter, I propose a combination of statistical ranking of sensor observations and cluster-based cooperative transmission strategy to improve the performance of WSNs.

I consider a WSN with a clustered topology, where each cluster consists of $N$ sensors. Each sensor in a cluster is capable of collecting data from a source, processing the collected data, and transmitting it through its embedded antenna. The FC is modeled as a single unit with multiple receiving antennas. The goal is to find in each cluster, $K$ out of $N$ best source nodes for transmitting data to FC through a cooperation communication model. I propose two possible cooperative transmission models and derive the corresponding channel capacities.

I consider deterministic sources observed by a network of sensors and rank their observations based on their test statistics. The benefit is that by selecting the sensors with the smallest observation variances as source nodes, the system distortion can be dramatically reduced. I demonstrate the advantages of the proposed strategy through simulations.

The proposed data transmission involves two phases: (1) intra-cluster phase in which all $N$ sensors within a cluster will collect data from different sources. Then, through statistical ranking, I pick $K$ nodes with smallest observation variances out of $N$ nodes ($K < N$) as source nodes. All $K$ nodes communicate with the remaining ($L = N - K$) nodes (namely *cooperating nodes*) over broadcast channels (each node using one time unit to broadcast); and (2) inter-cluster phase in which all ($L$) cooperating nodes in the transmitting cluster communicate with the FC using beamforming. If I consider the FC as a receiving cluster, then, the idea is similar to transmitting data from one cluster to another [**3**]. The FC combines the received data using maximal ratio combining (MRC) technique, and thus achieves full diversity.

I optimize the proposed model through analyses of the system distortion, and show that the cooperating nodes achieve maximum channel capacity. I also simulate the system distortion and outage to show the benefits of the proposed strategies.

The simulation results demonstrate that: 1) by selecting the nodes with smallest observation variances as source nodes, the system distortion can be dramatically reduced; 2) through optimal power allocation between intra-cluster phase and inter-cluster phase, the system can have a better outage performance.

## 5.1. System Models and Channel Capacity

Two possible cooperation transmission models for transmitting observations from $K$ sensors to the FC are presented in this section. I also derive the corresponding channel capacity.

### 5.1.1. Basic Model

A basic sensor network consists of a group of nodes as sources and a FC as receiver. As shown in Fig. 5.1, assume the total number of nodes in the area of interest is $N$, and only $K < N$ nodes collect useful information for the application at hand. In order to send all useful data from $K$ source nodes to the FC, at least $K$ number of channels are needed. In this section, all the channels are assumed to be Raleigh fading channel, which means that the channels are all independent from each other and assumed to be affected by zero-mean additive white Gaussian noise (AWGN).

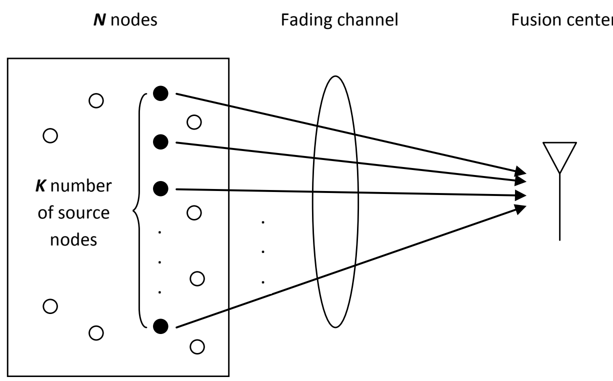



Figure 5.1. Basic model ($K < N$).

If the input to the $i^{th}$ channel is represented by $x_s(i)$, and the channel output is represented by $y_f(i)$, then the system shown in Fig. 5.1 can be represented by

(40) $$y_f(i) = x_s(i) + n_{sf}(i), \quad i = 1, 2, ..., K,$$

where $n_{sf}(i)$ is AWGN with variance $\sigma_{sf}^2(i)$, between the $i^{th}$ source node and the FC.

### 5.1.2. One-to-One Cooperation Model

Here, in order to transmit their observations to the FC, the $K$ source nodes needs to find cooperating nodes. As shown in Fig. 5.2, there are $L$ number of cooperating nodes. In the one-to-one cooperation model, $K = L$ and $K + L \leq N$.

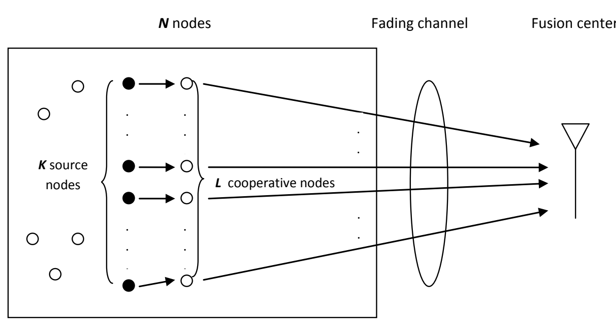



Figure 5.2. One-on-one cooperation model ($2L \leq N$).

