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UAV POSITION OPTIMIZATION FOR WIRELESS COMMUNICATIONS

by

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UAV POSITION OPTIMIZATION FOR WIRELESS COMMUNICATIONS

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ABSTRACT

This thesis explores autonomously positioning unmanned aerial vehicles (UAV) as wireless nodes in optimal locations to form robust, reliable communication links between static or slow-moving nodes, on land or at sea, in a wireless network. The presented approach explicitly accounts for variability associated with signal-to-noise ratio (SNR) estimates used for UAV navigation. A two-phased approach is presented to find a local SNR extremum as an optimal loitering point. This thesis focuses on phase one consisting of Kriging and semivariogram analysis as well as information theoretic local path planning. Kullback-Leibler divergence is used for path evaluation and selection. Phase two consists of an extremum control method developed in prior work for UAV navigation to the optimal loitering point. Emphasis is placed on accuracy and reducing model uncertainty. Simulated and experimental data is presented and used for Kriging of the SNR field produced by two ground nodes. Datasets produced with varying distances, altitudes, and flight patterns provide insight into the behavior of SNR degradation and flight trajectories that are most efficient at reducing estimate uncertainty. Analysis provides a greater understanding of the current capabilities, benefits, and limitations of employing UAVs as autonomous, mobile communication nodes. This includes the potential for implementing nonlinear optimal estimation and path planning processes onboard small UAVs in real time.

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TABLE OF CONTENTS

I.	INTRODUCTION.....	1
A.	MOTIVATION	1
B.	PROBLEM STATEMENT	2
C.	OBJECTIVES	3
II.	BACKGROUND	5
A.	MODELING WIRELESS COMMUNICATION NETWORKS.....	5
1.	Friis Transmission Model.....	7
2.	Antenna Pattern Loss	8
3.	Bank Angle Effect	8
4.	SNR Estimation	10
5.	Modeling Multi-Input Multi-Output Communication Systems.....	13
B.	CONTROL FOR HIGH-BANDWIDTH COMMUNICATIONS	14
1.	Phase One: Nonlinear SNR Estimation for Wireless Communications	15
2.	Phase Two: Extremum Control.....	17
III.	EXPERIMENTATION	19
A.	UAV SYSTEM DESCRIPTION.....	19
B.	COMMUNICATION SYSTEM DESCRIPTION	21
C.	EXPERIMENTAL SETUP AND OBJECTIVES	24
D.	CONDUCTED TESTS	24
1.	San Clemente Island, CA	24
2.	Camp Roberts, CA.....	26
3.	Yuma Proving Ground, AZ	26
IV.	EXPERIMENTAL RESULTS.....	29
A.	CAMP ROBERTS FLIGHT RESULTS.....	29
1.	UAV Flight Trajectory	29
2.	Degradation of SNR as a Function of Distance	31
3.	Degradation of SNR with Respect to Altitude.....	32
4.	Degradation of SNR with Respect to Distance and Altitude.....	33
B.	YUMA FLIGHT RESULTS	35
1.	UAV Flight Trajectory	35
2.	Degradation of SNR as a Function of Distance	36

3.	Degradation of SNR with Respect to Altitude.....	37
4.	Degradation of SNR with Respect to Distance and Altitude.....	38
V.	GAUSSIAN PROCESS REGRESSION: KRIGING.....	41
A.	KRIGING: OPTIMAL SPATIAL INTERPOLATION	42
1.	Kriging Approach	42
2.	Ordinary Kriging.....	43
3.	Kriging Weights	45
B.	SEMIVARIOGRAM CONSTRUCTION AND ANALYSIS.....	45
1.	Covariance, Correlation, and Semivariance	46
2.	Second-Order Stationarity	47
3.	Characteristics of the Semivariogram	48
4.	Modeling the Empirical Semivariogram	49
C.	KRIGING USING EXPERIMENTAL DATA.....	50
1.	Detrending Data	50
2.	Full Flight Path	51
3.	Comparison to Friis Transmission Model Assumption.....	56
VI.	INFORMATION THEORETIC PATH PLANNING WITH SYNCHRONOUS KRIGING	61
A.	PATH PLANNING OBJECTIVE	61
B.	CANDIDATE TRAJECTORY GENERATION	62
C.	PATH EVALUATION	63
1.	Information Gain Metric.....	64
2.	Energy Metric.....	66
3.	Information-Theoretic Objective Function	67
D.	LOCAL VS. GLOBAL PLANNING.....	68
E.	UPDATING THE GAUSSIAN PROCESS MODEL	70
F.	RESULTS	81
G.	SNR MAP CONFIDENCE AND STABILITY	91
VII.	CONCLUSIONS AND FUTURE WORK.....	93
A.	CONCLUSIONS	93
B.	FUTURE WORK.....	94
1.	Expansion of Network Topology	94
2.	Obstacle Avoidance.....	95
3.	Global Path Planning.....	95
4.	Real-Time Gaussian Process Modeling & Control.....	95

APPENDIX. SIMULINK MODELS	97
LIST OF REFERENCES.....	99
INITIAL DISTRIBUTION LIST	103

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LIST OF FIGURES

Figure 1.	UAV to ground node LOS path loss vector. Source: [1].	9
Figure 2.	UAV bank angle effect on signal incident angle. Source: [2].	10
Figure 3.	Simulated SNR field created by two wireless ground nodes	12
Figure 4.	Ascendable intersection of SNR fields created by two nodes	12
Figure 5.	The Boeing Insitu ScanEagle UAV at San Clemente Island, CA	20
Figure 6.	A ScanEagle UAV being recovered by its SkyHook	21
Figure 7.	Persistent Systems Wave Relay MPU5 radio. Source: [11].	22
Figure 8.	ODROID-XU4 with mounted cooling fan. Source: [16].	23
Figure 9.	Google Earth image of San Clemente Island MTX location	25
Figure 10.	Google Earth image of Camp Roberts testing and data	26
Figure 11.	Google Earth image of Yuma testing and collected data	27
Figure 12.	Camp Roberts data for ScanEagle link to Node 1 (ECEF)	30
Figure 13.	Camp Roberts data for ScanEagle link to Node 2 (ECEF)	31
Figure 14.	Camp Roberts SNR data vs. distance from each ground node	32
Figure 15.	Camp Roberts SNR data vs. altitude from each ground node	33
Figure 16.	Camp Roberts SNR data vs. distance and altitude for Node 1	34
Figure 17.	Camp Roberts SNR data vs. distance and altitude for Node 2	34
Figure 18.	Yuma SNR data for ScanEagle link to Node 1 (ECEF)	35
Figure 19.	Yuma SNR data for ScanEagle link to Node 2 (ECEF)	36
Figure 20.	Yuma SNR data vs. distance from each ground node	37
Figure 21.	Yuma SNR data vs. altitude from each ground node	38
Figure 22.	Yuma SNR data vs. distance and altitude for Node 1	39
Figure 23.	Yuma SNR data vs. distance and altitude for Node 2	39

Figure 24.	Semivariogram characteristics. Source: [19].	48
Figure 25.	Removal of 1 st order distance trend from collected SNR data.	51
Figure 26.	Binned variogram cloud of SNR data for Node 1.	52
Figure 27.	Binned variogram cloud of SNR data for Node 2.	53
Figure 28.	Empirical semivariogram of SNR data for Node 1.	54
Figure 29.	Empirical semivariogram of SNR data for Node 2.	54
Figure 30.	Variogram fit of SNR data for Node 1.	55
Figure 31.	Variogram fit of SNR data for Node 2.	56
Figure 32.	Kriging Estimate of SNR fields	57
Figure 33.	SNR fields computed from Friis transmission model.	57
Figure 34.	Kriging estimate of SNR field intersection.	58
Figure 35.	SNR field intersection computed from Friis model.	59
Figure 36.	Candidate trajectories at constant heading rates and speed	63
Figure 37.	Friis model assumption with added uncertainty bounds.	71
Figure 38.	Friis model of intersection with added uncertainty bounds	71
Figure 39.	Initial variance map assigned to Node 1	72
Figure 40.	Initial variance map assigned to Node 2	72
Figure 41.	Initial empirical variogram model for Node 1	73
Figure 42.	Initial empirical variogram model for Node 2	74
Figure 43.	Semivariogram based on SNR measurements for Node 1	75
Figure 44.	Semivariogram based on SNR measurements for Node 2	76
Figure 45.	Updated empirical semivariogram model for Node 1	77
Figure 46.	Updated empirical semivariogram model for Node 2	78
Figure 47.	Executed local trajectories	79
Figure 48.	Local update to SNR field intersection	79

Figure 49.	Local update to variance map for Node 1	80
Figure 50.	Local update to variance map for Node 2	80
Figure 51.	Updated SNR field after UAV exploration (side view).....	82
Figure 52.	Updated SNR field after UAV exploration (top view)	82
Figure 53.	Updated SNR field intersection (side view)	83
Figure 54.	Updated SNR field intersection (top view).....	83
Figure 55.	Updated variance map after UAV exploration for Node 1	84
Figure 56.	Updated variance map after UAV exploration for Node 2	84
Figure 57.	Overall UAV flight path	85
Figure 58.	Resulting mean SNR intersection	86
Figure 59.	Resulting measurement variogram for Node 1	87
Figure 60.	Resulting measurement variogram for Node 2	87
Figure 61.	Resulting empirical semivariogram model for Node 1	88
Figure 62.	Resulting empirical semivariogram model for Node 2.....	88
Figure 63.	Accumulated information gain during UAV flight for Node 1	89
Figure 64.	Accumulated information gain during UAV flight for Node 2	90
Figure 65.	Simulink model of UAV dynamics (outer level).....	97
Figure 66.	Simulink model of UAV dynamics (inner level).....	97

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LIST OF TABLES

Table 1.	ScanEagle specifications. Source: [15].	20
Table 2.	MPU5 S-Band radio specifications. Source: [11].	22

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LIST OF ACRONYMS AND ABBREVIATIONS

APF	Artificial Potential Field
API	Application Programming Interface
BDA	Battle Damage Assessment
CAVR	Center for Autonomous Vehicle Research
CPU	Central Processing Unit
ECEF	Earth-Centered, Earth-Fixed
GPS	Global Positioning System
ISR	Intelligence, Surveillance, and Reconnaissance
LAN	Local Area Network
LOS	Line-of-Sight
MIMO	Multi-Input Multi-Output
MTX	Multi-Thread Experiment
N-SI	Non-SI Units
NCS	Network Control System
NPS	Naval Postgraduate School
NTP	Network Time Protocol
ROS	Robot Operating System
RRT	Rapidly Exploring Random Tree
SCI	San Clemente Island
SI	International System of Units
SISO	Single-Input Single-Output
SNMP	Simple Network Management Protocol
SNR	Signal-to-Noise Ratio
UAV	Unmanned Aerial Vehicle
UxV	Unmanned Vehicle

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I. INTRODUCTION

This thesis addresses optimal positioning of an unmanned aerial vehicle (UAV) to serve as a communications bridge between two ground radios serving as wireless network nodes. Prior work presented in [1], [2], [3], and [4] utilized a decentralized, self-tuning extremum controller to autonomously position a UAV in an optimal loitering location for communications relay between distributed nodes in a wireless network. This approach used signal-to-noise ratio (SNR), computed according to the well-known Friis transmission model, explained in [5], as the primary metric for communications quality between two nodes. However, this work did not adequately take into consideration the variability and uncertainty associated with actual SNR measurements in flight, as this is not represented by the Friis model. This thesis addresses the need to accurately model SNR between ground nodes as well as its uncertainty to determine the optimal loitering location. Our approach leverages nonlinear optimal spatial estimation techniques and an information theoretic path planning approach to efficiently discover and reduce uncertainty associated with the SNR field between nodes. This represents a novel contribution that is more robust than prior algorithms, since it explicitly considers measurement variability and can adapt to ground node locations and inaccuracies in the assumed Friis transmission model. Data collected during experiments, described in Chapter III, is analyzed in Chapter IV. The results from datasets produced at varying distances, altitudes, and with different flight patterns provide insight into the degradation of SNR as a function of distance and altitude as well as flight trajectories which are most efficient at reducing the uncertainty associated with the SNR field. A data-driven method for nonlinear optimal spatial estimation is presented in Chapter V. An information theoretic local path planning method is presented in Chapter VI. The combined methods afford quick and accurate discovery and estimation of the optimal loitering location.

