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Analysis of Localization algorithms for Wireless Sensor Networks Using Binary Data

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ABSTRACT

ANALYSIS OF LOCALIZATION ALGORITHMS FOR WIRELESS SENSOR NETWORKS USING BINARY DATA

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The detection, localization, and tracking of environmental and physical conditions can be accomplished using wireless sensor networks (WSNs). Recent advancements in sensors, processors, and wireless communications have improved the quality and acquisition speed of data in WSNs. However, the data gathered by a WSN is inherently random due to component and environmental variations. Thus, statistical signal processing algorithms are needed to analyze the random data in a robust way. Though many algorithms for the analysis of random data are established and available, they are problem-specific and must be adapted to the application. This thesis provides an analysis of established localization algorithms for wireless sensor networks using single-bit received signal strength (RSS) data.

The algorithms are evaluated via Monte Carlo simulation using root mean square error performance metric with respect to design parameter variations. Three scenarios are considered including a single source scenario with known parameters, a single source scenario with unknown parameters, and a multi-source scenario where an additional source is present to add interference to sensor measurements. Two algorithms are selected: the Varshney algorithm, based on the most popular maximum likelihood estimator and the Michaelides

algorithm, an empirical variant where prospective locations are scored based on observations of nearby sensors. The algorithms are evaluated in [7] and [8] under different conditions. Here, each is evaluated under identical conditions and assumptions. It is shown that the algorithms perform similarly under ideal conditions, and the empirical Michaelides algorithm can outperform the Varshney algorithm under high interference scenarios.

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Special thanks are in order to my advisor, Dr. Benedito Fonseca, for his guidance and support throughout my undergraduate and graduate studies. Thanks to my family, friends, and peers for their constant love and support.

DEDICATION

To my parents, and two sisters.

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CHAPTER 1

INTRODUCTION

The detection, localization, and tracking of environmental and physical conditions can be accomplished using wireless sensor networks (WSNs) [1][2][3][4][5] [6]. Recent advancements in sensors, processors, and wireless communications have improved the quality and acquisition speed of data in WSNs. However, the data gathered by a WSN is inherently random due to component and environmental variations. Thus, statistical signal processing algorithms are needed to analyze the random data in a robust way. Though many algorithms for the analysis of random data are established and available, they are problem-specific and must be adapted to the application. After adaptation, a validation step is necessary to understand when an algorithm is likely to work well or to fail. This thesis provides an analysis of two established localization algorithms for wireless sensor networks using single-bit received signal strength (RSS) data. This chapter motivates the use of wireless sensor networks for localization in a variety of applications. An overview of our approach for validation of the selected algorithms is provided followed by a description of the contributions made by the study.

1.1 Problem Description

A *positioning system* is one in which its objective is to provide an estimate of the location of a target. The use of WSNs for positioning is beneficial in cases where sensors must be deployed in a flexible way. The nodes of a wireless sensor network are small and low-power devices; the nodes can be distributed in a wide range of environments for monitoring. Modern WSNs can operate across spaces large and small supporting dense deployment of sensors for both [1][2].

WSNs have been used for a variety of applications including underwater detection and localization of submarines and oil spills, earthquake detection, aerosol monitoring, and urban gas leak detection. Agencies such as the National Aeronautics and Space Administration (NASA) have taken an interest in these systems for human and robotic space exploration. Networked sensors for environmental monitoring of space stations and cooperative mobile robots are examples of recent research in this domain [17][18].

As mentioned, established algorithms have been developed and analyzed for localization with WSNs. However, many of the existing algorithms are new and leave room for characterization of their performance with respect to design parameters. When designing an algorithm, assumptions must be made for mathematical tractability or to reduce system complexity. In reality, these assumptions may not always be satisfied but still the algorithm must deliver the level of performance required. This is especially true for the mission critical applications mentioned above.

The data gathered by sensors in a WSN is used for obtaining simple information such as range between a target and the sensor. The parameters measured by sensors used for obtaining this information, referred to as positioning parameters, can vary. Localization procedures making use of measured RSS are becoming more practical since modern WSNs can be distributed across greater distances with higher density. These methods in constrast to others have the benefit of not requiring accurate synchronization between the nodes. Further, measured RSS can be reduced to a single bit using binary decision based on the measured RSS value. In this case, less energy and bandwidth are needed which is beneficial for resource constrained wireless sensor networks.

The objective of this thesis is to evaluate the performance of two existing localization algorithms for wireless sensor networks using binary data from measured received signal strength. The algorithms under study are the Varshney and Michaelides algorithms described in [7] and [8]. The Varshney and Michaelides algorithms can both be considered fusion-based; in both algorithms the measurements from all sensors are combined. The Varshney algorithm is based on the most popular maximum likelihood estimator. The Michaelides algorithm is an empirical adaptation, where prospective locations are scored based on observations of surrounding sensors. While there are many issues involved in the study of statistical signal processing algorithms for target localization, this thesis addresses the evaluation of performance with respect to variation of design parameters.

1.2 Approach

The general approach to evaluating the performance of any statistical signal processing algorithm is the same. A performance criterion is selected and a subsequent testing is carried out to determine the performance with respect to the chosen criterion. Typically, at the testing stage, the algorithm is encoded in software and tested with computer-generated data. Field testing should follow this step but is outside of the scope of the study.

In this study, Monte Carlo methods are used to evaluate the performance of the previously proposed Varshney and Michaelides algorithms for target localization using wireless sensor networks. A Monte Carlo simulation generates independent, identically distributed (iid) random samples of the distributions for the random variables which influence the outcome of the system under study.

The use of Monte Carlo simulation tools is the preferred approach for the evaluation of statistical signal processing algorithms because their complexity makes an analytical evaluation difficult to obtain. The evaluation of statistical signal processing algorithms requires the use of a statistically meaningful performance criterion or performance metric which Monte Carlo simulation tools are conducive to. Other benefits of using Monte Carlo methods include rapid assessment of performance and algorithm robustness to variation of design parameters, assessment of computational complexity, and easy comparison of multiple algorithms.

A performance and sensitivity analysis of the proposed Varshney and Michaelides algorithms is carried out with respect to variation of design parameters under a variety of conditions. An isotropic and continuous propagation model is used for the target source; two scenarios are considered which include the single-source and multi- source cases. A series of Monte Carlo simulations are performed to measure the performance and sensitivity of the Varshney and Michaelides algorithms with respect to the variable parameters for each scenario using the root mean square error performance metric.

1.3 Contributions

Many issues are involved in the proper design of statistical signal processing algorithms and positioning systems in general. The scope of the thesis does not include many of the challenges posed in an end-to-end system such as detection, communication, and security. We assume that these issues have been resolved and focus on the evaluation of the Varshney and Michaelides algorithms with respect to variation of design parameters. In particular, the evaluation described in the thesis has lead to two contributions:

1. Performance analysis of Varshney and Michaelides algorithms proposed in [7] and [8] with respect to variation of design parameters in a single-target scenario, under identical conditions and assumptions.