The one-to-one cooperation model can be represented by

$$y_{co}(i) = x_s(i) + n_{sc}(i), \quad i = 1, 2, ..., L,$$

(41)

$$y_f(j) = h_{cf}(j)x_{co}(j) + n_{cf}(j), \quad j = 1, 2, ..., L,$$

where $h_{cf}(j)$ is the channel gain from the cooperating nodes to FC, $n_{sc}(i)$ is AWGN, i.e. $n_{sc}(i) \sim N(0, \sigma_{sc}^2(i))$, between $i^{th}$ source and cooperating node, and $n_{cf}(j)$ is AWGN, i.e. $n_{cf}(j) \sim N(0, \sigma_{cf}^2(j))$, between $S$ $j^{th}$ cooperating node and the FC. Also, $x_s(i)$ is the source data, $y_f$ is the data received by FC, $x_{co}(j)$ is decoded from $y_{co}(j)$, and $max\{\sigma_{sc}^2(i), \sigma_{cf}^2(j)\} \leq \sigma_{sf}^2(i)$. The power allocated for $j^{th}$ source node is $P_{sc}(j)$, and the power allocated for $j^{th}$ cooperating node is $P_{cf}(j)$. To keep the total power the same as the basic model for the optimization purpose, $P_{sc}(j) + P_{cf}(j) = P_{sf}(j)$, where $P_{sf}(j)$ is the power form $j^{th}$ source to FC through its corresponding cooperating node $j$.

Assume the channel capacity from source node $i$ to its cooperating node is $C_{sc}(i)$, and the channel capacity from cooperating node $j$ to the FC is $C_{cf}(j)$. The cumulative channel capacity of the one-to-one cooperation model can be described as

$$C_{one} = \frac{1}{2} min\{\sum_{i=1}^{L} C_{sc}(i), \sum_{j=1}^{L} C_{cf}(j)\}$$

(42)

$$= \frac{1}{2} \sum_{j=1}^{L} min\{log(1 + \frac{P_{sc}(j)}{\sigma_{sc}^2(j)}),$$

$$log(1 + \frac{P_{cf}(j)|h_{cf}(j)|^2}{\sigma_{cf}^2(j)})\}.$$

5.1.3. Many-to-Many Cooperation Model

Another possible way of using cooperating nodes to help source nodes with noisy channels is shown in Fig. 5.3. First, chose $L$ number of nodes with the best channels as cooperating nodes. All $K$ source nodes one-by-one broadcast their data to all cooperating nodes, and all cooperating nodes will transmit their aggregated data to the FC. In many-to-many cooperation model, $1 \leq L \leq (N-K)$ and $K+L \leq N$.

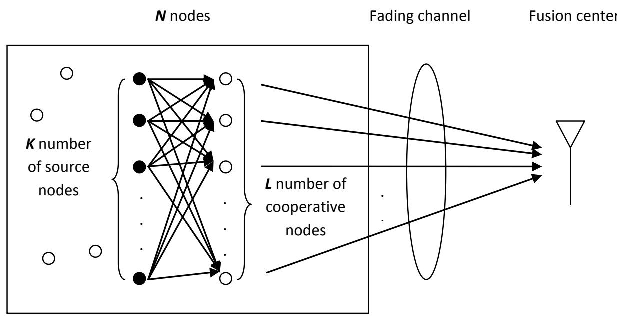



Figure 5.3. Many-to-many cooperation model ($K+L \leq N$).

The many-to-many cooperation system can be represented by

$$y_{co}(j) = \sum_{i=1}^{K} \{x_s(i) + n_{sc}(i)\},$$

(43)

$$y_f = \sum_{j=1}^{L} \{h_{cf}(j) x_{co}(j) + n_{cf}(j)\},$$

where $x_{co}(j)$ represents the channel input from cooperating node $j$ and $x_{co}(j)$ is the decoded version of $y_{co}(j)$. The power allocated for source node $i$ to communicate with cooperating node $j$ is $P_{sc}(i,j)$ ($i = 1, 2, ..., K$, and $j = 1, 2, ..., L$), and the power allocated for each cooperating node to communicate with FC is $P_{cf}(j)$. To keep the total power same as the basic model for the optimization purpose, $\sum_{i=1}^{K} P_{sc}(i,j) + P_{cf}(j) = P_{sf}(j)$. In this section, $P_{sc}(j)$ (the power from all source nodes to cooperating node $j$) are assumed to be uniformly allocated on $K$ source nodes (it is worse than the optimal case - waterfilling, but easy for comparison), so $P_{sc}(i,j) = \frac{P_{sc}(j)}{K}$ for every source $i$.

Assume that the capacity of the channel between all source nodes to cooperating node $j$ is $C_{sc}(j)$, and the capacity of the channel from cooperating node $j$ to FC is $C_{cf}(j)$. The cumulative channel capacity of many-on-many cooperation model can be described as

$$C_{many} = \frac{1}{2}\sum_{j=1}^{L} min\{C_{sc}(j), C_{cf}(j)\}$$

(44) $$= \frac{1}{2}\sum_{j=1}^{L} min\{Klog(1+\frac{P_{sc}(j)}{K\sigma_{sc}^2(j)}),$$

$$log(1+\frac{P_{cf}(j)|h_{cf}(j)|^2}{\sigma_{cf}^2(j)})\},$$

where $\sigma_{sc}^2(j)$ is the variance of AWGN on the channel from all source nodes to cooperating node $j$.

5.1.4. Optimization

The main purpose of developing different cooperation techniques is to maximize the cumulative channel capacity under fixed $P_{total}$.