A. MOTIVATION

Unmanned mobile systems, including aerial, surface, and underwater vehicles, are becoming increasingly prevalent in the civilian and military sectors due to their utility,

efficiency, cost-effectiveness, and minimization of risk to humans in operational environments. At present, many missions conducted using these vehicles involve single vehicles, leaving room for further development in conducting missions with teams of multiple, heterogeneous unmanned vehicles. A key challenge associated with multi-vehicle operations is maintaining robust and reliable communications for continuous coordination. Communications between autonomous systems are often limited by bandwidth or line-of-sight (LOS) constraints imposed by their onboard communication systems. These limitations can be overcome by utilizing other autonomous systems, namely UAVs, as communications relay nodes, forming a wireless communication network.

To ensure reliable and swift transferring of information, the relay vehicles must be positioned to afford the highest bandwidth transmissions possible. By exploring the capability to autonomously position UAVs as wireless nodes to maintain optimum loitering flight paths for maximum communication throughput, an effective control scheme can be developed to make large-scale, multi-vehicle operations viable. Such a capability would minimize the required amount of human interaction needed to conduct such operations and enable a greater variety of potential mission sets.

B. PROBLEM STATEMENT

The SNR field generated between two wireless ground nodes can be computed according to free-space path loss based on the Friis transmission model and antenna pattern loss theory. It can also be empirically characterized by taking SNR measurements with respect to each node at varying distances and altitudes. However, both the model assumption and empirical data have associated uncertainties that reduce the level of confidence and accuracy of the computed field. Prior to using the SNR field for UAV navigation to an optimal loitering position, the uncertainty of the field must be sufficiently reduced. Once the uncertainty is reduced, the optimal loitering location can be asserted with greater confidence. In order to minimize the level of uncertainty, optimal spatial estimation techniques can be used to estimate the SNR field and its variance from the SNR measurements. These estimates are used for information theoretic path planning to direct the UAV to efficiently explore uncertain regions of the field with an added incentive to

explore the intersection region between the two ground nodes. During this information-gathering phase, the UAV effectively learns the nature of the field while reducing the uncertainty of its estimates to ultimately determine the optimal loitering location.

C. OBJECTIVES

The Naval Postgraduate School (NPS) Center for Autonomous Vehicle Research (CAVR) has conducted multiple flight tests using UAVs as communications relay nodes between two or more ground nodes. This thesis seeks to develop new control methods for guiding a UAV to an optimal loitering location between two nodes to afford maximum communication throughput. The proposed control methods utilize a Bayesian approach to estimate the SNR field formed between two wireless ground nodes via nonlinear optimal spatial estimation. The resulting field provides insights on not only the optimal loitering location for an aerial communications relay, but also on which flight trajectories are most efficient at reducing the uncertainty in the estimated SNR field used for controlling the UAV.

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II. BACKGROUND

A. MODELING WIRELESS COMMUNICATION NETWORKS

A network is comprised of multiple communication devices, able to both send and receive messages from one another. These can include radios, computers, routers, access points, and cellular phones. A common example is a local area network (LAN) in which each device must either be directly hardwired into the network or in close proximity to a wireless router. In recent years, wireless mesh networks have been developed [1]. Within a wireless mesh network, each node is capable of communicating with every other node without relying on a single centralized device, such as a LAN router [6]. A software component, included as part of the radio system, autonomously determines the best communications route between nodes. As explained by Dixon and Frew, this permits effective communications coverage over a wide area given a sufficient number of devices [7]. Within a mesh network, information can easily be rerouted, accounting for the addition and removal of nodes, which makes it robust to possible node failure [8]. Mesh networks make use of the same protocols commonly used by everyday wireless devices, including IEEE 802.11 a, b, and c [1].

Wireless sensor networks consist of multiple sensors that can send and receive data from one another as nodes within a mesh network. These sensor networks are popular for oceanographic and environmental surveying purposes, using teams of autonomous vehicles to collect data across wide areas [1]. Wireless sensor networks also have common military applications, including information, surveillance, and reconnaissance (ISR) mission sets and having communication relays to extend beyond LOS communications [1]. Their robustness allows groups of sensors to continue carrying out a specified mission despite multiple node failures within the network [1]. In some cases, since these systems can autonomously determine the most efficient path between nodes, wireless nodes can autonomously reposition themselves to form a configuration that optimizes network communications during a desired mission [1]. In this thesis, we propose methods which enable UAVs to serve as mobile communication relays. These methods provide some of

the building blocks for developing intelligent ad hoc wireless mesh networks in support of various mission sets.

The communications link quality between the radio antennas of any two nodes in a wireless mesh network is susceptible to many factors. Kam presents several primary factors, including: received signal power, antenna specifications, and environmental factors [2]. Each of these factors weakens the power of a given received signal. As Richard states, “to detect and demodulate an incoming signal, the received [signal] power must be greater than the sensitivity [of the receiving antenna]. If the received signal power is not above this minimum threshold,” the link could be broken [1] [2]. Kam defines the received signal power and minimum receiver threshold given by the receiver sensitivity are related by the link margin [2]

$$\text{Link Margin} = P_r - R_{sens} \quad (2.1)$$

where P_r is the received signal power (dB) and R_{sens} is the minimum received signal (dB) to guarantee reliable communications. In wireless communication networks, “it is desirable to maximize the received signal power” [2]. However, link quality is also subject to the noise level within the overall system. Noise within a network can be attributed to both the communication environment as well as the nodes themselves. If the noise power approaches or exceeds the received signal power, it can prevent the receiver from detecting and demodulating a given signal [1]. Therefore, it is also desired to minimize noise power [1].

A common metric to evaluate the quality of a communications link is the signal-to-noise ratio (SNR). SNR is the “ratio between received [signal] power and noise power” [1]. A larger SNR means that the received signal power is larger compared to the noise power in a given environment [1]. This, in turn, results in fewer communication errors and better link quality [2].

$$SNR = \frac{\text{Received Signal Power}}{\text{Noise Power}} \quad (2.2)$$

A communication link within a wireless mesh network is considered to have optimal throughput “when its channel capacity is maximized” [1]. “The Shannon-Hartley theorem relates channel capacity, C (bits per second), to bandwidth, W (Hz), and SNR” [1]

$$C = W \log_2 (1 + \text{SNR}) \quad (2.3)$$

As shown in Equation 2.3, SNR and channel capacity are directly proportional, so the throughput and data transfer rate of a communication link is maximized when the associated SNR is maximized [1], [5].

1. Friis Transmission Model

The received power, P_r , of an antenna for LOS communication can be described by the Friis transmission model, or Friis free space transmission equation [2], [5]

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 D^2} \quad (2.4)$$

where P_t is the transmitted power, G_t is the transmitter gain, G_r is the receiver gain, λ is the wavelength (meters), and D is the separation distance between the transmitter and the receiver (meters). The Friis model is a method for computing the path loss between any two antennas across free space [1]. As is clear from Equation (2.4), the Friis model does not account for obstructions along the direct propagation path between the transmitter and receiver [2]. Within this model, the gain of an antenna represents its efficiency and directivity, and the squared inverse of the separation distance describes the spreading of a spherical wavefront [1]. When expressed in decibels (dB), the Friis model converts to

$$P_r = P_t + G_t + G_r - L_{path} \quad (2.5)$$

with LOS path loss, L_{path} , described by

$$L_{path} = P_r - P_t = 32.4 + 20 \log(f) + 20 \log(d) \quad (2.6)$$

$$d(t) = \sqrt{(x(t) - x_{node})^2 + (y(t) - y_{node})^2 + (z(t) - z_{node})^2}$$

where f is the frequency of the signal (MHz) and d is the separation distance between transmitter and receiver (km) [2]. Using the Friis model expressed in dB, the SNR of the receiver node can be computed as

$$SNR = P_r - NL \quad (2.7)$$

where NL is the power of the system noise level (dB) [2]. The gains, signal power, and noise level characteristics for a specific antenna used during testing can be obtained from data sheets produced by the manufacturer.

2. Antenna Pattern Loss

In addition to LOS free space path loss according to the Friis transmission model, losses can be caused by the relative orientation of both the transmitting and receiving antennas [1]. “In a spherical coordinate system, the radiation pattern of an antenna is determined by measuring electric field intensity of a sphere at a fixed radius” [1]. As explained in Kam’s thesis and later clarified by Richard, field intensity is described by a gain that varies with elevation and position about the azimuth of an antenna, depending on its polarization and specifications [1], [2]. Within the free space path loss equation, the attenuation of a signal due to the antenna patterns of a transmitting and receiving antenna is accounted for by determining the relative orientation between a given pair of antennas [1]. As a result, the free space equation becomes

$$P_r = P_t + G_t + G_r - L_{path} - L_{AP} \quad (2.8)$$

where L_{AP} accounts for antenna gain pattern losses [2].

3. Bank Angle Effect

A model of the antenna pattern loss between a ground node and a UAV can be created from manufacturer-provided antenna gain patterns [1]. Antenna pattern loss is dependent on the incident angle for both the ground and UAV antennas, which can be calculated using ray tracing [1]. The position vectors for a UAV and a ground node, can be expressed in a local tangent plane as:

$$P_{UAV,LTP} = \begin{bmatrix} x(t) \\ y(t) \\ z(t) \end{bmatrix} \text{ and } P_{node,LTP} = \begin{bmatrix} x_{node} \\ y_{node} \\ z_{node} \end{bmatrix} \quad (2.9)$$

From this relationship, we can compute the incident angle

$$\theta(t) = \tan^{-1} \left(\frac{(z(t) - z_{node})}{\sqrt{(x(t) - x_{node})^2 + (y(t) - y_{node})^2}} \right) \quad (2.10)$$

as illustrated in Figure 1 [1].

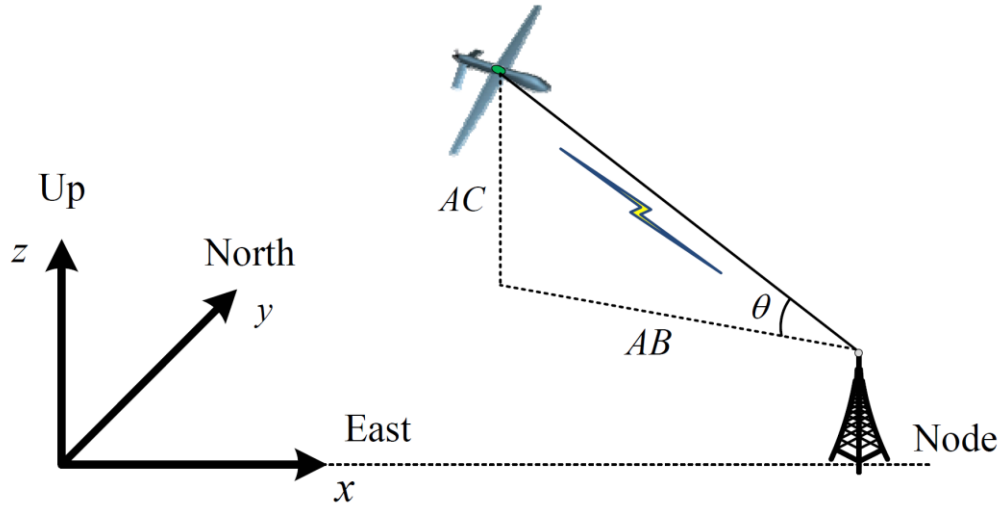


Figure 1. UAV to ground node LOS path loss vector. Source: [1].