2. Sensitivity analysis of Varshney and Michaelides algorithms proposed in [7] and [8] with respect to variation of design parameters in a single-target scenario, under identical conditions and assumptions.

3. Performance analysis of Varshney and Michaelides algorithms proposed in [7] and [8] with respect to variation of design parameters in a multi-target scenario, under identical conditions and assumptions.

1.4 Thesis Outline

Chapter 2 provides a background of positioning systems including positioning parameters traditionally used for target localization. A short description of time of arrival, time delay of arrival, and angle of arrival based methods is given, followed by an extended description of received signal strength based methods. In particular, the section on RSS-based methods focuses on those under study from [7] and [8] which use single bit quantization of measured RSS. Chapter 3 provides a model for the system in which the algorithms operate, as well as formulation of the signal model, algorithms, and performance metric used. In Chapters 4, 5, and 6, the results from the performance and sensitivity analysis in the two scenarios are presented with an interpretation of the results. The thesis is summarized in Chapter 7 which includes conclusions and future areas of research.

CHAPTER 2

BACKGROUND

In this chapter, a background is provided to the reader covering the general positioning problem and common procedures for estimating the location of a target. Time of arrival and time delay of arrival (TOA/TDOA), angle of arrival (AOA), and received signal strength (RSS) procedures are described. An overview is provided for localization procedures which use binary data gathered by wireless sensor networks; in particular those described by [7] and [8], as these procedures are the focus of this thesis.

2.1 Positioning Problem

Assuming a target source is known to exist and has been correctly detected by the positioning system, the positioning problem is described as estimating the location of the target in a 2-D or 3-D space within a coordinate system, constructed using known reference points, based on observations. The observations are often of basic information such as range or observable angles between the target source and the known references. Range and angle between the target source and the references can be obtained through positioning parameters. Those considered here are time of arrival or time delay of arrival (TOA/TDOA) of a signal, angle of arrival (AOA) of a signal, or the received signal strength (RSS) [16].

Ideally, the location of the target would be determined exactly. In reality, this goal is not obtainable due to noise processes which are not deterministic or possible constraints for a given system. Generally, it is necessary to settle for an estimate of the location of the target, striking a balance between accuracy and cost. To provide simple examples, variance in RSS measurements due to electronic noise or in the coordinates of sensors may contribute to errors in the estimated location of the target [20]. It is common to consider these and similar error sources as random processes. Errors are reduced by increased data acquisition and computation speed from improvements in sensors, processors, and communications. Improvements in estimation procedures also help cope with errors, for example, data fusion techniques [16][9]. If errors are inevitable then it is advantageous to be aware of how much error is present for a given system. The root mean square error (RMSE) is a statistically meaningful performance metric commonly used to evaluate the performance of an estimator [19]. The formulation for the RMSE metric is given in Chapter 3.

2.2 Positioning Parameters

Many localization algorithms make use of range or relative angle measurements between the target source and fixed points of the space being measured. The measurements of range and relative angle between the target source and the fixed points are achieved by TOA/TDOA, AOA, and RSS positioning parameters. The positioning parameters are measured by networked sensors (fixed points) and the measurements are used to infer the location of the target source. Each method has inherent trade-offs, limitations, and costs to consider.

In this section, an overview of TOA/TDOA, AOA, and RSS-based positioning methods is provided to the reader for background. A more extensive background of RSS-based, specifically the subset of those which use binary observations, is provided to the reader as the algorithms methods studied in this thesis are of this type.

2.2.1 TOA/TDOA

TOA is related to the time of travel of a transmitted signal between a transmitter and receiver. The distance can be determined if the propagation speed of the channel is known and a direct line of sight exists. TDOA measurements are obtained indirectly with two TOA estimates obtained by two separate sensors. In both TOA and TDOA, some level of synchronization is required which can be a difficult task due to cost and system limitations [16]. This cost is offset since TOA/TDOA positioning schemes do not have an increasing variance with distance as in AOA and RSS-based positioning [16]. TOA/TDOA-based positioning schemes are well known by the research community [3][4]. These methods have been long applied by intelligence, aerospace, and defense industries among others.

2.2.2 AOA

Information about the location of the target can be obtained by measuring the angle or direction of arrival of the signal when it arrives at the sensor. In many AOA-based techniques, estimation of the AOA parameter relies on observations by multiple sensors using special sensor placements [16]. The signals arriving at each of the sensors will arrive with some time difference; each sensor will measure a time- and phase-delayed version of the received signal. Then the angle of arrival information can be extracted with array processing techniques [16]. The performance of AOA-based positioning techniques is dependent on the number of sensors in the sensor array, as well as the separation between those sensors. They often require large sensor networks making them costly and computationally expensive [16]. This cost is offset since AOA-based methods do not require precise synchronization of the sensors, which can be seen as an advantage compared to TOA/TDOA based methods [16]. AOA-based positioning schemes are well known by the research community [5][6].

2.2.3 RSS

If a reasonably accurate propagation model has been obtained, measurements of received signal strength are useful in determining the distance between a transmitter (source) and receiver. Obtaining a reasonably accurate propagation model can be a major challenge of RSS-based positioning methods since they usually depend highly on environmental parameters which vary greatly case by case. Though this poses a challenge, RSS-based methods have the advantage of not requiring synchronized sensors. The RSS measurements require the simplest hardware and there are existing commercial- off-the-shelf products which gather RSS data readily, such as Zigbee and WiFi. RSS-based methods do not require precise synchronization of sensors, a benefit over TOA/TDOA and a shared characteristic of AOA.

Maximum Likelihood estimators are commonly used to determine parameters of the propagation model such as power and range [16][7]. Previously, RSS-based positioning procedures consider raw measurements from sensors to estimate the location of the source [10][11]. A special case of RSS-based positioning methods are those that use binary data or data which has been quantized to a single bit.

2.3 Single Bit RSS

Energy and bandwidth are typically limited for wireless sensor network systems. In this case, it is advantageous to use single bit data to limit communication in the network [7]. Quantization of raw measurements to a single bit is also advantageous in the case that the noise process which corrupt the raw measurements cannot be fully characterized. In this case, the probability that a raw measurement crosses a threshold can be determined and this threshold used to characterize raw measurements as positive or negative observations of the source. The binary observations are less sensitive to sensor variabilities [8]. Several methods for RSS-based positioning using binary data have been proposed [7][8][9] [12][13][14][15].

The algorithm described in [7] uses multi-frame binary data gathered by a wireless sensor network measuring received signal strength. The raw RSS measurements are compared to a threshold value; a binary observation is assigned depending on whether the raw measurement crosses the threshold. The full set of binary data from the network is transmitted to the central processing node. The coordinate system defined by the sensor network where the source lies is partitioned into a grid. This algorithm is based on the likelihood principle. A likelihood function is evaluated for each point in the grid, to a specified resolution. The estimate is obtained by maximization of this grid. The procedure has been shown to perform well under conditions of a single source present [7] and has been adapted for multi-bit quantization.