*One-to-One Cooperation Model Optimization.* In this case, the goal is to maximize $log(1+\frac{P_{sc}(i)}{\sigma_{sc}^2(i)})$ and $log(1+\frac{P_{cf}(j)|h_{cf}(j)|^2}{\sigma_{cf}^2(j)})$. Since $P_{sc}(i)+P_{cf}(j) = P_{sf}(j)$, where $P_{sf}(j)$ is fixed, $\frac{P_{sc}(i)}{\sigma_{sc}^2(i)}$ and $\frac{P_{cf}(j)|h_{cf}(j)|^2}{\sigma_{cf}^2(j)}$ should be close each other, that is when $\frac{P_{sc}(i)}{\sigma_{sc}^2(i)} = \frac{P_{cf}(j)|h_{cf}(j)|^2}{\sigma_{cf}^2(j)}$, $C_{one}$ reaches maximum. If I define the channels between source nodes and cooperating nodes as S-C channels, and the channels between cooperating nodes and the FC as C-F channels, the above observation can be seen as the optimal strategy for pairing S-C channels with C-F channels. That is pairing S-C channels and C-F channels with similar SNR values. In this case, the cumulative channel capacity of one-to-one model ($C_{one}max$) can be maximized as

$$C_{one}max = \frac{1}{2}\sum_{i=1}^{K} log(1+\frac{P_{sc}(i)}{\sigma_{sc}^2(i)})$$

(45)

$$= \frac{1}{2}\sum_{j=1}^{L} log(1+\frac{P_{cf}(j)|h_{cf}(j)|^2}{\sigma_{cf}^2(j)}).$$

*Many-to-Many Cooperating Model Optimization.* Comparing $C_{one}$ and $C_{many}$ under $\frac{P_{sc}(i)}{\sigma_{sc}^2(i)} = \frac{P_{cf}(j)|h_{cf}(j)|^2}{\sigma_{cf}^2(j)}$ is equivalent to comparing two terms: $log(1+c)$ and $Klog(1+\frac{c}{K})$. It is easy to see that when $K=1$, the second term is equal to the first term.

Assume $f(K) = Klog(1+\frac{c}{K})$ and $c$ is a positive real constant, then $\frac{df}{dK} > 0$, which means $f(K)$ is a monotonically increasing function of $K$. Therefore, when $K > 1$, $C_{many} > C_{one}$. The result indicates that in a node cluster with $N$ nodes and $K$ source nodes, choosing many-to-many cooperation model and using as many cooperating nodes as possible can maximize the cumulative channel capacity. In the proposed model, this means $L = N - K$.

5.2. System Distortion Reduction Based on Statistical Ranking

In the previous section, the best cooperation model chosen for sending the data of $K$ source nodes to the FC is to use $L = N - K$ number of cooperating nodes based on many-to-many cooperation model, which can maximize the channel capacity. However, using many-to-many cooperation model brings another question which is: "How to choose the $K$ source nodes from a cluster with $N$ nodes?"

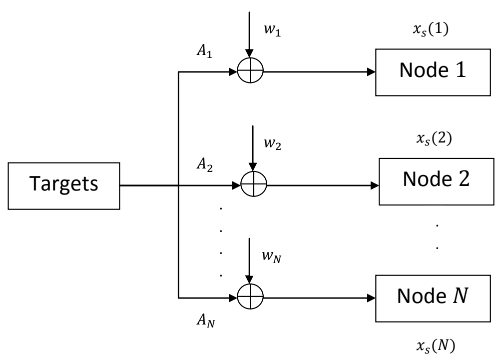



Figure 5.4. Typical observation model

Consider an observation model for WSN deployed for typical applications as shown in Fig. 5.4. It is assumed that the observed signal is deterministic and that the observations are corrupted by AWGN.

$$x_s(i) = A_i + w_i, \quad 1 \leq i \leq N, \tag{46}$$

where $A_i$ represents the deterministic signal, $w_i$ is a zero-mean AWGN with known variance $\sigma_{wi}^2$, $N$ represents the total number of nodes in the cluster. Therefore, the source $x_s(i)$ is also Gaussian, i.e. $x_s(i) \sim \mathcal{N}(A_i, \sigma_{s(i)}^2)$, and $\sigma_{s(i)}^2 = \sigma_{wi}^2$.

### 5.2.1. System Distortion Analysis

I randomly pick $K$ out of $N$ nodes from the cluster to create a many-to-many cooperation model with $L = N - K$ cooperating nodes. To evaluate the importance of the choice of the source nodes, I use system distortion to analyze system performance. Since the channels from all source nodes to cooperating node $j$ are independent from each other, according to [**?**], the distortion from all source nodes to cooperating node $j$ can be represented as

$$D_{sc}(j) = \sum_{i=1}^{K} \frac{\sigma_{s(i)}^2}{2^{2R_{sc}(i,j)}}, \quad 1 \leq j \leq L, \tag{47}$$

where $R_{sc}(i,j)$ is the transmission rate from source node $i$ to cooperating node $j$. The rate $R_{sc}(i,j)$ is the information rate, which is upper-bonded by the capacity of the channel. The data $C_j$ in $j^{th}$ cooperating node is also white Gaussian i.e. $C_j \sim \mathcal{N}(A_i, \sigma_{C_j}^2)$, with variance $\sigma_{C(j)}^2 = \sum_{i=1}^{K} \sigma_{s(i)}^2$.

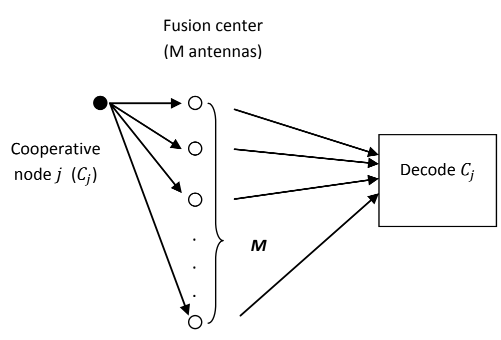



Figure 5.5. Transmission model from cooperating node $j$ to the FC

Assume there are $M$ number of receiving antennas at the FC. According to [**?**, **?**], the distortion of the transmission model shown in Fig. 5.5 can be represented as,

$$D_{cf}(j) = \left( \frac{1}{\sigma^2_{C(j)}} + \sum_{i=1}^{M} \frac{1}{\sigma^2_{C(j)} + \frac{\sigma^2_{cf}(j)}{P_{cf}(j)|h_{cf}(j)|^2}} \right)^{-1}, \tag{48}$$

where $1 \le j \le L$.