As a fixed-wing UAV flies, its banking motion affects the orientation of its onboard antenna, which in turn affects the signal's incident angle, introducing noise into the SNR measurement for the link [2]. The bank angle of the UAV can either increase or decrease the signal's angle of arrival, "depending on its heading with respect to the ground node," as illustrated in Figure 2 [1]. The UAV's bank angle has the greatest effect on measured SNR when traveling perpendicular to a given ground node. Conversely, Richard observes

there is little to no effect on the measured SNR when the UAV flies directly away from or directly towards the ground node [1].

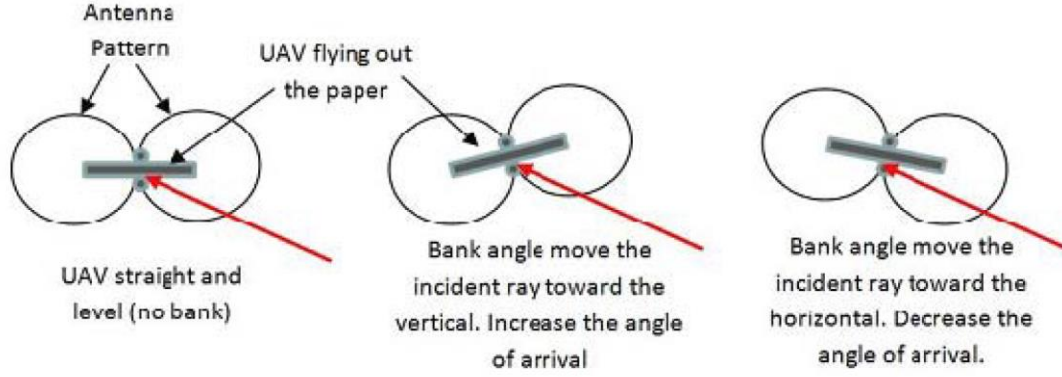


Figure 2. UAV bank angle effect on signal incident angle. Source: [2].

According to Kam, the influence of the UAV's bank angle on the arrival angle of a signal can be modeled using a sine function based on its heading

$$\text{Bank Angle Effect} = \phi \cdot \sin(\varphi - \psi) \quad (2.11)$$

where ϕ is the UAV's roll, φ is its bearing to the ground node, and ψ is the UAV's heading [2]. The arrival angle is computed as the "difference between the incident angle and the bank angle" [1]:

$$\text{Arrival Angle} = -\theta(t) - \text{Bank Angle Effect} \quad (2.12)$$

The arrival angle is used as the input for a look-up table of antenna pattern gains based on manufacturer data, the output of which is the antenna pattern loss for a particular communications link [1].

4. SNR Estimation

In a realistic operational environment, actual SNR measurements taken by an autonomous vehicle, such as a UAV, have a great deal of noise and inherent uncertainty due to the variability of the environment and onboard sensor properties. For this thesis, the

UAV's mesh networking radio, discussed in Chapter III, autonomously broadcasted SNR measurements via its radio management interface. This data was recorded by an onboard computer. To supplement these sensor measurements when finding the optimal loitering location, the SNR can be modeled using the free space path loss with antenna pattern loss described by Equation (2.8). Assuming the ground node locations are known, the predicted SNR for each link between the nodes and the UAV "can be modeled with the free space transmission equations to create a continuous SNR map," as shown in Figure 3 [1], [4], [3]. The gradient of the generated SNR field can then be ascended by the UAV to discover an optimal loitering location. This is similar to the concept of artificial potential fields (APF), utilized by Horner and Healey in [9], in which objectives are represented by attractive forces, obstacles are represented by repulsive forces, and the resulting gradient field is used to guide the vehicle. For the problem presented by this thesis, the intersection of the measured SNR fields between wireless ground nodes would be represented by attractive gradient vectors directed towards the peak of the intersection, ensuring the UAV locates and maintains an optimal loitering location for communications throughput [9].

In a two-node scenario, the optimal loitering location between nodes would be governed by the lower of the two SNR values, and the objective is to maximize the minimum value between them. In other words, the optimal loitering location would be located at the peak of the intersection as illustrated in Figure 4. Note that our model also includes the Fresnel zone, which describes losses due to diffraction as a result of path propagation differences and any obstructions about the antennas. This region is visible in Figure 3 at the origin of each node's SNR field, where the SNR rounds-out and rapidly decreases to zero [5]. This is the result of adding antenna pattern loss factors to the Friis transmission model. Without taking antenna pattern loss into consideration, the SNR would rapidly spike to an unrealistic value, unsupported by actual measurements, at the origin of each field.

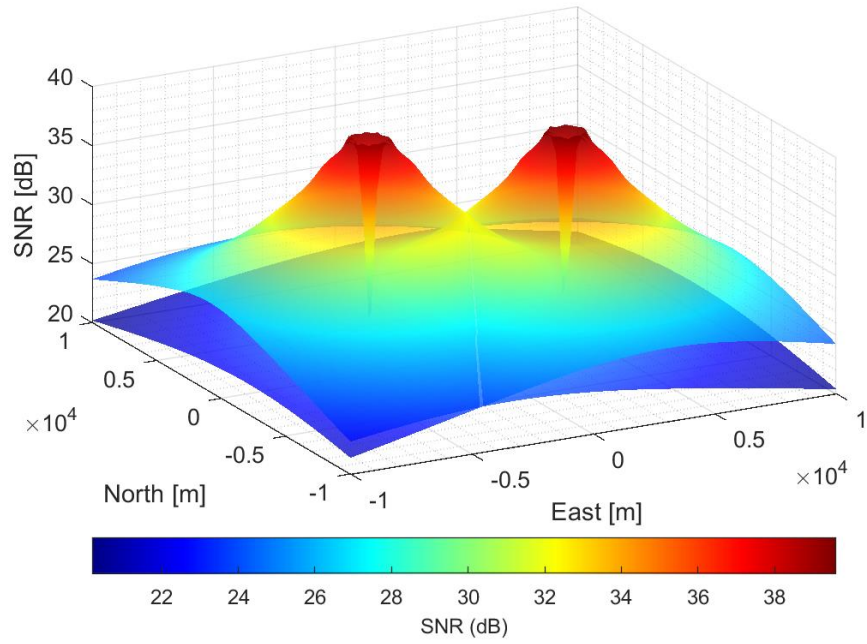


Figure 3. Simulated SNR field created by two wireless ground nodes

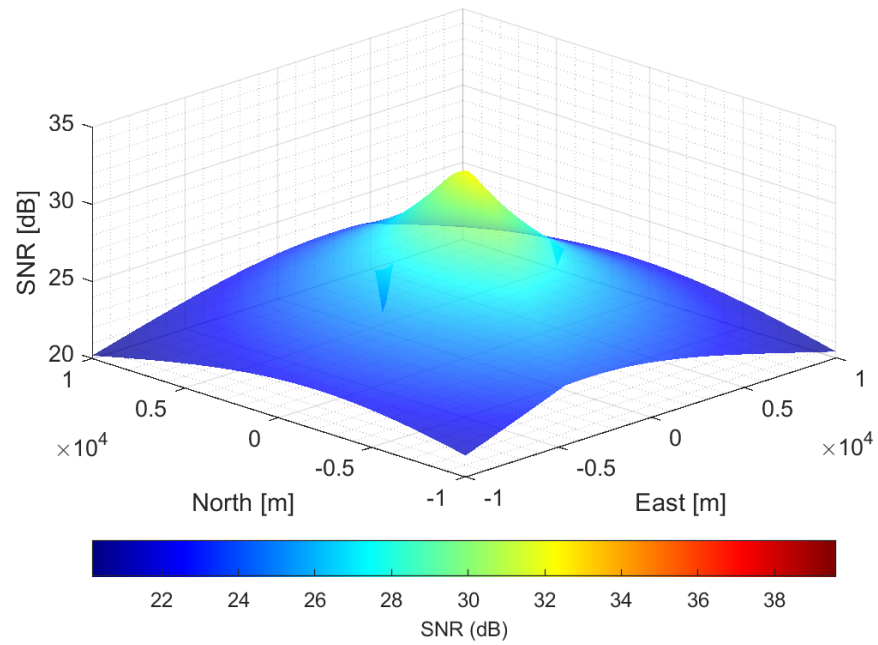


Figure 4. Ascendant intersection of SNR fields created by two nodes

However, the predictive free space model would introduce uncertainties of its own, since it does not account for attenuating effects such as reflection, refraction, scattering, and environmental noise [2]. Using optimal spatial estimation, the map could be augmented using the measured SNR data to produce a more accurate combined map with minimized uncertainty.

5. Modeling Multi-Input Multi-Output Communication Systems

Prior work presented in [1], [7], [2], [4], [3], and [10] made use of single input, single output (SISO) radio systems in which a radio uses a single antenna to transmit and receive information. Likewise, preliminary field testing conducted on San Clemente Island, discussed in Chapter III, made use of SISO radio communications and experienced routine connectivity issues. The Friis transmission model previously described models the free space path loss between single antennas as well. Follow-on tests conducted for this thesis, described in Chapter III, made use of Persistent Systems Wave Relay MPU5 radios [11]. The MPU5 is a multi-input multi-output (MIMO) system with three omnidirectional antennas on the same channel for both transmitting and receiving. Using free space path loss and antenna pattern loss to provide an estimate of the SNR for links between nodes in wireless mesh networks, one must also consider the effects of using a MIMO communication system. According to Bluesocket, MIMO is “a significant departure in the architecture and technology from [current] SISO systems... accomplished through the implementation of multiple transmitters and receivers in a single [node]” [12]. Bluesocket states that MIMO advantages include increased range, throughput, and link robustness. While there exist drawbacks and tradeoffs, the existence of multiple transmitters and receivers greatly improves all three parameters [12]. The ability to provide higher data-rates over greater ranges results in “greater throughput over a much larger coverage range than traditional SISO antennas” [12]. The primary drawbacks associated with MIMO systems are greater component costs due to the need for more antennas and higher performing hardware, as well as greater power requirements for both transmit and receive operations [12].

MIMO is not to be confused with beam forming, in which “the same signal is sent from multiple antennas, but is adjusted in phase and power to form a coherent signal in the direction of the desired [receiver node]” [12]. MIMO systems depend on multipath and utilize multiple antennas to collect and transmit multiple sets of data, which are subsets of the original data rather than full copies. Therefore, these subsets must be mathematically processed by the receiver in to recover the originally transmitted data [12]. “The ability to use signal characteristics and signal processing to make the communications more reliable is called processing gain” [12]. MIMO systems operate best with simple, omnidirectional antennas, most often deployed in small arrays [12]. However, since MIMO systems benefit in terms of processing gain, unlike beam forming, the omni array “does not have any overall increased transmit or receive gain beyond the individual antenna gain specification” [12]. Since MIMO systems do not benefit from increased transmit or receive gain, the inputs to the Friis transmission model, this thesis utilizes the same SISO path and antenna loss models for estimating link SNR to model the MIMO nodes utilized during experimentation. For simplicity, as the signal is simply divided between multiple antennas and reassembled by the receiver, we assume that the ratio of the signal to noise power between identical sets of transmitting and receiving antennas are the same as the ratio for a single pair of antennas found in a SISO system.