The algorithm described in [8] uses multi-frame binary data gathered by a wireless sensor network measuring received signal strength. The raw RSS measurements are compared to a threshold value; a binary observation is assigned depending on whether the raw measurement crosses the threshold. The full set of binary data from the network is transmitted to the central processing node. The coordinate system defined by the sensor network where the source lies is partitioned into a grid. This algorithm is based on a novel concept referred to as Region of Coverage (ROC). The ROC defines a region around each sensor; a source could lie at any point in this region and cause the sensor to make a positive binary observation with certain probability. Depending on the observation made by a sensor, the points of the grid which fall in this region are assigned positive or negative values. The contributions from all sensors are summed, and the maximum is considered the final estimate. This algorithm has been shown to be a fault-tolerant alternative [8][9] to the Varshney algorithm. Other algorithms consider unique approaches such as particle filtering and evaluation for butterfly radiation models [12][13][14] [15].

2.4 Summary

The positioning problem is described generally as estimating the location of a source in a 2-D or 3-D space, constructed with reference points, based on observations. Positioning systems often use basic information extracted from positioning parameters to infer the location of the target. It is not a feasible task to determine the location exactly; errors attributed to sensor variation and environmental conditions are present. Improvements in both algorithms and hardware help cope with these errors.

This study provides an analysis of two existing positioning methods which use binary data gathered from wireless sensor networks measuring received signal strength. In particular, two algorithms are considered here which are described in [7] and [8]. From here on they are referred to as Varshney and Michaelides algorithms, respectively. The Varshney algorithm differs from the Michaelides algorithm in that it is based on the likelihood principle; the Michaelides algorithm is a fusion based procedure. The formulation for propagation model, signal model, and grid population functions are now provided.

CHAPTER 3

SYSTEM MODEL

In this chapter, a full system model is provided for a 2-D scenario. The propagation and signal models are introduced as well as the formulation for the Varshney and Michaelides algorithms. For each algorithm, the propagation model, signal model, sampling process, and quantization process are identical. Generally speaking, a network of sensors is distributed across a 2-D field where a target source lies. Each sensor collects a raw measurement which is modeled as a random process. Each raw measurement is quantized to a single bit before being transmitted to the base station for processing.

At the base station, the 2-D field is partitioned into cells which make up a grid. A matrix is constructed parallel to this grid; each coordinate of the grid is assigned an element of the matrix. At the matrix population step, the algorithms are differentiated. The Varshney algorithm will populate this grid by evaluating a likelihood function which requires assumptions about the sources propagation and the distribution of the raw sensor measurements. The Michaelides algorithm populates the grid based on a summation of values contributed to each cell by each sensor in the network depending on the sensors region of coverage. Section 3.2.1 and Section 3.2.2 describe the algorithms in greater detail.

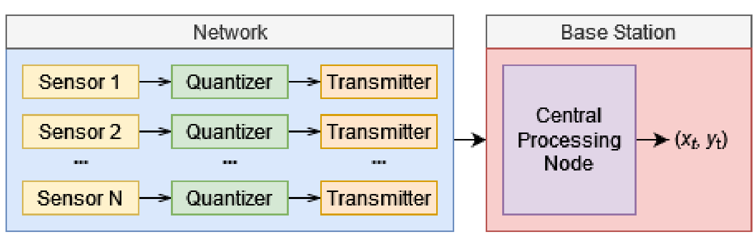

Figure 3.1: Model for the positioning system for a single frame of data.

The area to monitor is a 2-D rectangular field with area $A = l \times l$. Let the domain $D = \{(x, y) : \frac{-l}{2} \leq x, y \leq \frac{l}{2}\}$ be the set of all points within the rectangular field. It is assumed a set of N nodes of known location are uniformly placed across the domain D. The location of each node is known, denoted by $(x_i, y_i) \in D$ with $i = \{1, 2, \cdots, N\}$ being the sensor number. It is assumed that at least one source has been correctly detected by the network. An isotropic and continuous propagation model is selected for the source; it is assumed that no environmental changes occur throughout the propagation path and the location of the source $(x_t, y_t) \in D$ is unknown.

3.1 Signal Model

The signal amplitude a measured by the i-th sensor is determined by an isotropic signal intensity attenuation model, written

$$a_i = \frac{P_0}{d_i^n}, \tag{3.1}$$

where P_0 is the signal energy at the emitter location (x_t, y_t). The signal amplitude measured by the i-th sensor, a_i, is inversely proportional to the Euclidean distance between the unknwon source location $(x_t, y_t) \in D$ and the sensor location $(x_i, y_i) \in D$. The Euclidean distance between the source and the i-th sensor is denoted d_i and is determined by

$$d_i = \sqrt{(x_i - x_t)^2 + (y_i - y_t)^2}. \tag{3.2}$$

To account for path losses, the Euclidean distance between the source and i-th sensor is raised to a power n, the attenuation constant.

It is assumed that the sensors in the network are synchronous and so during the sampling period, the 2-D space D is sampled by all N sensors simultaneously. There are T samples collected by the network during the sampling period with $j = \{1, 2, \cdots, T\}$ denoting the sample number. It is assumed that each sensor contributes a random variation to its measurements due to electronic noise. For this reason, an additive noise is included in the signal model for each sensor. The j-th sample collected by sensor i is denoted s_{ij} and is determined by

$$s_{ij} = a_i + \omega_i \tag{3.3}$$

where $\omega_i \sim N(0, \sigma)$ is a Gaussian additive noise of the i-th sensor.

3.1.1 Quantization

As previously mentioned, this study focuses on a specific type of localization algorithms which are those for wireless sensor networks using binary data only. Thus, when a sample collects a measurement, the measurement is quantized to a single bit value. The quantization of the measurement by a sensor is done so using a pre-designed threshold value. Each measurement is compared to the threshold value to determine the quantized value. The design of the threshold value is not the focus of this study and so it is not done here. The value chosen for the threshold is specified later on.

The binary observation of a sensor is determined as follows. The sample s_{ij} is collected by the i-th sensor during sample period j. The sample s_{ij} is compared to the pre-designed threshold value η to produce the binary observation I_{ij}.

The binary observation of sensor i from sample j is denoted I_{ij}. The binary observation I_{ij} is determined by comparing the sample s_{ij} to the pre-designed threshold value, denoted η. The binary observation I_{ij} is determined as follows

$$I_{ij} = \begin{cases} 0, & s_{ij} < \eta \\ 1, & s_{ij} \geq \eta \end{cases} \tag{3.4}$$

The full data set from a sampling period is denoted $\mathbf{I}_{ij}$ and is written as

$$\mathbf{I} = \{I_{ij} : i = 1, 2, \cdots, N, j = 1, 2, \cdots, T\} \tag{3.5}$$

3.2 Central Processing Node

After the full data set $\mathbf{I}$ is transmitted to the base station it is ready for processing by the central processing node using either of the Varshney or Michaelides algorithms. Within the central processing node, a map of the 2-D field A is partitioned into $G \times G$ cells of area $a = g \times g$ together making a grid Γ. A matrix Λ exists in parallel to the grid with $G \times G$ dimensions. Each cell of the grid Γ has an associated element in the matrix Λ. The next step is to populate the matrix Λ; the process differs depending on the algorithm used.