Since the source data is decoded at the cooperating node before being sent to the FC, the distortion from source nodes to cooperating nodes and the distortion from cooperating nodes to the FC are independent. Therefore, the distortion from source nodes to the FC through $j^{th}$ cooperating node can be represented as,

$$D_{sf}(j) = E[(\hat{A} - A)^2] = D_{sc}(j) + D_{cf}(j), \quad 1 \le j \le L. \tag{49}$$

where $\hat{A}$ represents the decoded signal $A$ at FC.

### 5.2.2. System Distortion Optimization through Statistical Ranking

In this part, I optimize the system distortion under the local power constraint, that is the total power used for all source nodes to communicate to a cooperating node is fixed.

Assuming the transmission rate $R_{sc}(j) = \sum_{i=1}^{K} R_{sc}(i,j)$ is also fixed. In this case, the product of $\frac{\sigma^2_{s(i)}}{2^{2R_{sc}(i,j)}}$, i.e. $\prod_{i=1}^{K} \frac{\sigma^2_{s(i)}}{2^{2R_{sc}(i,j)}}$ is fixed for certain $K$ number of sources. When the product of $K$ numbers is fixed, their sum reaches minimum if and only if they are all equal. Since $D_{sc}(j) = \sum_{i=1}^{K} \frac{\sigma^2_{s(i)}}{2^{2R_{sc}(i,j)}}$, $D_{sc}(j)$ reaches minimum when $\frac{\sigma^2_{s(1)}}{2^{2R_{sc}(1)(j)}} = \frac{\sigma^2_{s(2)}}{2^{2R_{sc}(2)(j)}} = \ldots = \frac{\sigma^2_{s(K)}}{2^{2R_{sc}(K)(j)}}$.

Let us assume that the cooperating node-to-FC channel state information is known, that is the inverse of the SNR $\frac{\sigma^2_{cf}(j)}{P_{cf}(j)|h_{cf}(j)|^2}$, then minimizing $D_{cf}(j)$ is equal to minimizing $\sigma^2_{C(j)}$. I known that $\sigma^2_{C(j)} = \sum_{i=1}^{K} \sigma^2_{s(i)}$. Hence, if all $N$ sensor observations are ranked based on their variance, i.e. $\sigma^2_{x(1)} \le \sigma^2_{x(2)} \le \ldots \le \sigma^2_{x(N)}$, $D_{cf}(j)$ is minimized. Therefore, the optimal method to choose the $K$ source nodes from a cluster with $N$ nodes is that "$K$ number of nodes with the smallest observation variance should be chosen from $N$ sensor observations as the source nodes".

Since finding the distribution of the sum of $K$ smallest number in $N$ numbers is still an open question without knowledge of the distribution of $N$ numbers, I can not find out theoretically how much distortion can be reduced from choosing $K$ number of nodes with smallest variance as sources. However, I can show the benefit of statistical ranking in simulation.

## 5.3. System Outage Reduction Based on Random Beamforming

In the previous section, I explained how to choose $K$ sources among $N$ sensor observations to improve system distortion performance. In this section, I will discuss how to allocate the power between intra-cluster (source-to-cooperating nodes) phase and inter-cluster (cooperating nodes-to-FC) phase to further improve the system performance in outage.

### 5.3.1. Communication Model and Outage Probability

There are $K$ source nodes each with one transceiver transmitting data to the FC through $L$ cooperating nodes. Also, the FC is equipped with $M$ antennas. The total power allocated for all the nodes communicating their observations to the FC is $P_{total}$. The transmission occurs in two phases as described below.

During the intra-cluster phase, each sensor broadcasts its observations to all cooperating nodes in the same cluster with a certain power. Assume that all nodes decode the received data simultaneously [**47**]. Half-duplexing transmission is assumed in this phase, where all the nodes in the cluster cannot send and receive at the same time on the same frequency. The total power used for all source nodes to accomplish broadcasting (each node using one time unit to broadcast) is $P_1$. Therefore, the number of source nodes $K$ in each cluster depends on the selection of $P_1$.

During the inter-cluster phase, all $L$ cooperating nodes in the cluster will transmit the data they aggregated to the FC using total power $P_2$, and the complete transmission process takes one time unit. I propose a random beamforming technique during this phase with a transmit power for each cooperating node set to be $a_i$. I pre-multiply the input

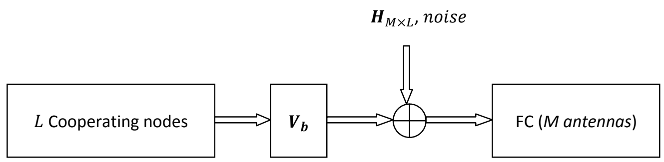



Figure 5.6. Proposed system model: Communicating aggregated sensor observations over $M \times L$ random beamforming channel.

vector with a diagonal beamforming matrix $\mathbf{V}_b$ consisting of $K$ complex numbers $a_i exp(j\theta_i)$, where $\theta_i \in [0, 2\pi]$ for $i = 1, ..., K$. The random beamforming matrix is designed such that $a_i \sim U(0, 1)$ and normalized, and such that $\sum_{i=0}^{K} a_i^2 = P_2$.

The total power ($P_{total}$) used for both phases is given by $P_1 + P_2$. Based on this power constraint, the number of source nodes $K$ in the cluster is selected to be proportional to $\frac{P_1}{P_{total}}$.