B. CONTROL FOR HIGH-BANDWIDTH COMMUNICATIONS

For this thesis, we assume that the optimal loitering location to maximize communication between wireless ground nodes occurs at the peak of the intersection of their SNR fields. Once the peak value of this intersection is discovered, then its location can be used as the center of a loitering orbit to afford optimal communications throughput between the ground nodes. Finding and maintaining an optimal loitering location is achieved by a two-phase process. The first phase, addressed by this thesis, involves the efficient discovery and construction of spatial models for the SNR between two ground nodes. Once the models are constructed with sufficient confidence with low uncertainty surrounding the intersection, a transition is made to the second phase. The second phase, addressed by prior work, involves navigating to the optimal loitering position using the constructed SNR models. The control method used in prior work and described by Richard

“combines an extremum seeking gradient estimation scheme with a traditional gradient ascent controller” [1], [2], [4], [8].

1. Phase One: Nonlinear SNR Estimation for Wireless Communications

The fundamental assertion posed by this thesis is that the uncertainty surrounding the degradation of SNR as a function of distance must be understood before a spatial model of SNR can be used for control purposes. While it is possible to utilize the developed SNR model to reach a theoretical optimum loitering location, there remains a great deal of uncertainty associated with its inherent approximations. Furthermore, an assumption must be made that the modeled SNR fields are sufficiently accurate when compared to the actual SNR measured with respect to a node at a specified location. The measured SNR also has a significant amount of uncertainty due to environmental noise and other attenuation factors. Previously derived communication bridging techniques do not sufficiently take into consideration the noise associated with SNR measurements and model uncertainty. They are not generalizable for different configuration spaces with many potential noise sources and obstructions present in an adverse communication environment. The variability and noise associated with SNR measurements demand a more robust, generalizable, probabilistic estimation of the SNR environment, which takes uncertainty into consideration. Such an approach must be adaptable to a variety of scenarios, network configurations, and configuration spaces.

This thesis seeks to develop and explore a nonlinear estimation problem to formulate a generalized, model-independent approach for mathematically increasing the confidence in the estimated SNR field created by nodes in a wireless communication network. This generalized approach for communications optimization will utilize machine learning and information-theoretic control techniques to enable greater autonomy for the UAV. These techniques are manifested in the learning of two SNR map models and the autonomous generation of trajectories to facilitate optimal learning of the model parameters, particularly the region of intersection. This information-theoretic approach allows the aircraft to learn the parameters of the SNR model.

An initial assumption for the model can be made using the Friis transmission model for free space path loss and antenna pattern loss. This is necessary for the initial step of the path planning approach to select a trajectory that will afford the greatest gain in information with respect to the current model. After selecting a trajectory, measurements gathered along it and used to update the model, which is initialized as the Friis model. The Friis model is a well know model for free-space path loss. However, a simple uniform distribution could also be used and potentially be a better initial assumption to converge and achieve confidence more quickly and efficiently. This is true because if the initial model assumption is ill-suited for the configuration space, i.e., if the measurements do not agree with the initial model assumption, you must “unlearn” the initial model to converge to the situation represented by your measurements. Depending on the situation, unlearning the Friis model may take longer than unlearn a simple, uniform distribution. Specific realizable scenarios that could occur are dense urban or indoor configuration spaces in which the free space path loss model would likely be highly inaccurate due to obstructions and environmental factors.

In extreme cases, not knowing the locations of ground nodes, or even not knowing the location of the UAV could pose serious challenges that require an adaptable, generalized approach. In prior work, ground node positions are known, allowing an initial expectation as to where the optimal loitering point is located, based on the initial SNR models. However, it is necessary for that point to be discovered by the UAV in the most efficient and reliable way possible for scenarios in which ground node locations are unavailable. By using adaptive sampling techniques in which a UAV collects near-real-time SNR measurements during a mission, the UAV can deliberately fly patterns in order to collect data with the most utility for discovering and reducing its uncertainty about the SNR environment [13].

After deciding on an *a priori* model assumption, the mathematical technique used for estimating SNR as a function of distance from ground nodes is posed as a nonlinear optimal spatial estimation problem. A discretized grid region is superimposed as a random field over the ground radio positions where each grid point is represented as a Gaussian process with a mean and variance. The mean at each grid point is initialized based on SNR

values computed according to the Friis transmission model, and the variances are set at two standard deviations from the mean. The advantages of this approach include computational simplicity and a consideration for the uncertainty and spatial variability of the SNR fields. The mean and variance of these estimated models are routinely updated with collected measurements, and the models are used to approximate information gain metrics for selecting candidate flight trajectories [10]. This thesis proposes and develops a path planning approach to reduce SNR model estimate uncertainty using information theoretic exploration techniques that allow a UAV to ultimately discover and loiter about the optimal location for maximizing communication throughput between ground nodes. An information theoretic metric for evaluating potential exploration flight paths is proposed and tested in Chapter VI.

2. Phase Two: Extremum Control

Due to the variability of actual SNR data, it is more robust to fly a UAV using gradient ascent of an estimate of the SNR field that is well supported by measurements than simply using an *a priori* model. Once the uncertainty of the SNR environment has been sufficiently reduced, a switching logic is used to transition to the second phase. A possible switching logic could be proven asymptotic stability and concavity, ensuring the UAV would be able to navigate to the optimal loitering point, according to Lyapunov stability, as discussed in [14], which is proposed as follow-on work for this thesis. During this phase, the UAV will fly using gradient estimation and ascent techniques to fly toward and loiter about the peak of the SNR field intersection with a constant heading rate. The peak of the SNR field intersection is considered to be the optimal loitering location to facilitate maximum communications throughput between the two ground nodes. The same extremum control methods previously developed and tested in [1] and [2] can be used to control the UAV to fly toward and loiter about the optimal location.

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III. EXPERIMENTATION

Multiple field experiments were conducted to collect data sets and better understand the degradation of SNR as a function of distance and altitude. The setup included two radios to serve as ground nodes and a UAV platform to serve as a mobile communications relay in a wireless mesh network. Each experiment implemented the same test scenario in an attempt to characterize the SNR field and gain insight into the degradation of SNR as functions of distance and altitude, as well as the effects of UAV bank angle on SNR. Additionally, the UAV executed several flight patterns which were postulated to maximize information gain about the SNR field. In Chapter IV, these datasets are analyzed to assess the utility of these patterns for autonomously discovering an optimal loitering location.

A. UAV SYSTEM DESCRIPTION

The UAV used for experimentation was the ScanEagle created by INSITU Inc., shown in Figure 5. The ScanEagle is an unmanned system configured for both land and sea-based operations. The aircraft is easily configurable with different payloads and is built to carry customer-supplied sensors and processors. The platform is designed for a multitude of persistent sensing roles including [15]:

- Intelligence, surveillance, and reconnaissance (ISR)
- Over the horizon data communications relay
- Battle damage assessment (BDA)
- Escort Operations
- Sea-lane and convoy protection

The ScanEagle is designed to be a high endurance UAV composed of modules that are replaceable and interchangeable in the field. The aircraft is launched using a portable pneumatic catapult that can also be utilized aboard ship for maritime missions. The aircraft is recovered via a SkyHook retrieval system whereby the aircraft uses differential GPS to fly into a suspended rope, which snags the aircraft by via a hook on its wingtip. The

SkyHook eliminates the need for a runway or large volume to recover the aircraft and can be deployed for shipboard use. The launch and recovery systems are shown in Figure 6. Aircraft specifications are listed in Table 1.

Table 1. ScanEagle specifications. Source: [15].

Specification	SI	N-SI
Length	1.6 [m]	5.3 [ft]
Wing Span	3.1 [m]	10.2 [ft]
Max Level Speed	41.2 [m/s]	80 [kn]
Cruise Speed (max wt.)	25-30 [m/s]	50-60 [kn]
Maximum Turn Rate	10 [deg/sec]	10 [deg/sec]
Service Ceiling	5,944 [m]	19,500 [ft]
Endurance	24+ [hr]	24+ [hr]
Still Air Range / No Reserve	2,000 [km]	1,100 [nm]
Operating Empty Weight	16 [kg]	35.3 [lbs]



Figure 5. The Boeing Insitu ScanEagle UAV at San Clemente Island, CA



Figure 6. A ScanEagle UAV being recovered by its SkyHook

B. COMMUNICATION SYSTEM DESCRIPTION

The communication systems utilized during each experiment were Persistent Systems Wave Relay products [11]. Experimentation on San Clemente Island made use of the Wave Relay MPU4 radio, a SISO system. Follow-on experiments utilized the newer MPU5 S-Band radio, a 3x3 MIMO-capable system with three antennas, shown in Figure 7, with specifications listed in Table 2.



Figure 7. Persistent Systems Wave Relay MPU5 radio. Source: [11].

Table 2. MPU5 S-Band radio specifications. Source: [11].

Frequency Range	2200-2507 [MHz]
Antenna Chains	3
Channel Bandwidth	5, 10, and 20 [MHz] Software Configurable
Max Aggregate Transmit Power	6 [W] (2 [w] per RF chain)
Minimum Receiver Sensitivity	-98 [dBm] at 5 [MHz] Bandwidth
Max Peak Power Consumption, TX	40 [W] (3 Chains at 6[W])
Power Consumption, RX	1.9 [W] (3 Chains)

For these experiments, a Wave Relay radio module and dedicated power board were integrated on a ScanEagle UAV. In addition to this communications payload, an ODROID-XU4 computer, shown in Figure 8, running the Ubuntu 16.04 operating system was installed onboard to serve as a central processing unit (CPU). This computer will eventually serve as a secondary controller for implementing the algorithms developed in Chapters V and VI.

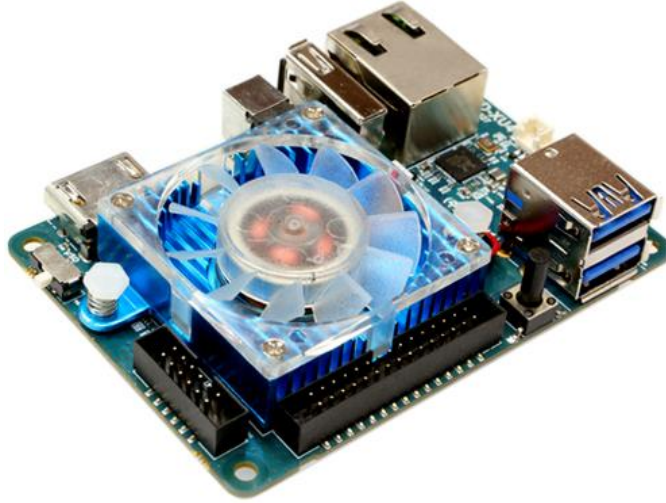


Figure 8. ODROID-XU4 with mounted cooling fan. Source: [16].

The ODROID CPU ran software which leveraged the Robot Operating System (ROS) middleware [17]. A ROS process was developed to record UAV state information, including position and orientation, received via the power board. Another ROS process logged SNR measurements for each communications link, which are broadcast via the application programming interface (API) of the Persistent Systems Wave Relay radio module. All data was saved to a ROS bag file for post-processing. In addition to state information and SNR, network performance parameters were measured using the Simple Network Management Protocol (SNMP). Measured parameters included roundtrip time, throughput in, throughput out, and bit error rate. In addition to the data collected during flight onboard the ScanEagle, ground node data was collected by laptops running the same software while connected to each ground node. During these experiments, an SNMP polling agent running onboard each laptop logged SNR, link quality, Global Positioning System (GPS) data, and SNMP parameters to a text file for each ground node. Collecting data from all three wireless nodes allowed for post-processing and comparative analysis of the SNR measured with respect to each node, ensuring a complete dataset for characterizing the SNR field created by the two ground nodes.