3.2.1 Varshney Algorithm

The Varshney algorithm is a maximum likelihood estimator, as shown by [7]. The goal is to estimate the parameter $\theta = [x_t, y_t]'$. The estimate can be obtained by maximizing the likelihood function evaluated for the full range of possiblities for θ. This is analagous to populating the matrix Λ and determining the coordinates in Γ corresponding to the maximum value of the matrix. The likelihood function of the Varshney algorithm is derived in [7], written

$$p(\mathbf{I} \mid \theta) = \prod_{i=1}^{N} \prod_{j=1}^{T} [Q(\eta_{ij} - a_{ij}(\theta))]^{I_{ij}} \times [1 - Q(\eta_{ij} - a_{ij}(\theta))]^{1-I_{ij}} \tag{3.6}$$

where $Q(\cdot)$ is the complementary distribution function of the standard Gaussian distribution, written

$$Q(x) = \int_{x}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} \, dt \tag{3.7}$$

Often the log-likelihood function is used for computation over the likelihood function for convenience. The log-likelihood function is derived from the likelihood function, written

$$\ln p(\mathbf{I} \mid \theta) = \sum_{i=1}^{N} \sum_{j=1}^{T} I_{ij} \ln[Q(\eta_{ij} - a_{ij}(\theta))] + (1 - I_{ij}) \ln[1 - Q(\eta_{ij} - a_{ij}(\theta))] \tag{3.8}$$

Then the estimated location of the source is determined by the optimzation problem

$$\max_{\theta} \ln p(\mathbf{I} \mid \theta) \tag{3.9}$$

3.2.2 Michaelides Algorithm

The Michaelides algorithm is a fusion-based algorithm, as shown in [8][9]. Similar to the Varshney algorithm, the estimate for (x_t, y_t) is obtained by populating the matrix Λ and determining the coordinates in Γ corresponding to the maximum value of the matrix. In the Michaelides algorithm, each sensor contributes to Λ based on its binary observation and the

ROC of the sensor. The ROC of the sensor i is defined as the circular region with its center at (x_i, y_i) with radius

$$ROC_i = \sqrt[n]{P_0/\eta} \tag{3.10}$$

Let $C(e, f)$ for $e, f = 1, \cdots, G$ denote the center of the $G \times G$ cells (making up the grid Γ) in matrix form. Then Λ is constructed by the following

$$\Lambda(e, f) = \sum_{i=1}^{N} \sum_{j=1}^{T} R_{ij}(e, f) \tag{3.11}$$

for $e, f = 1, \cdots, G$ where

$$R_{ij} = \begin{cases} +1, & I_{ij} = 1 \text{ and } (e, f) \in ROC_i \\ -1, & I_{ij} = 0 \text{ and } (e, f) \in ROC_i \\ 0, & \text{otherwise} \end{cases} \tag{3.12}$$

The maximum of the matrix Λ is first determined by

$$\Lambda(e^*, f^*) \geq \Lambda(e, f) \tag{3.13}$$

$\forall e, f = 1, \cdots, G$, where e^*, f^* are the element of Λ with the maximum value. Then the estimated event position is the centroid of the corresponding cells.

3.3 Performance Metrics

To evaluate the performance of an estimator, a statistically meaningful performance metric is needed since the data fed to the estimator is inherently random. A statistically meaningful performance metric measures the performance of an estimator in the long-run, after many attempts and under controlled and identical conditions. The bias and variance of an estimator are simple metrics that can be used for measuring the performance of an estimator.

The bias of an estimator is defined as the average distance between the estimate and the true value, written

$$b(\theta) = E[\hat{\theta}] - \theta, \text{ for } -\infty < \theta < \infty \tag{3.14}$$

where θ is the unknown parameter value to be estimated and $\hat{\theta}$ is the estimator. A bias of zero guarantees the estimate is correct on average. The variance is defined as the squared deviation of a random variable from its mean. Then for an estimator the variance is the squared deviation of the estimator from its average, written

$$var(\hat{\theta}) = E[(\hat{\theta} - \mu)^2] \tag{3.15}$$

where μ is the mean of the estimator $\hat{\theta}$. The mean squared error (MSE) performance metric is defined as the average squared deviation from the true parameter value, written

$$mse(\hat{\theta}) = var(\hat{\theta}) + b^2(\theta) \tag{3.16}$$

which shows the MSE is constructed from the bias and variance of the estimator $\hat{\theta}$.

In this study, the Varshney and Michaelides algorithms are evaluated via Monte Carlo simulation. A scenario is constructed by passing parameters to the Monte Carlo simulation such as network size, source power, or instrument noise. During a Monte Carlo simulation, each algorithm is called on to provide an estimate for the location of the source for the scenario defined by the parameters. Each Monte Carlo simulation results in a number of estimates for the source under identical conditions which are used to measure the performance.

The performance metric used is the root mean square error, based on the MSE defined in Equation 3.16, written

$$RMSE = \sqrt{\frac{1}{L}\sum_{1}^{L} d_e^2} \tag{3.17}$$

where L is the number of runs in the Monte Carlo simulation and d_e is the Euclidean distance between the estimated location and the true location of the source for the e-th run of the simulation.

3.4 Summary

A system model is provided describing the positioning system used for estimating the location of possible targets. The 2-D field where the target lies is defined as well as the network and target propagation model. The signal model for the sensors is provided followed by the quantizer used for converting raw measurements to binary data. The formulation of the Varshney and Michaelides algorithms is provided in Section 3.2.1 and 3.2.2. The statistically meaningful performance metric is introduced generally and a formulation for the RMSE is given in Equation 3.17.

CHAPTER 4

PERFORMANCE ANALYSIS

In this chapter, the performance analysis conducted for the Varshney and Michaelides algorithms is described. The simulation environment and signal parameters are outlined by the tables included. Plots of the root mean square error of each simulation for each algorithm are provided with respect to the variable parameters. The analysis is conducted with respect to variable maximum source power P_0 and variable instrument noise power σ. For each of these parameters, a series of Monte Carlo simulations were run producing a set of estimates; the variable parameter was changed for each simulation and other parameters remained constant. The root mean square error is computed from the resulting estimates of the simulation. In this scenario, it is assumed that a single source with *known* P_0 is placed near the center of the 2-D field and sensors with *known* σ are placed uniformly across the field with known locations.

4.1 Variation of Source Power

This section describes the parameters and results for the performance analysis of the Varshney and Michaelides algorithms with respect to variable maximum source power P_0. As previously mentioned, a series of Monte Carlo simulations were run varying P_0. For each Monte Carlo simulation, 100 estimates are obtained before computing the root mean square error for the simulation. The simulation environment and signal parameters are outlined in Table 4.1 and Table 4.2. The result of the performance analysis is shown by Figure 4.1.