The FC receives data from each cluster over $L \times M$ random beamforming channel. In order to obtain full receiver diversity, I propose maximal ratio combining (MRC) technique to reconstruct the received data. For evaluating the performance of the random beamforming strategy, I use V-BLAST MIMO channel [**48**] with the same amount of total power as in random beamforming for comparison, i.e.,

$$P_{MIMO} = P_{total}, \tag{50}$$

where $P_{MIMO}$ represents the power used for transmission over the MIMO channel. Since V-BLAST MIMO is a technique applied to MIMO channels as in Phase-2 of the proposed algorithm, I actually compare the performance of Phase-2 of the proposed strategy with that of V-BLAST MIMO with the same power constraint and time duration.

Before transmission, the input is pre-multiplied by a random beamforming matrix $\mathbf{V}_b$. The proposed system model is shown in Fig. 5.6.

The random beamforming communication model can be described by

$$\mathbf{y}_f = \mathbf{H}_{cf}\mathbf{V}_b\mathbf{x}_{co} + \mathbf{n}_{cf}, \tag{51}$$

where $\mathbf{y}_\mathrm{f} = [y_f(1), y_f(2), ..., y_f(M)]^T$ is the channel output vector, $\mathbf{x}_\mathrm{co} = [x_{co}(1), x_{co}(2), ..., x_{co}(L)]^T$ is the channel input vector, and $\mathbf{n}_\mathrm{cf}$ represents the channel noise vector, whose elements are assumed to be zero-mean AWGN with variance $\sigma^2_{n_{cf}}$, i.e., $n_{cf\,i} \sim \mathcal{N}(0, \sigma^2_{n_{cf}})$ $(i = 1, 2, ..., m)$. $\mathbf{H}_\mathrm{cf}$ represents the channel fading coefficient matrix, and $\mathbf{V}_\mathrm{b}$ represents random beamforming matrix. In comparison, a V-BLAST communication is assumed for MIMO model which is described in [**48**]:

$$\mathbf{y} = \mathbf{H}_\mathrm{MIMO}\mathbf{x} + \mathbf{n}. \tag{52}$$

At the FC, the decoder employs the MRC method to reconstruct the source, which is described as

$$\hat{\mathbf{x}}_\mathrm{s} = \mathbf{x}_\mathrm{s} + \frac{(\mathbf{H}_\mathrm{cf}\mathbf{V}_\mathrm{b})^\mathrm{H}\mathbf{n}_\mathrm{cf}}{||\mathbf{H}_\mathrm{cf}\mathbf{V}_\mathrm{b}||^2}, \tag{53}$$

where $\hat{\mathbf{x}}_\mathrm{s}$ represents the reconstructed source and $(\mathbf{H}_\mathrm{cf}\mathbf{V}_\mathrm{b})^H$ represents the conjugate transpose of $\mathbf{H}_\mathrm{cf}\mathbf{V}_\mathrm{b}$.

The SNR for the received signal can be described as [**21**]

$$SNR = \frac{P_2}{\sigma^2_{n_{cf}}}||\mathbf{H}_\mathrm{cf}\mathbf{V}_\mathrm{b}||^2, \tag{54}$$

where $\sigma^2_{n_{cf}}$ represents the variance of the channel noise.

Let us assume that the transmission rate between a cluster and FC is $R_{cf}$. Then, according to Shannon's limit theorem, when

$$R_{cf} \leq log_2(1 + \frac{P_2}{\sigma^2_{n_{cf}}}||\mathbf{H}_\mathrm{cf}\mathbf{V}_\mathrm{b}||^2), \tag{55}$$

the receiver is expected to decode the received data correctly. Unsatisfactory reception or outage occurs when this condition is not met.

I assume outage-free transmission during the intra-cluster phase and focus on the inter-cluster phase. The system outage probability is given by

$$P_{out} = P(||\mathbf{H}_{\text{cf}}\mathbf{V}_{\text{b}}||^2 < \frac{2^{R_{cf}} - 1}{\frac{P_2}{\sigma^2_{n_{cf}}}}), \tag{56}$$

which I use as a performance measure for the proposed system. System optimization requires us to find the optimum power allocation strategy for the system to minimize this outage probability.

5.3.2. Optimum Power Allocation Strategy

In this section, I discuss an optimum power allocation strategy for the proposed system. The discussion is divided into two parts: broadcasting and random beamforming.

In the intra-cluster phase, I assume that the broadcast rate for all the nodes in the cluster is the same and can be represented as $R_{sc}$. Each node will broadcast its data to all other nodes. According to Shannon limit, when

$$R_{sc} \leq log_2(1 + \frac{P_1}{K\sigma^2_{n_{sc}}}), \tag{57}$$

the receiver is expected to reconstruct the source correctly, where $\sigma^2_{n_{sc}}$ represents noise on the broadcast channel. The inequality of (57) can also be rewritten as,

$$P_1 \geq K(2^{R_{sc}} - 1)\sigma^2_{n_{sc}}, \tag{58}$$

which shows the lower bound on power used for broadcasting ($P_1$) for reliable transmission. I choose $P_1$ and $R_{sc}$ such that they satisfy (58). Therefore, there is no outage during broadcasting.