C. EXPERIMENTAL SETUP AND OBJECTIVES

The typical scenario for each field experiment began with two Wave Relay ground nodes located sufficiently far apart, so the SNR of the direct link between them was too low for reliable LOS communications. A ScanEagle UAV with an onboard Wave Relay module then flew various flight patterns at different altitudes to collect SNR measurements relative to each ground node. The objective of each experiment was to capture data for characterizing the degradation of SNR as functions of distance, altitude, and UAV orientation. The Friis transmission model provided an *a priori* expectation about the optimal loitering point for communications relay that would afford maximum throughput. The ScanEagle flew over this location, the expected intersection of the SNR fields created by the two ground nodes, to gain insight into which flight paths were most efficient at maximizing information gain and discovering the optimal loitering location. Additionally, the UAV was flown directly over each ground node to characterize its empirical SNR field.

D. CONDUCTED TESTS

A total of three field experiments were conducted in various locations. Each experiment implemented the target scenario for SNR and UAV telemetry data collection described earlier.

1. San Clemente Island, CA

The first experiment was conducted as part of the Naval Postgraduate School (NPS) Multi-Thread Experiment (MTX) on San Clemente Island (SCI). MTX posed a realistic operational scenario involving multiple unmanned undersea, surface, and aerial assets. The purpose of the experiment was to understand the opportunities and challenges associated with using networked unmanned vehicles (UxV) for expeditionary. A primary goal of the experiment was to advance the autonomy of a collaborative UxV network control system (NCS) in a multi-domain environment. Datasets were gathered at various stages of the operational scenario using the SNMP polling agent. This experiment made use of the Persistent Systems MPU4 SISO radio, a predecessor to the MPU5 [11]. The MPU4 radios did not perform as expected in this environment, and we observed connectivity problems and poor range performance under the MTX test conditions. The data sets collected at MTX

were not particularly valuable for the development of this thesis. In general, all in-flight SNR values measured at an altitude of 1,830 meters (6,000 feet), the minimum flight altitude permitted in this airspace, were not a suitable input for an extremum control algorithm envisioned for phase two of our communications optimization approach. Furthermore, the onboard radio's antenna was located on the belly of the aircraft for this experiment. This may have exacerbated the impact of aircraft orientation on measured SNR. Nevertheless, lessons learned from these experiments were instrumental in planning follow-on experiments including the decisions to use more capable MPU5 radios and locate the onboard radio's antenna in the ScanEagle's right winglet instead of on its belly.



Figure 9. Google Earth image of San Clemente Island MTX location

2. Camp Roberts, CA

We implemented our desired experimental scenario during a second flight test event held at Camp Roberts, CA. One wireless ground node was positioned at the ScanEagle launch site, while a second node was positioned approximately three kilometers away behind several hills which obstructed LOS communications. The ScanEagle was flown in specified patterns at target altitudes of 610, 1220, and 1830 meters (2,000, 4,000, and 6,000 feet, respectively), the maximum permissible flight ceiling of our designated airspace. The SNMP polling agent successfully collected SNR data on both ground nodes and on the ScanEagle UAV.

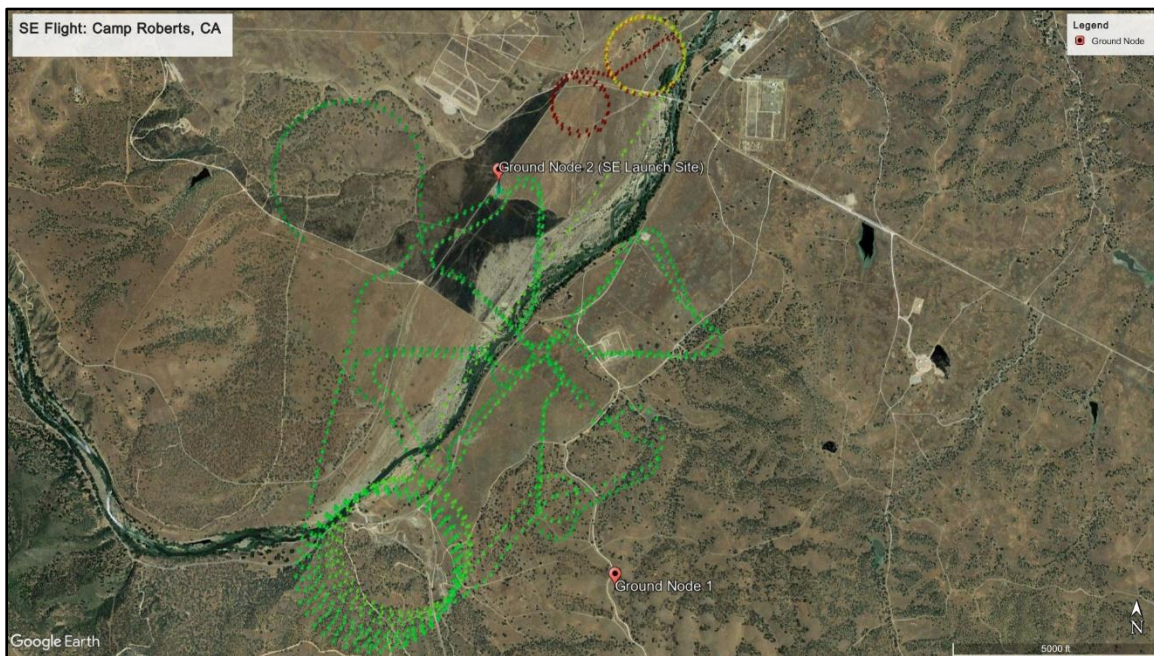


Figure 10. Google Earth image of Camp Roberts testing and data

3. Yuma Proving Ground, AZ

A final experiment was conducted at the Yuma Proving Ground in Yuma, AZ. In Yuma, we conducted the same target scenario tested at Camp Roberts, but at a much greater node separation distance. This provided more insight into the LOS range of the MPU5 radios and the communications performance achievable at greater distances with

ScanEagle serving as a communication relay. The ground nodes were placed approximately seven kilometers apart, with one positioned at the ScanEagle launch site. The ScanEagle was then flown in specified patterns at target altitudes of 915, 1220, and 1525 meters (3,000, 4,000, and 5,000 feet, respectively), the maximum permissible flight ceiling in the designated airspace. The SNMP polling agent successfully collected SNR data on both ground nodes and on the ScanEagle UAV, where all data was captured in a single ROS bag file.

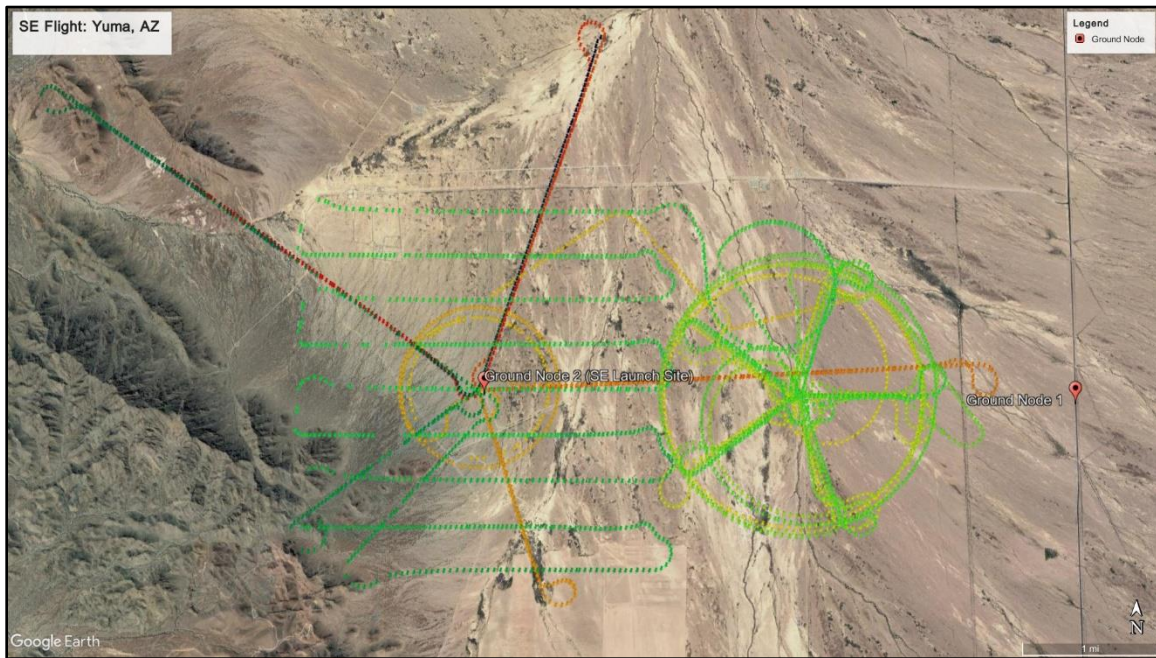


Figure 11. Google Earth image of Yuma testing and collected data

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IV. EXPERIMENTAL RESULTS

During field testing in Camp Roberts, CA and Yuma, AZ, SNR data was successfully collected by both ground nodes and the UAV using the SNMP agent. The dataset primarily consisted of SNR values [dB] for each node's neighbors, measured relative to that node's location, corresponding to each link in the wireless mesh network. The SNR data collected from the UAV's perspective was the primary dataset to examine, since this data will be used for our eventual communications optimization algorithm. The objective is to use onboard SNR measurements to autonomously plan flight trajectories to build a spatial estimate of the SNR field, reduce its uncertainty, and then navigate to an optimal loitering location. To facilitate analysis of this SNR data, time-stamped GPS position data for each node in the network was also logged. Prior to testing, the system time for each computer was synchronized to GPS time using network time protocol (NTP). This ensured accurate correlation of the SNR measurements with node position and orientation data. Ultimately, the resulting data from both field experiments supported our initial hypothesis for SNR degradation as a function of increasing distance and increasing altitude. Analysis of the data with respect to aircraft orientation is ongoing and not yet completed.

A. CAMP ROBERTS FLIGHT RESULTS

1. UAV Flight Trajectory

During testing in Camp Roberts, CA, the ScanEagle was flown in specified patterns at different altitudes above the center point between the two ground nodes. The patterns specified were shaped like flower petals based on the assumption that they would provide the greatest amount of coverage. The patterns also ensured the UAV flew straight and level for the majority of the flight to minimize the effect of bank angle. The center point was of particular interest because it was expected to coincide with the peak of the intersection of the SNR fields generated by both ground nodes. As the UAV was flown along its specified trajectory, SNR data for its communications links to each ground node was collected. The collected data for each link is presented in Figure 12 and Figure 13, displayed in Earth-

Centered, Earth-Fixed (ECEF) coordinates, where the SNR measured at each location is represented by the color bar shown.