Table 4.1: Environment parameters for the performance analysis study with respect to variable source power P_0.

Algorithm	Domain length, $l(m)$	Grid length, $G(m)$	Grid cell, $g(m)$	# sensors, N	# samples, T
Varshney	$\{60\}$	$\{60\}$	$\{1\}$	$\{36\}$	$\{1\}$
Michaelides	$\{60\}$	$\{60\}$	$\{1\}$	$\{36\}$	$\{1\}$

Table 4.2: Signal parameters for the performance analysis study with respect to variable source power P_0.

Algorithm	Source coords., (x_t, y_t)	Max. signal power, P_0	Atten. constant, n	Noise power, σ
Varshney	$\{(0,0)\}$	$\{1, 20, 40, \cdots, 480, 500\}$	$\{2\}$	$\{1\}$
Michaelides	$\{(0,0)\}$	$\{1, 20, 40, \cdots, 480, 500\}$	$\{2\}$	$\{1\}$

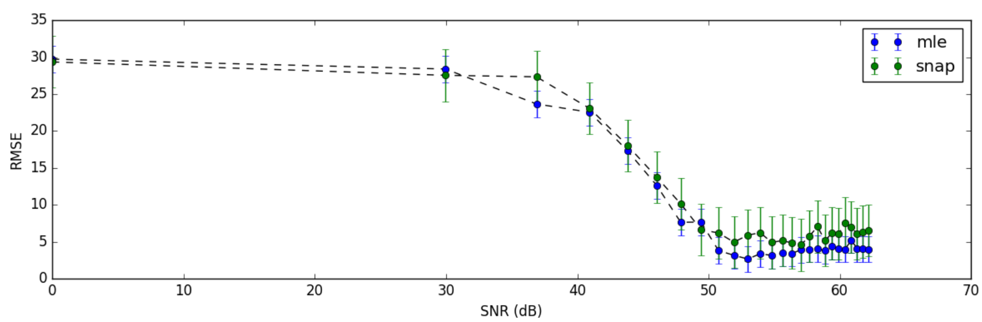

Figure 4.1: Result of the performance analysis study with respect to source power P_0 for Varshney (blue) and Michaelides (green) algorithms. The root mean square error (y-axis) is plotted with respect to maximum source power P_0 (x-axis). Each point is the result of a Monte Carlo simulation of 100 runs, with the bars representing two standard deviations of the simulation.

From the result shown in Figure 4.1, the Varshney and Michaelides algorithms perform similarly under the conditions described in Table 4.1 and Table 4.2. For each value of P_0 the root mean square error resulting from the Monte Carlo simulation tends to decrease from the previous. Observing the error bars in Figure 4.1, the results from simulating with different algorithms are overlapping; it cannot be said whether either algorithms performs better in this case. The RMSE goes tends toward zero, as expected, because the signal-to-noise ratio is increasing with P_0.

4.2 Variation of Instrument Noise

This section describes the parameters and results for the performance analysis of the Varshney and Michaelides algorithms with respect to variable instrument power σ. As previously mentioned, a series of Monte Carlo simulations were run varying σ. For each Monte Carlo simulation, 100 estimates are obtained before computing the root mean square error for the simulation. The simulation environment and signal parameters are outlined in Table 4.3 and Table 4.4. The result of the performance analysis is shown by Figure 4.2.

Table 4.3: Environment parameters for the performance analysis study with respect to variable instrument noise power σ.

Algorithm	Domain length, l	Grid length, G	Grid cell, g	# sensors, N	# samples, T
Varshney	{60}	{60}	{1}	{36}	{1}
Michaelides	{60}	{60}	{1}	{36}	{1}

From the result shown in Figure 4.2, the Varshney and Michaelides algorithms perform similarly under the conditions described in Table 4.3 and Table 4.4. For each value of σ the root mean square error resulting from the Monte Carlo simulation tends to increase from the previous. Observing the error bars in Figure 4.2, the results from simulating with different algorithms are overlapping; it cannot be said whether either algorithms performs better in this case. The RMSE increases with noise, since the SNR is reduced as σ is increased.

Table 4.4: Signal parameters for the performance analysis study with respect to variable instrument noise power σ.

Algorithm	Source coords., (x_t, y_t)	Max. signal power, P_0	Atten. constant, n	Noise power, σ
Varshney	$\{(0,0)\}$	$\{200\}$	$\{2\}$	$\{1, 2, \cdots, 24, 25\}$
Michaelides	$\{(0,0)\}$	$\{200\}$	$\{2\}$	$\{1, 2, \cdots, 24, 25\}$

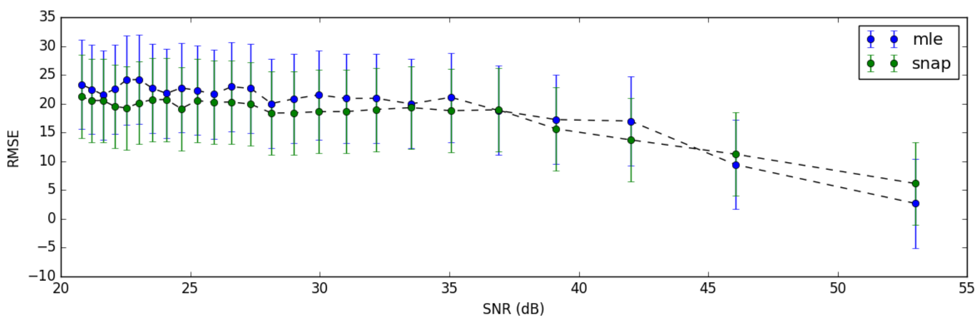

Figure 4.2: Result of the performance analysis study with respect to instrument noise power σ for Varshney (blue) and Michaelides (green) algorithms. The root mean square error (y-axis) is plotted with respect to instrument noise power σ (x-axis). Each point is the result of a Monte Carlo simulation of 100 runs, with the bars representing two standard deviations of the simulation.

4.3 Summary

A performance analysis of the Varshney and Michaelides algorithms was conducted with respect to maximum source power P_0 and instrument noise power σ. The performance analysis consisted of a series of Monte Carlo simulations for ranges of the variable parameters. The root mean square error of each simulation is determined by the resulting estimates of the simulation. The scenario considers a single source located at the center of the 2-D field with sensors placed uniformly across the field with known locations. It was determined that the Varshney and Michaelides algorithms perform similarly for the range studied of the maximum source power P_0 and instrument noise power σ parameters.