Given two statistically independent random variables $X$ and $Y$, the distribution of the random variable $Z$ that is formed as the product $Z = XY$ [**49**]. Therefore, in the inter-cluster phase, given that $\mathbf{H}_{\text{cf}} \sim \mathcal{N}(0, I)$ and $\mathbf{V}_{\text{b}} \sim U(0, I)$, $\mathbf{H}_{\text{cf}}\mathbf{V}_{\text{b}} \sim PDF\ of\ H_{cf} \times PDF\ of\ V_b = PDF\ of\ H_{cf}$, thus, $\mathbf{H}_{\text{cf}}\mathbf{V}_{\text{b}} \sim \mathcal{N}(0, I)$, and $||\mathbf{H}_{\text{cf}}\mathbf{V}_{\text{b}}||^2 \sim \chi^2_{n_t}$ (Chi-Square distributed random varaible with $n_t$ degrees of freedom), where $n_t = M \times L$ [**50**]. Since the cumulative density function (CDF) of $\chi^2_{n_t}$ is the regularized lower incomplete Gamma function $\gamma(...)$, the outage probability ($P_{out}$) can be described as [**51**]

$$P_{out} = \frac{\gamma\left(\frac{ML}{2}, \frac{2^{R_{cf}}-1}{\frac{2P_2}{\sigma^2_{n_{cf}}}}\right)}{\Gamma(\frac{ML}{2})}, \tag{59}$$

where $\Gamma(.)$ is the Gamma function. A closed form expression for $P_{out}$ is too complex to derive. I used simulations for our optimization analysis.

The optimization problem is to minimize $P_{out}$ subject to the total power ($P_{total}$) constraint. Let us assume that $P_1 = \alpha P_{total}$ such that $P_2 = (1-\alpha)P_{total}$. Then, the optimization problem can be expressed as follows:

$$\begin{aligned} P^*_{out} = &\min_{\alpha, K} P_{out}, \\ &s.t.\ P_1 + P_2 = P_{total}, P_1 = \alpha P_{total}, P_2 = (1-\alpha)P_{total} \end{aligned} \tag{60}$$

where $P^*_{out}$ is the minimum outage probability. To maintain an error-free broadcasting, the broadcast power for each node is assumed to be $P_s$ and $M$ is a fixed number, then $P_1 = KP_s = \alpha P_{total}$. Therefore, the relation between $\alpha$ and $K$ is given by $K = \alpha \frac{P_{total}}{P_s}$.

According to (59) and (60), outage probability can be reduced by increasing the number $K$ of source nodes. Since increasing $K$ will increase the multiuser diversity deployed in the random beamforming phase, the outage probability will be reduced. However, increasing $K$ will result in increased $\alpha$, which in turn, will reduce the power $P_2$ allocated for random beamforming. Reduced transmission power $P_2$ in the random beamforming phase will lead to decreased receiving SNR at the FC, and that will degrade the transmission performance in outage probability. Therefore, increasing the power allocation factor ($\alpha$) will introduce more multiuser diversity and deduct transmission power in random beamforming at the same time,

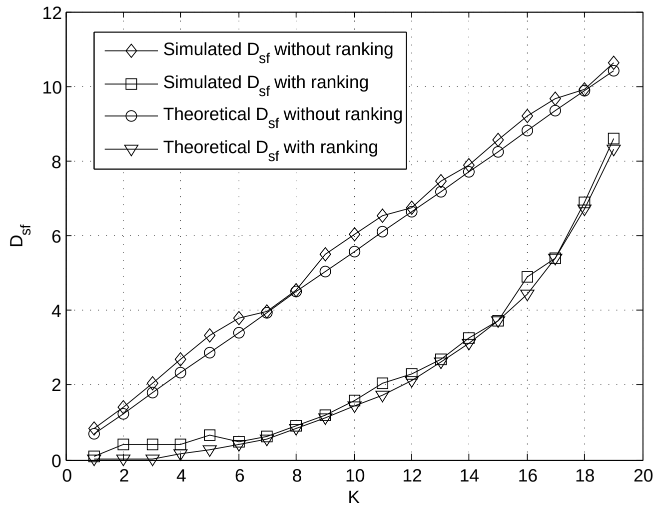



Figure 5.7. System distortion comparison.

and there exists an optimal power allocation that minimizes the outage probability. In the following section, numerical results are provided to illustrate the effect of $\alpha$.

## 5.4. Performance Evaluation

The proposed model is simulated in MATLAB and its performance is evaluated in terms of system distortion (in mean square error (MSE)) and outage probability.

### 5.4.1. System Distortion

In this simulation, I assume that the variances of all $N$ sensor observations follow standard normal distribution. I chose $N = 20$, and the number of source nodes $K$ varies from 1 to 19. I compare the end-to-end distortion $D_{sf}$ in two case: (1) with ranking of sensor observations, and (2) without ranking of sensor observations. The results are shown in Fig. 5.7.

The results demonstrate that: 1) when the number of source nodes $K$ increases, both $D_{sf}$ with ranking and $D_{sf}$ without ranking increase; 2) when $1 < K < N$, $D_{sf}$ with ranking outperforms $D_{sf}$ without ranking in MSE; 3) when $K$ varies, the difference between the two distortion varies. From the simulation results, I can see that by selecting the sensors with the

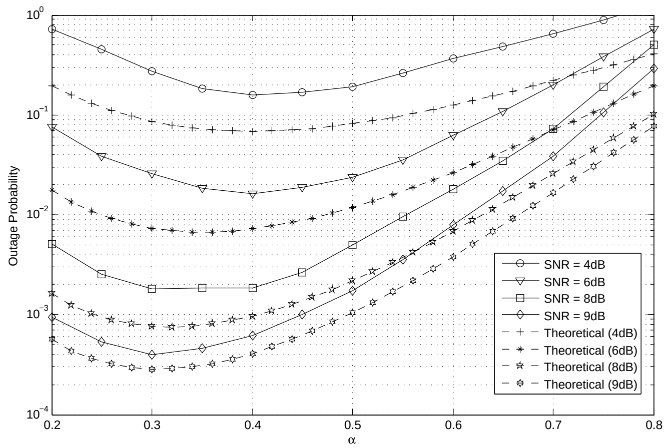



Figure 5.8. Outage probability as a function of the power allocation factors for different channel SNRs.

smallest observations variances as the source nodes, the system distortion can be dramatically reduced.