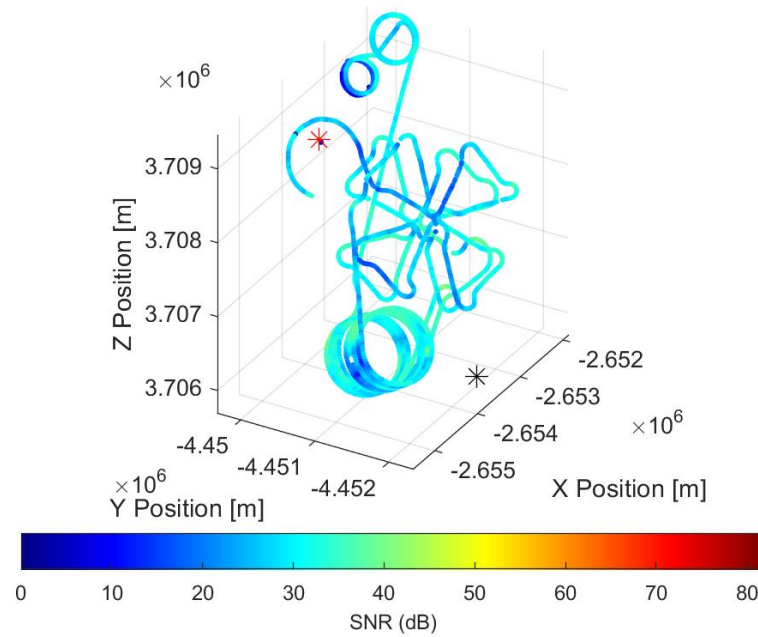


Figure 12. Camp Roberts data for ScanEagle link to Node 1 (ECEF)

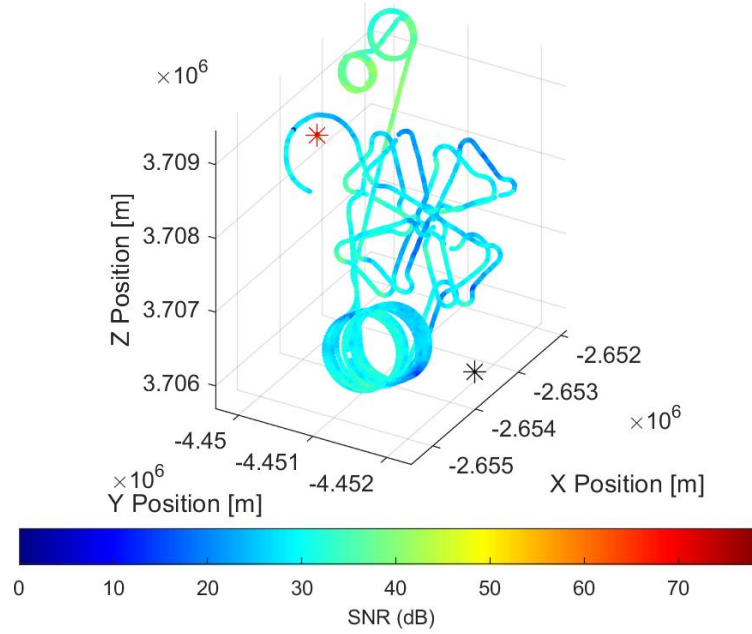


Figure 13. Camp Roberts data for ScanEagle link to Node 2 (ECEF)

These plots illustrate how the majority of SNR data collected for both communications links was measured between 20 dB and 40 dB. This suggests that this test did not explore the full range and capability of the MPU5 ground nodes, i.e., the ground nodes were placed too close to one another to sufficiently capture the degradation of SNR with distance for each node. Unfortunately, this test was the last scheduled experiment of the day, which did not afford the ability to repeat this experiment with the ground nodes spaced further apart. Ultimately, due to the limited range of this test, it was difficult to ascertain trends in the SNR data as a function of the UAV's flight altitude.

2. Degradation of SNR as a Function of Distance

The SNR data for each node, as measured by the ScanEagle, is plotted as a function of distance in Figure 14.

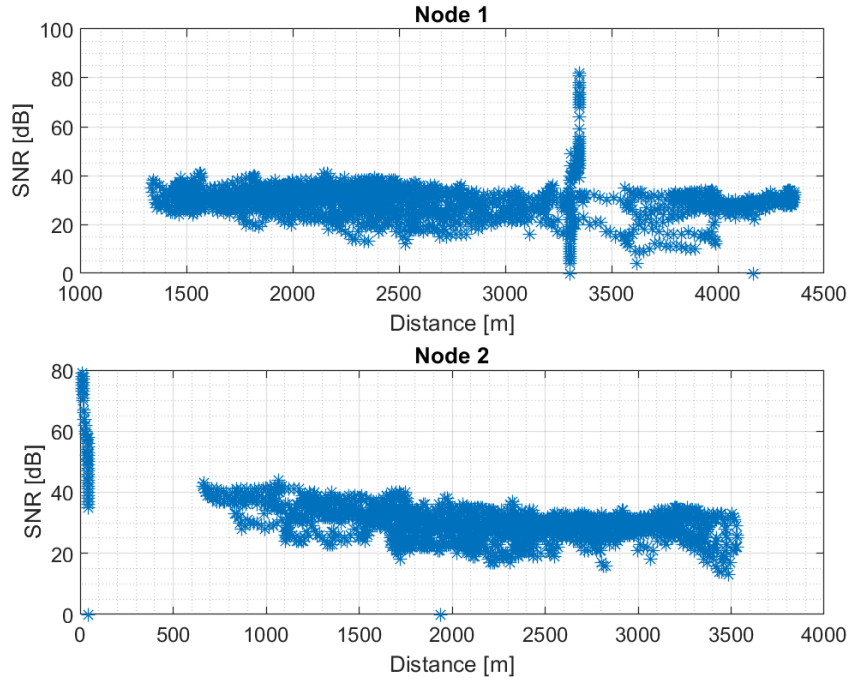


Figure 14. Camp Roberts SNR data vs. distance from each ground node

These plots illustrate that over a range of approximately 4,000 meters, SNR measurements were concentrated in a narrow band between 20 dB and 40 dB. From these results, we determined that follow-on tests should seek to explore the capabilities of the MPU5 nodes and position the ground nodes at much greater distances from each other. Note that in Figure 14 there are SNR values that are highly variable in both plots. In the top plot for Ground Node 1, a spike in measured SNR occurs at a range of approximately 3,300 meters. In the bottom plot for Ground Node 2, a spike in measured SNR occurs at the node location. It seems likely that these SNR spikes were captured prior to take-off or post-flight when the SNMP polling agents for each node were running and the UAV was on the ground, which could be verified by plotting SNR versus time and distance or altitude.

3. Degradation of SNR with Respect to Altitude

The SNR data for each node, as measured by the ScanEagle, is plotted against altitude in Figure 15. Due to the limited communication ranges tested during this flight, we

observed only a minor degradation with altitude, particularly when measured with respect to Ground Node 2.

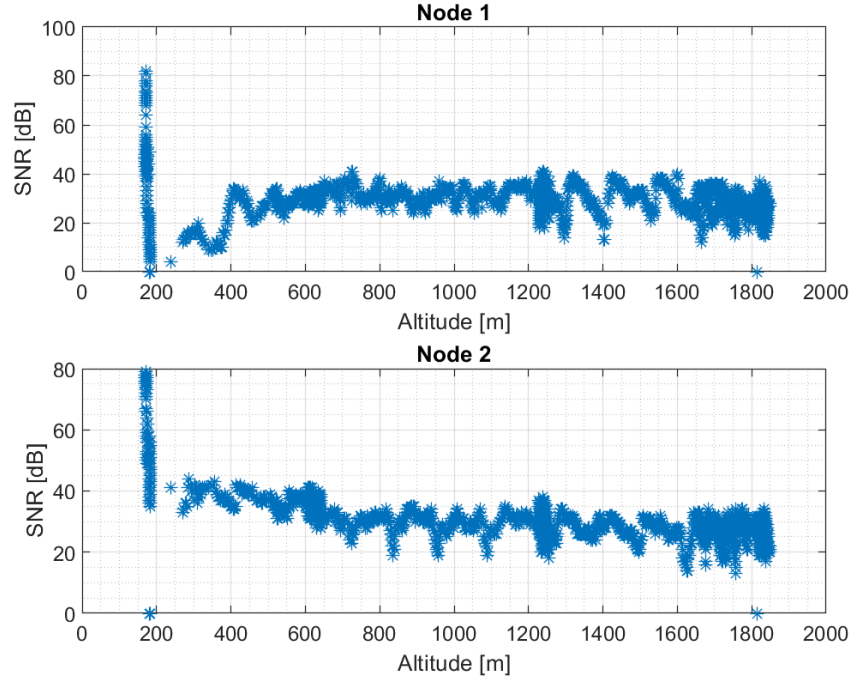


Figure 15. Camp Roberts SNR data vs. altitude from each ground node

4. Degradation of SNR with Respect to Distance and Altitude

Finally, we conducted an analysis of SNR with respect to both distance and altitude from each ground node in Figure 16 and Figure 17. These plots illustrate only minor variation in SNR. Distances varied between zero and 3,000 meters as the aircraft executed various flight patterns at altitudes of 610, 1220, and 1830 meters (2,000, 4,000, and 6,000 feet, respectively). Nevertheless, we observe a slight SNR degradation with increasing distance and altitude, which supports our initial hypothesis. These plots indicate the location of SNR measurement spikes much more clearly than the preceding plots, reinforcing our hypothesis that these measurements occurred prior to take-off or post-flight while the aircraft was on the ground.

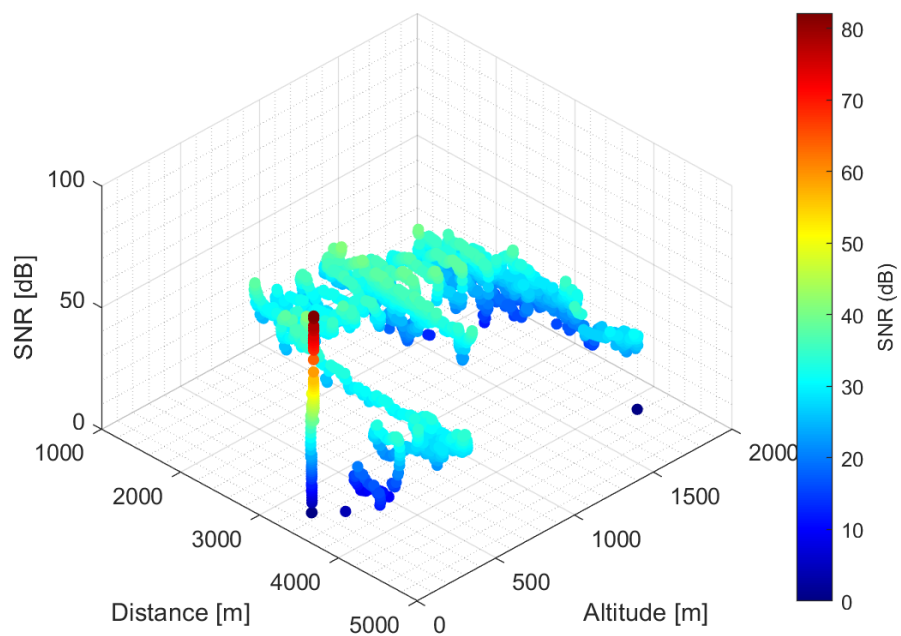


Figure 16. Camp Roberts SNR data vs. distance and altitude for Node 1

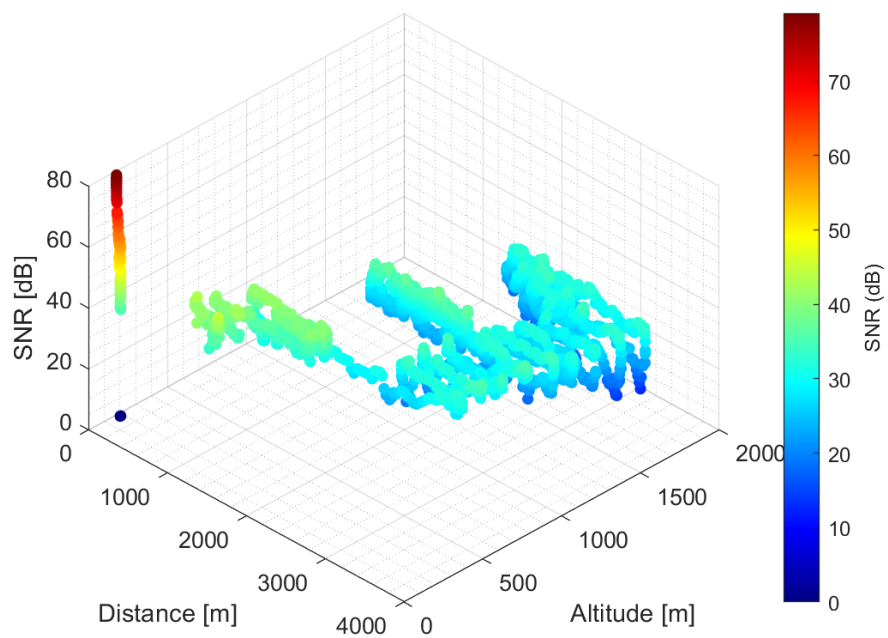


Figure 17. Camp Roberts SNR data vs. distance and altitude for Node 2

B. YUMA FLIGHT RESULTS

1. UAV Flight Trajectory

During our flight tests at Yuma Proving Ground, in the ScanEagle executed specified flight patterns similar to the ones executed at Camp Roberts. These patterns were flown at different altitudes above both the center point between two ground nodes and directly above the ground node positioned at the launch site. Patterns included simple orbits, lawnmower tracks, and radial stars to ensure a wide coverage area and minimize the impact of aircraft orientation on measured SNR. The flat desert terrain presented negligible environmental obstructions to LOS wireless communication. Once again, the center point was of particular interest because we expected that the peak of the intersection of the SNR fields generated by the ground nodes would be located there. As the UAV flew along its specified trajectory, SNR measurements were collected relative to each ground node. The collected data for each link is shown in Figure 18 and Figure 19, displayed in ECEF coordinates.