CHAPTER 5

SENSITIVITY ANALYSIS

In this chapter, the sensitivity analysis conducted for the Varshney and Michaelides algorithms is described. The simulation environment and signal parameters are outlined by the tables included. Plots of the root mean square error of each simulation for each algorithm are provided with respect to the variable parameters. The analysis is conducted with respect to variable maximum source power P_0 and variable instrument noise power σ. For each of these parameters, a series of Monte Carlo simulations were run producing a set of estimates; the variable parameter was changed for each simulation and other parameters remained constant. The root mean square error for each Monte Carlo simulation is computed from the resulting estimates of the simulation. In this scenario, it is assumed that a single source with *unknown* P_0 is placed near the center of the 2-D field and sensors with *unknown* σ are placed uniformly across the field with known locations. In the sensitivity analysis varying source power, the algorithms assume a value for P_0 and use the known σ value. Likewise, when varying noise power, the algorithms assume a value for σ and use the known P_0.

5.1 Variation of Source Power

This section describes the parameters and results for the sensitivity analysis of the Varshney and Michaelides algorithms with respect to variable maximum source power P_0. As previously mentioned, a series of Monte Carlo simulations were run varying P_0. For each Monte Carlo simulation, 100 estimates are obtained before computing the root mean square error for the simulation. The simulation environment and signal parameters are outlined in Table 5.1 and Table 5.2. The result of the sensitivity analysis is shown by Figure 5.1.

Table 5.1: Environment parameters for the sensitivity analysis study with respect to variable source power P_0.

Algorithm	Domain length, l	Grid length, G	Grid cell, g	# sensors, N	# samples, T
Varshney	{60}	{60}	{1}	{36}	{1}
Michaelides	{60}	{60}	{1}	{36}	{1}

Table 5.2: Signal parameters for the sensitivity analysis study with respect to variable source power P_0.

Algorithm	Source coords., (x_t, y_t)	Max. source power, P_0	Atten. constant, n	Noise power, σ
Varshney	$\{(0,0)\}$	$\{1, 20, 40, \cdots, 280, 300\}$	{2}	{1}
Michaelides	$\{(0,0)\}$	$\{1, 20, 40, \cdots, 280, 300\}$	{2}	{1}

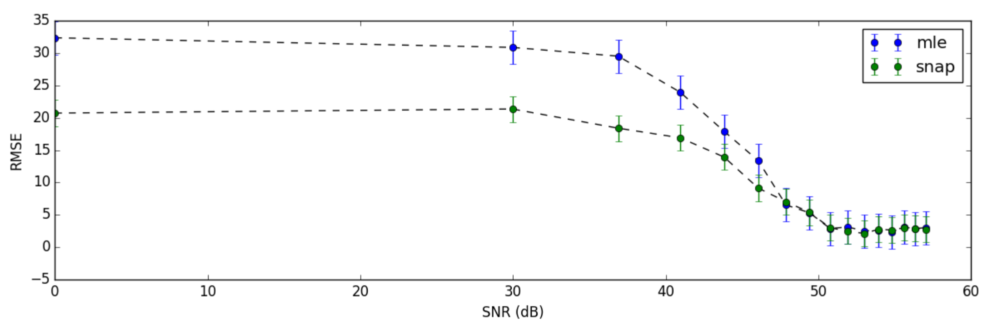

Figure 5.1: Result of the sensitivity analysis study with respect to source power P_0 for Varshney (blue) and Michaelides (green) algorithms. The root mean square error (y-axis) is plotted with respect to maximum source power P_0 (x-axis). Each point is the result of a Monte Carlo simulation of 100 runs, with the bars representing two standard deviations of the simulation.

From the result shown in Figure 5.1, the Varshney and Michaelides algorithms perform differently the conditions described in Table 5.1 and Table 5.2. For each value of P_0 the root mean square error resulting from the Monte Carlo simulation tends to decrease from the previous. For the series of simulations the Michaelides algorithm produces consistently lower RMSE values while the actual maximum source power approaches the assumed ($P_0 < 200$). The standard deviation bars of each algorithm for the Monte Carlo simulations in this range are distinct; the distributions of the RMSE for each algorithms are separated. With these observations, under these conditions, the Michaelides algorithm appears less sensitive to error in the assumed source power.

5.2 Variation of Instrument Noise

This section describes the parameters and results for the sensitivity analysis of the Varshney and Michaelides algorithms with respect to variable instrument power σ. As previously mentioned, a series of Monte Carlo simulations were run varying σ. For each Monte Carlo simulation, 100 estimates are obtained before computing the root mean square error for the simulation. The simulation environment and signal parameters are outlined in Table 5.3 and Table 5.4. The result of the sensitivity analysis is shown by Figure 5.2. A σ is assumed by each algorithm and the actual σ value is varied.

Table 5.3: Environment parameters for the sensitivity analysis study with respect to variable instrument noise power σ.

Algorithm	Domain length, l	Grid length, G	Grid cell, g	# sensors, N	# samples, T
Varshney	$\{60\}$	$\{60\}$	$\{1\}$	$\{36\}$	$\{1\}$
Michaelides	$\{60\}$	$\{60\}$	$\{1\}$	$\{36\}$	$\{1\}$

Table 5.4: Signal parameters for the sensitivity analysis study with respect to variable instrument noise power σ.

Algorithm	Source coords., (x_t, y_t)	Max. signal power, P_0	Atten. constant, n	Noise power, σ
Varshney	$\{(0,0)\}$	$\{200\}$	$\{2\}$	$\{1, 2, \cdots, 24, 25\}$
Michaelides	$\{(0,0)\}$	$\{200\}$	$\{2\}$	$\{1, 2, \cdots, 24, 25\}$

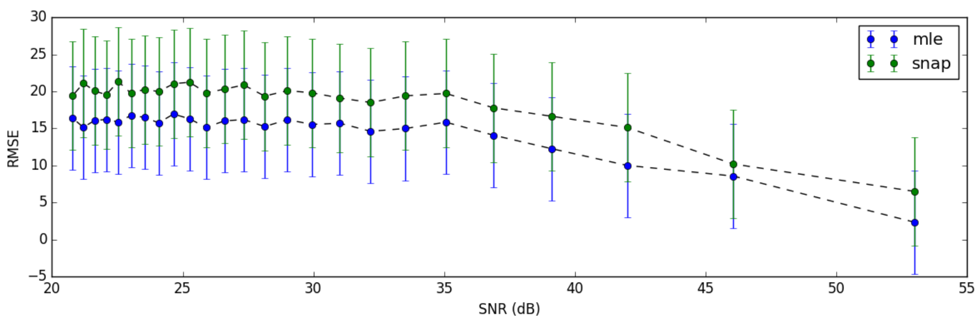

Figure 5.2: Result of the sensitivity analysis study with respect to instrument noise power σ for Varshney (blue) and Michaelides (green) algorithms. The root mean square error (y-axis) is plotted with respect to instrument noise power σ (x-axis). Each point is the result of a Monte Carlo simulation of 100 runs, with the bars representing two standard deviations of the simulation.

From the result shown in Figure 5.2, the Varshney and Michaelides algorithms perform similarly under the conditions described in Table 5.3 and Table 5.4. For each value of σ the root mean square error resulting from the Monte Carlo simulation tends to increase from the previous. Observing the error bars in Figure 5.2, the results from simulating with different algorithms are overlapping; it cannot be said whether either algorithm has more robust sensitivity.