5.4.2. System Outage

The outage probability is simulated on slow fading uncorrelated Rayleigh channels. All nodes are assumed to be uniformly distributed in each cluster, so that the broadcast power $P_1$ is directly proportional to the number of cooperating nodes. Also, $\alpha \in [0.2 to 0.8]$ such that the transmission quality is maintained, and $\frac{P_{total}}{P_s}$ is assumed to be 15, so that $K = 15\alpha$. For all simulations, broadcasting rate $R_{br}$ is set to 2 bits/Hz and random beamforming $R_{tr}$ $= 3$ bits/Hz.

Consider the case of slow fading uncorrelated Rayleigh channel in which the channel gains remain constant for each use of the channel. The channel fading states are modeled as independent and identically distributed zero mean and unit variance complex Gaussian random variables. In order to implement random beamforming, the FC only needs to know the overall SNR, which is defined as $\frac{P_{total}}{\sigma_n^2}$. To achieve multiuser diversity, I need to add fast time-scale fluctuations on the channel using $\mathbf{V}_\mathrm{b}$.

As shown in Fig. 5.8, when SNR is equal to 4 dB, $P_{out}$ reaches the minimum at $\alpha_\tau = 0.4$. As SNR is increased, the value of $\alpha_\tau$ gets reduced. For instance, when SNR is

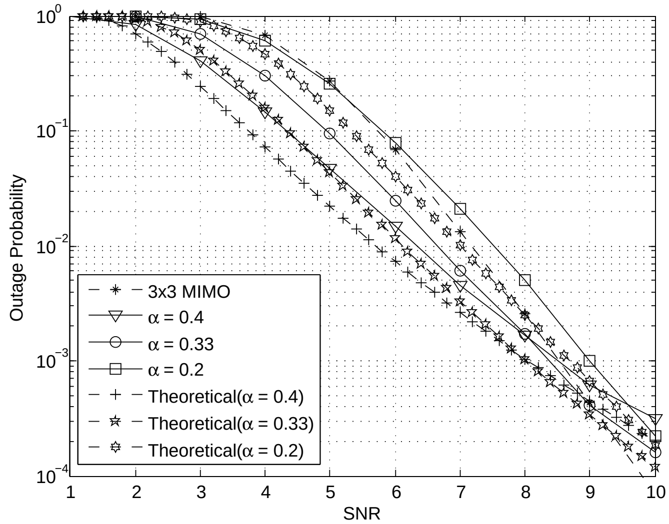



Figure 5.9. Outage probability as a function of the channel SNR for different power allocations.

equal to 9 dB, $P_{out}$ achieves the minimum at $\alpha_\tau = 0.3$. Also, please note that the theoretical value is a lower bound of the outage.

As shown in Fig. 5.9, when SNR is equal or lower than 9 dB, the proposed system performs better compared with the 3x3 MIMO [**48**] in terms of outage probability, where $K$ equals to 3, 5, and 6.

Fig. 5.9 also demonstrates that when SNR is lower than 8dB, the proposed system exhibits the lowest outage probability when $\alpha_\tau = 0.4$. When SNR is higher than 8dB, $\alpha_\tau$ gets reduced to 0.3.

## 5.5. Conclusions

In this paper, I explores source-channel cooperation strategies in wireless sensor network to improve system performance.

First, by comparing the end-to-end distortion $D_{sf}$ obtained when using statistical ranking, with the one obtained by not using statistical ranking in term of MSE, I demonstrated that when $1 < K < N$, $D_{sf}$, the ranking approach outperforms $D_{sf}$ the no-ranking approach. I can conclude that by selecting the sensors with the smallest observation variances as source nodes, the system distortion can be dramatically reduced.

Second, by comparing the outage performance between the proposed system and V-BLAST MIMO, I demonstrated that when the received SNR is low, the outage probability of the proposed system is better compared with that of the MIMO system on slow fading Rayleigh fading channels.

Finally, by analyzing the optimal power allocation factor ($\alpha$) under different overall SNRs, I find out that: (1) when the overall SNR is low, e.g. lower than 8dB, increased multiuser diversity ($\alpha = 0.4$, $P_1 = 0.4P_{total}$, $P_2 = 0.6P_{total}$) show greater advantage in combating the channel fading and noise compared with increasing transmission power in random beamforming phase ($\alpha = 0.3$, $P_1 = 0.3P_{total}$, $P_2 = 0.7P_{total}$); (2) when the overall SNR is high, e.g. higher than 8dB, increased transmission power in random beamforming phase ($\alpha = 0.3$) will show more benefits in reducing the outage probability than increased multiuser diversity ($\alpha = 0.4$).

# CHAPTER 6

# CONCLUSION

In this dissertation, I focus on source coding techniques as well as channel coding techniques. I developed: (1) a new source coding strategy for erasure channels that has better distortion performance compared to multiple description coding (MDC); (2) a new cooperative channel coding strategy for multiple access channels that has better channel outage performances compared to multiple input multiple output (MIMO); (3) a new source-channel cooperation strategy to accomplish source-to-fusion center communication that reduces system distortion and improves outage performance.