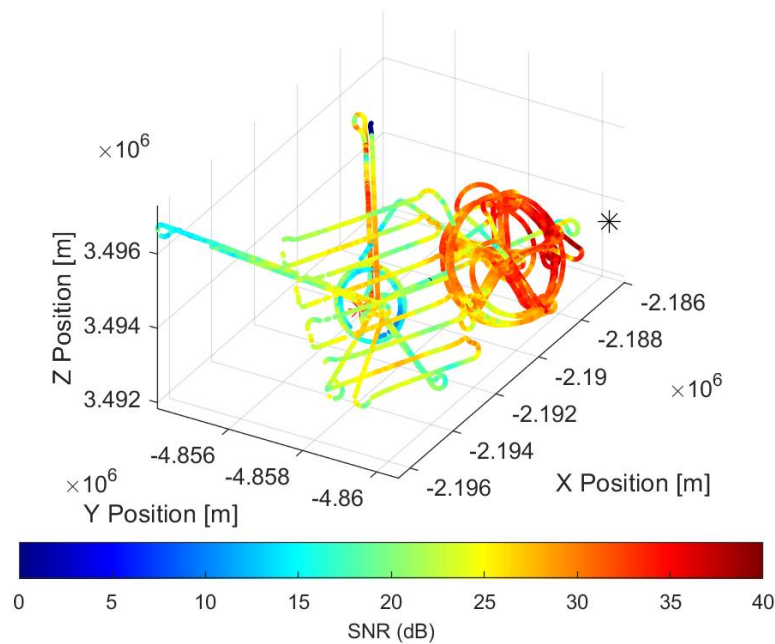


Figure 18. Yuma SNR data for ScanEagle link to Node 1 (ECEF)

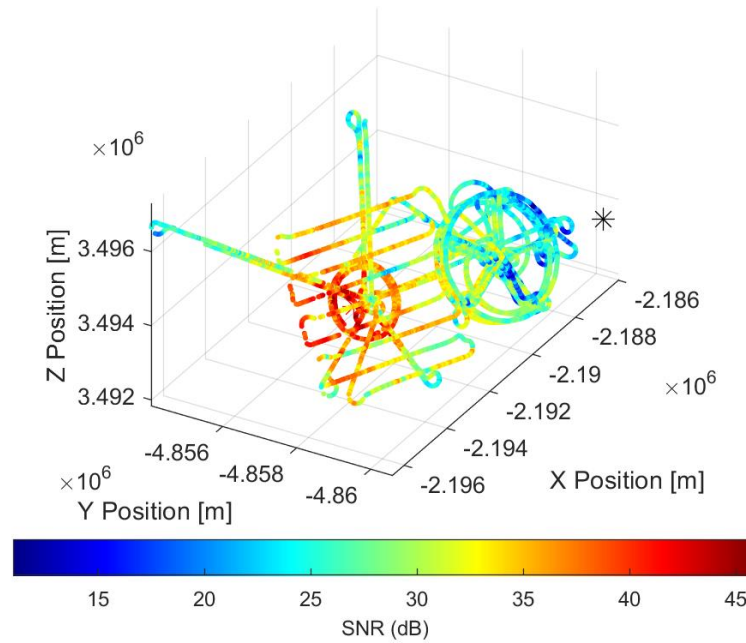


Figure 19. Yuma SNR data for ScanEagle link to Node 2 (ECEF)

As shown by the colorbar, a much greater range of SNR values was collected compared to the SNR data collected at Camp Roberts, spanning from 0 dB to over 45 dB, which was deemed to be an acceptable and realistic range. The test was planned to further explore the range and capability of the MPU5 ground nodes, so these nodes were positioned 7,000 meters apart, more than double the link distance tested in Camp Roberts. As shown in Figure 18 and Figure 19, there is a noticeable trend in the data for each node. As the UAV flew closer to each node, the SNR values associated with their respective communications links increased, and they decreased as the UAV flew further away. This trend supports our initial hypothesis.

2. Degradation of SNR as a Function of Distance

The SNR data for each node, as measured by the ScanEagle, is plotted as a function of distance in Figure 20.

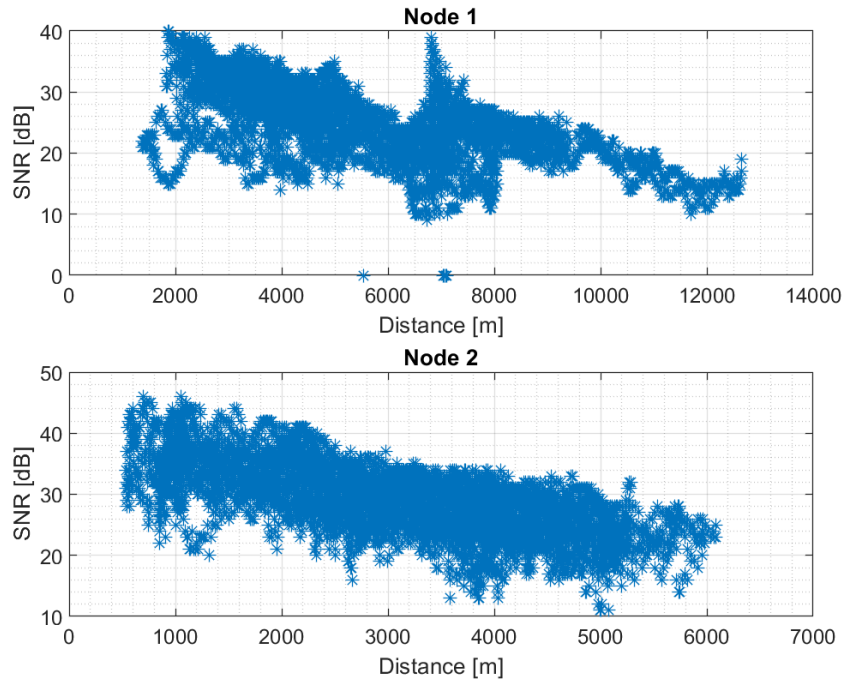


Figure 20. Yuma SNR data vs. distance from each ground node

A wide range of data is shown across the 7,000-meter range as well as data collected at greater ranges for Ground Node 1 from the longer, westerly legs of the star patterns flown above the launch site. There is a clear and noticeable trend in SNR degradation as a function of increasing distance with some outliers for Ground Node 1. Based on the distance at which the outliers are located, it seems likely that these SNR spikes were captured prior to take-off or post-flight when the SNMP polling agent for Ground Node 1 was running and the UAV was on the ground.

3. Degradation of SNR with Respect to Altitude

The SNR data for each node, as measured by the ScanEagle, is plotted against altitude in Figure 21. The data clearly reflects how the UAV primarily flew in different patterns at altitudes of 915, 1220, and 1525 meters (3,000, 4,000, and 5,000 feet, respectively). There is a significant variation in SNR value at each altitude reflected by the varying distances to each node associated with the different patterns flown. While it is

difficult to discern a trend for the link with Ground Node 1, we observed only minor degradation with altitude measured with respect to Ground Node 2.

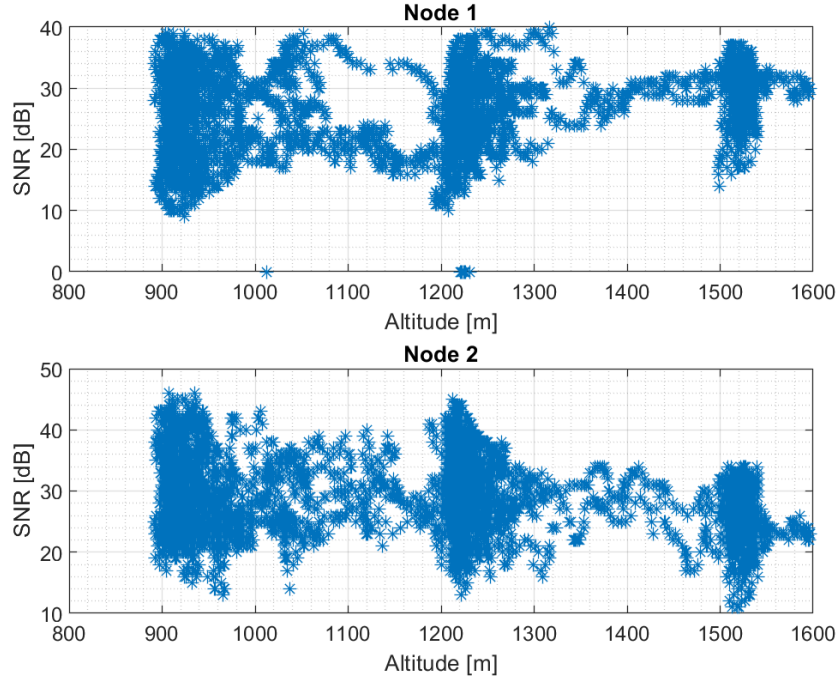


Figure 21. Yuma SNR data vs. altitude from each ground node

4. Degradation of SNR with Respect to Distance and Altitude

Finally, we conducted an analysis of SNR with respect to both distance and altitude from each ground node in Figure 22 and Figure 23. These figures clearly illustrated how the UAV primarily flew in different patterns ranging from 0 to over 7,000 meters at altitudes of 915, 1220, and 1525 meters (3,000, 4,000, and 5,000 feet, respectively). There is a clear trend of SNR degradation with increasing distance and altitude is observed for links with both nodes, which supports the initial hypothesis. Additionally, a spike can be seen more clearly than in Figure 20 at a low altitude, reinforcing our hypothesis that these measurements from Ground Node 1 occurred prior to take-off or post-flight while the aircraft was on the ground