5.3 Summary

A sensitivity analysis of the Varshney and Michaelides algorithms was conducted with respect to maximum source power P_0 and instrument noise power σ. The sensitivity analysis consisted of a series of Monte Carlo simulations for ranges of the variable parameters. The root mean square error of each simulation is determined by the resulting estimates of the simulation. The scenario considers a single source located at the center of the 2-D field with sensors placed uniformly across the field with known locations. It was determined that the Varshney and Michaelides algorithms have similar sensitivity for the range studied of the maximum source power P_0 and instrument noise power σ parameters. The Michaelides algorithm appears to be slightly less sensitive to error in the assumed source power.

CHAPTER 6

MULTI-SOURCE CASE

In this chapter, the performance analysis conducted for the Varshney and Michaelides algorithms is described for the case of multiple sources present in the field. The simulation environment and signal parameters are outlined by the tables included. Plots of the root mean square error of each simulation for each algorithm are provided with respect to the variable parameter. The scenario studied here considers two sources in the 2-D field. One source with known power and unknown location has been correctly detected by the network; this source is the target. A second source is present with unknown power and unknown location and the network is not aware this source is present; this is the interference source.

The analysis is conducted with respect to variable maximum source power P_0 of the interference source. A series of Monte Carlo simulations were run for the full range of the variable parameter were run, each producing a set of estimates for the target sources location. The root mean square error is determined for each Monte Carlo simulation from the resulting estimates. In this scenario, it is assumed that in the 2-D field the target source is located at the center and the interference source is located at a random location. Sensors are placed uniformly across the field with their locations known.

6.1 Variation of Interference Source Power

This section describes the parameters and results for the performance analysis of the Varshney and Michaelides algorithms with respect to variable maximum source power P_0

of the interference source. As previously mentioned, a series of Monte Carlo simulations were run varying P_0. For each Monte Carlo simulation, 100 estimates are obtained before computing the root mean square error for the simulation. The simulation environment and signal parameters are outlined in Table 6.1 and Table 6.2. The result of the performance analysis is shown by Figure 6.1.

Table 6.1: Environment parameters for the performance analysis study with respect to variable maximum source power P_0 of the interference source.

Algorithm	Domain length, l	Grid length, G	Grid cell, g	# sensors, N	# samples, T
Varshney	$\{60\}$	$\{60\}$	$\{1\}$	$\{36\}$	$\{1\}$
Michaelides	$\{60\}$	$\{60\}$	$\{1\}$	$\{36\}$	$\{1\}$

Table 6.2: Signal parameters for the performance analysis study with respect to variable maximum source power P_0 of the interference source.

Algorithm	Source coords., (x_t, y_t)	Target P_0	Interference P_0	Atten. constant, n	Noise power, σ
Varshney	$\{(0,0)\}$	$\{200\}$	$\{1, 40, 80, \cdots, 960, 1000\}$	$\{2\}$	$\{1\}$
Michaelides	$\{(0,0)\}$	$\{200\}$	$\{1, 40, 80, \cdots, 960, 1000\}$	$\{2\}$	$\{1\}$

From the result shown in Figure 6.1, the Varshney and Michaelides algorithms show different performance for the range of the variable parameter P_0 for the interference source power. Beginning with the Michaelides RMSE curve, the RMSE remains fairly constant across the full range of P_0. The result of the analysis for the Varshney algorithm is quite different; for levels of P_0 below the maximum power of the target, the RMSE begins below that of the Michaelides, eventually crossing and reaching a steady state after P_0 exceeds the maximum power of the target.

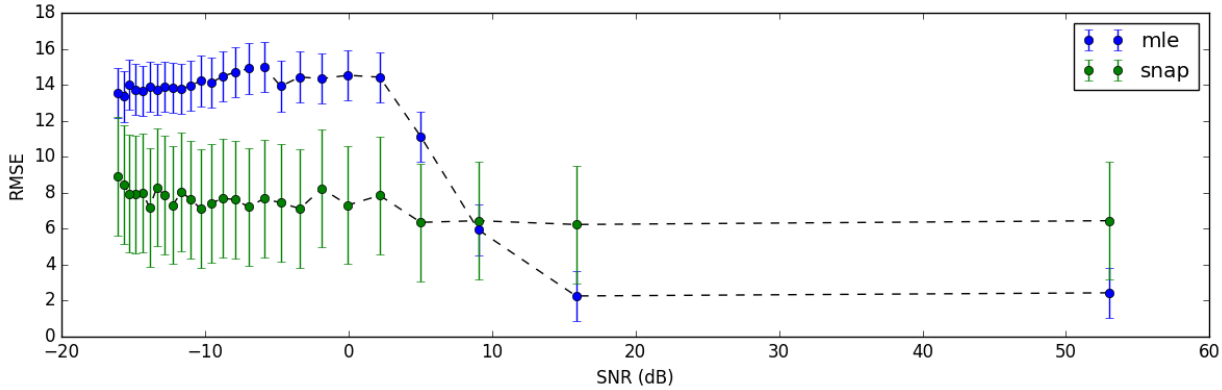

Figure 6.1: Result of the performance analysis study with respect to source power P_0 for Varshney (blue) and Michaelides (green) algorithms. The root mean square error (y-axis) is plotted with respect to maximum source power P_0 (x-axis). Each point is the result of a Monte Carlo simulation of 100 runs, with the bars representing two standard deviations of the simulation.

It is quite challenging to say exactly why the result of the Varshney algorithm is this way. Shown in Figure 6.2 and Figure 6.3 are heatmaps of the matrix Λ for the Varshney and Michaelides algorithm. These images seem to indicate that the Varshney and Michaelides perform similarly; the heatmaps indicate maximums at the locations of the target and interference source, shown by Figure 6.4 and Figure 6.5.

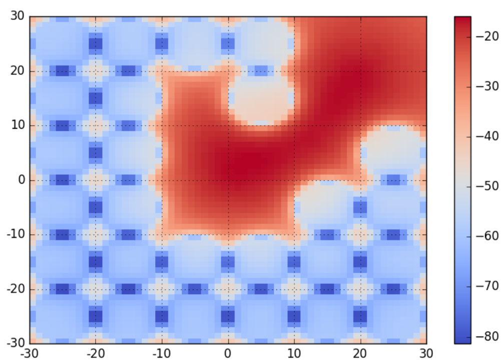

Figure 6.2: Varshney Heatmap Varshney Λ before maximization.

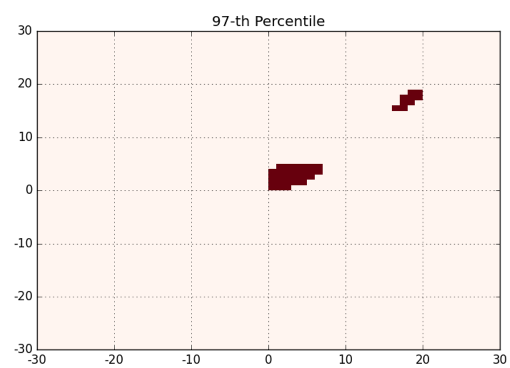

Figure 6.3: Varshney 97-th 97-th percentile of Varshney Λ before maximization.