In Chapter 3, I draw a parallel between the 2x2 MDC scheme and the Alamouti's space time block coding (STBC) scheme and observe the commonality in their mathematical models. This commonality allows us to observe the duality between the two diversity techniques. Making use of this duality, I develop an MDC scheme with pairwise complex correlating transform. By analyzing the relationship between the MDC transforms in terms of the redundancy-rate distortion, I find the factors that could affect both transforms.

Theoretically, I show that MDC scheme results in: 1) complete elimination of the estimation error when only one descriptor is received; 2) greater efficiency in recovering the stronger descriptor (with larger variance) from the weaker descriptor; and 3) improved performance in terms of minimized distortion as the quantization error gets reduced. The benefits are also shown in the simulations.

The simulation results demonstrate that MDC with complex transform can effectively reduced the estimation error when the lost descriptor needs to be recovered from the received one, with the same redundancy. When the redundancy reaches maximum for both complex and real transforms, MDC with complex transform can eliminate the estimation error. I also demonstrate that as the quantization error is reduced, the complex transform performs better than the real transform in terms of minimizing the distortion. Experiments are also preformed on real images to demonstrate these benefits.

In Chapter 4, I present a two-phase cooperative communication strategy and an optimal power allocation strategy to transmit sensor observations to a fusion center in a large-scale sensor network. Outage probability is used to evaluate the performance of the proposed system. Simulation results demonstrate that: 1) when signal-to-noise ratio is low, the performance of the proposed system is better than that of the MIMO system over uncorrelated slow fading Rayleigh channels; 2) given the transmission rate and the total transmission SNR, there exists an optimal power allocation that minimizes the outage probability; 3) on correlated slow fading Rayleigh channels, channel correlation will degrade the system performance in linear proportion to the correlation level.

Through analyzing the optimal power allocation factor ($\alpha$) under different overall SNRs, I find out that: (1) when the overall SNR is low, e.g. lower than 8dB, increased multiuser diversity ($\alpha = 0.4$, $P_1 = 0.4P_{total}$, $P_2 = 0.6P_{total}$) show greater advantage in combating the channel fading and noise compared with increasing transmission power in random beamforming phase ($\alpha = 0.3$, $P_1 = 0.3P_{total}$, $P_2 = 0.7P_{total}$); (2) when the overall SNR is high, e.g. higher than 8dB, increased transmission power in random beamforming phase ($\alpha = 0.3$) will show more benefits in reducing the outage probability than increased multiuser diversity ($\alpha = 0.4$).

I also compare the performance on correlated and uncorrelated Rayleigh fading channels. Our results demonstrate that since the channel capacity decreases with increased correlation level $\rho(\mathbf{C})$, channel correlation will degrade the proposed system outage performance in linearly proportional to the correlation level.

In Chapter 5, I combine the statistical ranking of sensor observations with cooperative communication strategy in a cluster-based wireless sensor network. This strategy involves two steps: 1) ranking the sensor observations based on their test statistics; 2) building a two-phase cooperative communication model with an optimal power allocation strategy. The result is an optimal system performance that considers both sources and channels. I optimize the proposed model through analyses of the system distortion, and show that the cooperating nodes achieve maximum channel capacity. I also simulate the system distortion and outage to show the benefits of the proposed strategies. The simulation results demonstrate that: 1) by selecting the nodes with smallest observation variances as source nodes, the system distortion can be dramatically reduced; 2) through optimal power allocation between intra-cluster phase and inter-cluster phase, the system can have a better outage performance.

First, by comparing the end-to-end distortion $D_{sf}$ obtained when using statistical ranking, with the one obtained by not using statistical ranking in term of MSE, I demonstrated that when $1 < K < N$, $D_{sf}$, the ranking approach outperforms $D_{sf}$ the no-ranking approach. I can conclude that by selecting the sensors with the smallest observation variances as source nodes, the system distortion can be dramatically reduced.

Second, by comparing the outage performance between the proposed system and V-BLAST MIMO, I demonstrated that when the received SNR is low, the outage probability of the proposed system is better compared with that of the MIMO system on slow fading Rayleigh fading channels.

# APPENDIX

## COMPLEX TRANSFORM REDUNDANCY

The equation describes the complex transform redundancy is given by (17). Given that

$$
\begin{aligned}
cos^4x + sin^4x &= cos^4x + sin^4x + 2cos^2xsin^2x - 2cos^2xsin^2x \\
&= (cos^2x + sin^2x)^2 - 2cos^2xsin^2x \\
&= 1 - 2cos^2xsin^2x
\end{aligned}
\tag{61}
$$

$\sigma_C^2\sigma_D^2$ can be further simplified as follows,

$$
\begin{aligned}
\sigma_C^2\sigma_D^2 &= (\sigma_A^2cos^2\theta_c + \sigma_B^2sin^2\theta_c)(\sigma_A^2sin^2\theta_c + \sigma_B^2cos^2\theta_c) \\
&= (\sigma_A^4 + \sigma_B^4)cos^2\theta_csin^2\theta_c + \sigma_A^2\sigma_B^2(cos^4\theta_c + sin^4\theta_c) \\
&= (\sigma_A^2 - \sigma_B^2)^2cos^2\theta_csin^2\theta_c + \sigma_A^2\sigma_B^2 \\
&= \tfrac{1}{4}(\sigma_A^2 - \sigma_B^2)^2sin^22\theta_c + \sigma_A^2\sigma_B^2.
\end{aligned}
\tag{62}
$$

Therefore, complex transform redundancy ($\rho_c$) can be simplified as

$$
\rho_c = \frac{1}{2}log_2\frac{\sqrt{(\sigma_A^2 - \sigma_B^2)^2sin^22\theta_c + 4\sigma_A^2\sigma_B^2}}{2\sigma_A\sigma_B}.
\tag{63}
$$

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