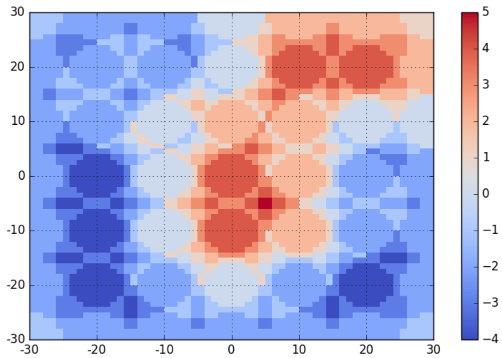

Figure 6.4: Michaelides Heatmap
Michaelides Λ before maximization.

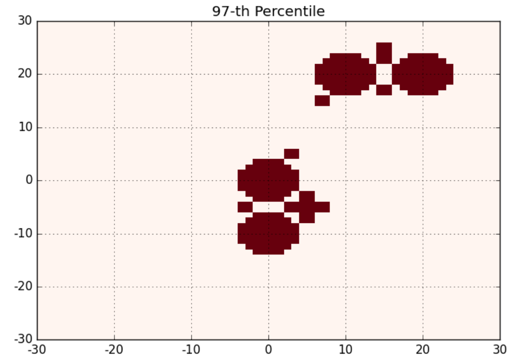

Figure 6.5: Michaelides 97-th
97-th percentile of Michaelides Λ before maximization.

Granted, these images only represent a single outcome for Monte Carlo simulation where $P_0 = 280$. It is possible that the run was lucky and the images are misleading. However, looking at the bars in Figure 6.1 representing two standard deviations of the set of estimates resulting from the Monte Carlo simulation, the Varshney algorithm consistently chooses coordinates at a distance near that of the interference source, for values of P_0 greater than that of the target. Although the Michaelides algorithm may be faced with a similar dilemma, it can cope because in this conflicting scenario where multiple coordinates show a maximum, the Michaelides uses their centroid. It appears the Michaelides algorithm is more robust to interference for the conditions specified; this is only one case, so this result is not considered definitive. Further study in broader conditions should be carried out. It is clearly the case that the Varshney algorithm tends to produce worse results after the interference power exceeds the source power, and reaches a steady state at around 15, the roughly the distance between the target and interference source.

6.2 Summary

A performance analysis of the Varshney and Michaelides algorithms was conducted with respect to maximum source power P_0 of an additional interference source. The performance analysis consisted of a series of Monte Carlo simulations for a range of the maximum power of the interference source. The root mean square error of each simulation was determined by the resulting estimates of the simulation. The scenario considered two sources in the 2-D field; one source as the target and the other source as interference. The results show that the Michaelides algorithm appears to be more robust against interference across the full range of the P_0 parameter of the interference source. However, this being only a short case study, further results should be obtained under broader conditions before the result is considered definitive.

CHAPTER 7

SUMMARY AND FUTURE DIRECTIONS

7.1 Conclusions

This thesis provides an evaluation of localization algorithms for wireless sensor networks using binary data previously proposed by [7] and [8]. The algorithms evaluated here are a subset of localization algorithms for wireless sensor networks measuring received signal strength which are then quantized to a single bit. The binary data from all sensors are processed simultaneously by the fusion-based algorithms. The Varshney algorithm is based on the most popular maximum likelihood estimator. The Michaelides algorithm is an empirical adaptation, where prospective locations are scored based on observations of surrounding sensors. The evaluations of the algorithms was carried out with Monte Carlo simulation tools. For each of the analyses, a series of Monte Carlo simulations were conducted while varying a design parameter. A statistically meaningful performance metric was selected to measure the performance of each algorithm under the simulation conditions. The performance metric, root mean square error, could be compared for each simulation, showing the performance with respect to the variation of design parameters. Five total experiments were conducted.

In the first analysis, it is assumed a single target source was correctly detected in the field. The power of the target source and the instrument noise are assumed to be known. The performance evaluation was conduccted with respect to variation of the maximum source power and instrument noise. The root mean square error for each of the Monte Carlo simulations is measured, for each algorithm. The analysis served as a validation of performance for each algorithm, as they performed similarly in both cases in comparison with the studies in [7] and [8]. As expected, the performance of each algorithm improved as the source power was increased and the instrument noise is decreased, each analagous to improved performance with high signal-to-noise conditions.

In the second analysis, it is assumed a single target source was correctly detected in the field. The sensitivity of each algorithm is measured with respect to variation of the maximum source power and instrument noise. When varying the maximum source power, it is assumed that this parameter is unknown and likewise for analysis with respect to instrument noise. It was determined that, generally, if either parameter is incorrectly assumed for either algorithm, the two algorithms perform similar under this condition. In particular, looking at the analysis with respect to variation of power, the Michaelides algorithm showed lower error when as the actual source power approached the assumed power from the left. Meaning, the Michaelides algorithm was able to cope better with the unknown power of the target when the power of the target was less than that of the assumed.

In the third analysis, it is assumed a single target source was correctly detected in the field along with a second source of interference which is unknown to the positioning system. The performance of each algorithm is measured with respect to variation of the maximum source power of the interference source. The power of the target source and instrument noise are assumed to be known by the system. The results showed that the Varshney algorithm is particularly sensitive to the interference source; the root mean square error for the algorithm begins to increase sharply as the power of the interference is increased from zero. Once the power of the interference source exceeds that of the target, the root mean square error reaches a steady state. The Michaelides algorithm shows a much different result, remaining stable for the full range of variation of the power of the interference source.

7.2 Future Directions

The simulator developed for the study was developed in a way that is conducive to adding additional algorithms to the experiments. The central processing node is implemented in software as a class which holds the algorithms as sub-classes. New algorithms can be implemented as sub-classes in the central processing node and easily called by the Monte Carlo simulator. This software is conducive to supporting new propagation models; similar to the algorithms, the emitter is implemented as a class with sub-classes for determining signal intensity based on the isotropic and continuous propagation model. While running the experiments, a major challenge was gathering results for the thesis efficiently. Thus, one area of work for the future is optimizing the simulator tool to speed up data collection. There is certainly a ceiling for the number of sensors supported as it could take days to complete a Monte Carlo simulation with enough sensors. Optimization of the simulator is necessary before exploring more complicated scenarios.

Additonal studies to carry out include analysis with respect to the number of sensors, sensor placement, and with more sophisticated noise models for the sensors. In each experiment here, it is assumed that the distribution of measurements from all sensors have identical variance. In reality, sensors in the same product line will have unique noise and drift characteristics. The placement of sensors are assumed to be known; in reality the locations cannot be known so precisely. The propagation model can be swapped to experiment with new sources such as gas leaks.

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