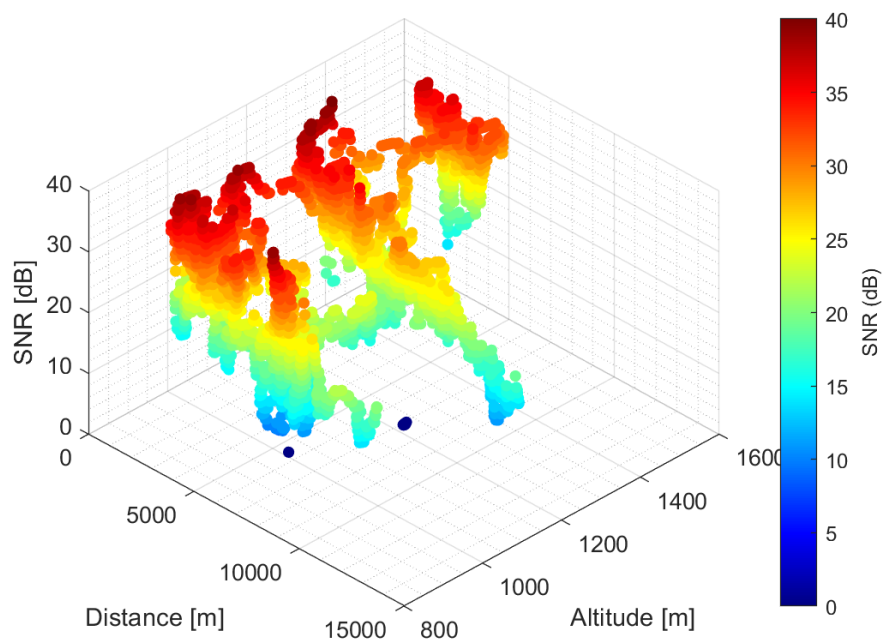


Figure 22. Yuma SNR data vs. distance and altitude for Node 1

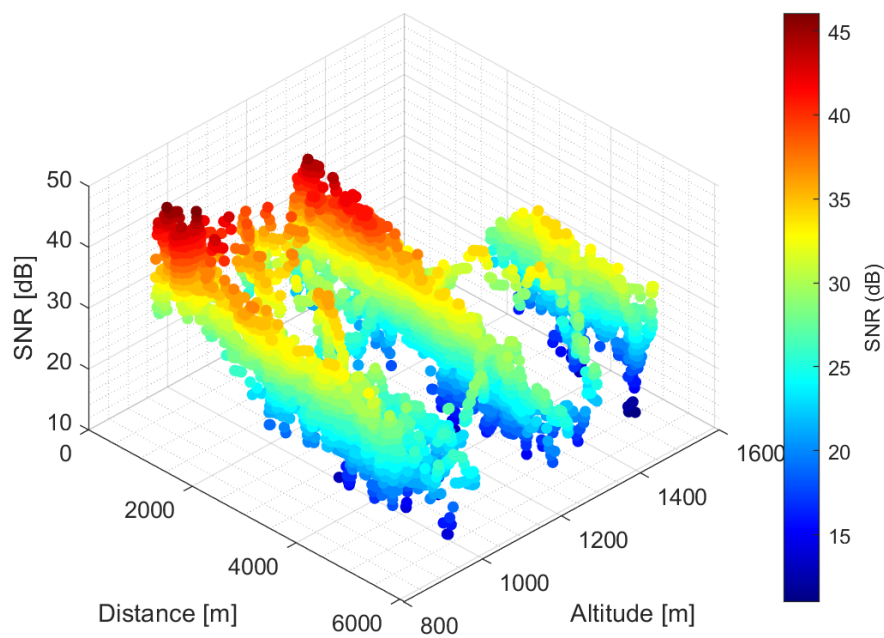


Figure 23. Yuma SNR data vs. distance and altitude for Node 2

Having examined the collected data from each experiment, clear trends associated with the degradation of SNR as a function of distance and altitude were observed. The initial hypothesis of SNR degradation as a function of increasing distance and increasing altitude was supported primarily by the large dataset collected in Yuma, AZ. Further analysis on the effects of UAV orientation, namely bank angle and heading, on SNR degradation has yet to be completed. Such analysis would give further insight into how the UAV orientations induced by the various trajectories flown during these experiments, impacted the SNR measurements. This information could inform a pilot or onboard flight controller how to fly in order to maximize the utility of SNR measurements collected during future field experiments.

V. GAUSSIAN PROCESS REGRESSION: KRIGING

A Gaussian process model is a spatial-temporal model of a random variable that can be used to describe unknown, noisy environmental phenomena and the uncertainty associated with them, including SNR [18]. For simulations conducted for this thesis, a 10,000-meter by 10,000-meter field is discretized into 200-meter by 200-meter grid cells. Each cell represents a Gaussian distribution with a mean SNR value and an associated variance value. There are implications associated with whether or not an a priori assumption, such as the Friis transmission model, is used. If the Gaussian process model is initialized incorrectly, it may take longer and require more measurements to converge on an updated representation of the measured process with a tolerable amount of uncertainty. By using accumulated measurements, a Gaussian process model can be used to predict the value of SNR as a function of both space and time [18].

In our application, we seek to enable a UAV to estimate the SNR fields of two ground nodes as a function of position and orientation, based upon actual, noisy SNR measurements. Our approach leverages a geostatistical nonlinear optimal spatial estimation technique known as Kriging, to estimate the SNR field with spatially autocorrelated data. The measurements collected are correlated to other measurements within the series that are separated by a given distance [19]. Bohling states that Kriging proves to be optimal when measurement data is normally distributed and satisfies an assumption of second-order stationarity. This assumption means that each measurement is considered to be a single statistical random process whose “mean and variance do not vary significantly in space” [19]. These assumptions of normality and second-order stationarity are significant and can prove dangerous if the data does not satisfy them as the farther away from a Gaussian distribution you get, the worse the optimal estimation performs [19]. For this reason, Bohling recommends constructing a binned histogram of the measurement data to ensure it fits a normal distribution before applying this technique [19].

A. KRIGING: OPTIMAL SPATIAL INTERPOLATION

Kriging, or Gaussian process regression, is an optimal spatial interpolation technique for “generating best linear unbiased estimates” of a random variable at unknown locations through the employment of a semivariogram model of the random variable [19]. Interpolation methods are used to estimate the unknown value of a random variable at a specified location by computing a weighted sum of measured values of this random variable at other neighboring locations [19]. Nearly every interpolation algorithm exhibits similar behavior; they assign smaller weights for greater separation distances between actual measurement locations and the location of the desired estimate [20]. Several other known properties of these interpolation methods include [20]:

- Fairly dense and uniformly distributed data points will provide accurate estimates, regardless of the chosen interpolation algorithm.
- Data points sampled in clusters at large distances apart from one another will provide inaccurate estimates, regardless of the chosen interpolation algorithm.
- Any interpolation algorithm will underestimate higher values and overestimate of lower values as an inherent consequence of averaging.

Kriging computes weights based on a “data-driven” weighting function and affords several advantages over other interpolation methods. Kriging, for example, assigns less weight to individual measurement points within a cluster to effectively treat clusters as a single data point. Another advantage is that Kriging provides an estimate of the estimation error, known as “Kriging variance,” in addition to the estimated random variable itself [20].

1. Kriging Approach

The basic form of Kriging estimation in two dimensions is mathematically defined as [20]

$$Z^*(u) - m(u) = \sum_{\alpha=1}^{n(u)} \lambda_{\alpha} [Z(u_{\alpha}) - m(u_{\alpha})] \quad (5.1)$$

where u, u_α are the (x, y) locations of the estimate and a neighboring data point. The quantity $n(u)$ is the number of neighboring data points being used to compute the estimate; $m(u), m(u_\alpha)$ are the expected mean values of the random fields $Z(u)$ and $Z(u_\alpha)$; and $\lambda_\alpha(u)$ are the Kriging weights assigned to the $Z(u_\alpha)$ data for estimating the value at location u . The Kriging weights are derived from a covariance or semivariogram function, taken from the semivariogram model, and characterize the residual component of the random field, $R(u) = Z(u) - m(u)$ [20]. The goal of Kriging is to determine the Kriging weights that minimize the variance of the estimate

$$\sigma_E^2(u) = \text{Var}\{Z^*(u) - Z(u)\} \quad (5.2)$$

under the unbiased estimate constraint, $E\{Z^*(u) - Z(u)\} = 0$ [20]. Ultimately, the entire mathematical process finds a set of weights used to estimate the value of a random variable at a desired location u relative to neighboring data points [20]. These weights generally decrease with a data point's distance from the estimate location [20].

2. Ordinary Kriging

Ordinary Kriging is a process that assumes the mean of a random variable is constant within a local neighborhood of each desired estimation point. This can be described mathematically as $m(u_\alpha) = m(u)$ for each neighboring data point, $Z(u_\alpha)$, used to estimate $Z(u)$ [20]. This is essentially an augmented version of Simple Kriging, which assumes the mean of a random variable is constant across an entire domain, $m(u) = m$, regardless of the estimation locations [20]. The resulting Kriging estimator for Ordinary Kriging can be written as [20]

$$\begin{aligned} Z^*(u) &= m(u) + \sum_{\alpha=1}^{n(u)} \lambda_\alpha(u) [Z(u_\alpha) - m(u)] \\ &= \sum_{\alpha=1}^{n(u)} \lambda_\alpha(u) Z(u_\alpha) + \left[1 - \sum_{\alpha=1}^{n(u)} \lambda_\alpha(u) \right] m(u) \end{aligned} \quad (5.3)$$

By requiring that the Kriging weights sum to one, $\sum_{\alpha=1}^{n(u)} \lambda_{\alpha}(u) = 1$, the unknown local mean of the random variable can be filtered out, leading to an Ordinary Kriging estimator [20]

$$Z^*(u) = \sum_{\alpha=1}^{n(u)} \lambda_{\alpha}(u) Z(u_{\alpha}) \quad (5.4)$$

To minimize the Kriging variance, subject to the constraint on the Kriging weights, the system seeks to minimize both the Kriging variance and an additional Lagrange parameter, $\mu(u)$

$$L = \sigma_E^2(u) + 2\mu(u) \left[1 - \sum_{\alpha=1}^{n(u)} \lambda_{\alpha}(u) \right] \quad (5.5)$$

such that the minimization forces the constraint on the Kriging weights to be obeyed [20]

$$\frac{1}{2} \frac{\partial L}{\partial \mu} = 1 - \sum_{\alpha=1}^{n(u)} \lambda_{\alpha}(u) = 0 \quad (5.6)$$

The resulting system of equations used to solve for the Kriging weights is:

$$\begin{cases} \sum_{\beta=1}^{n(u)} \lambda_{\beta}(u) C_R(u_{\alpha} - u_{\beta}) + \mu(u) = C_R(u_{\alpha} - u) & \alpha = 1, \dots, n(u) \\ \sum_{\beta=1}^{n(u)} \lambda_{\beta}(u) = 1 \end{cases} \quad (5.7)$$

where $C_R(h)$ is the local neighborhood covariance or semivariogram model function for the residual component of the random variable. This function is a mathematical representation of the spatial autocorrelation in the data [20]. For Simple Kriging with the assumption of a constant mean, it is common to equate $C_R(h) = C(h)$ [20].

The resulting system of equations can be written more simply in matrix form as

$$K\lambda(u) = k \quad (5.8)$$

where K is the covariance matrix for the data points used with elements $K_{i,j} = C(u_i - u_j)$ and k is the vector of covariances between the estimation point and each data point used. The vector k is computed from the semivariogram model function, with elements $k_i = C(u_i - u)$. Finally, $\lambda(u)$ is the vector of Kriging weights for the datapoints used [20]. If the semivariogram model is licit and none of the data points used are collocated, K will be positive definite such that the Kriging weights can be simply found by [20]:

$$\lambda(u) = K^{-1}k \quad (5.9)$$

Once the Kriging weights are computed, the Kriging estimate can be found using Equation (5.3), and the Kriging variance is calculated by [20]:

$$\sigma_E^2(u) = C(0) - \sum_{\alpha=1}^{n(u)} \lambda_{\alpha}(u) C(u_{\alpha} - u) - \mu(u) \quad (5.10)$$

3. Kriging Weights

The covariance among data points is heavily influential in the determination of Kriging weights. If two data points have a relatively strong correlation with one another, but one of the data points has a stronger correlation with the desired estimation point, the data from the other point will be weighted much lower and have much less influence on the estimate [20]. This is an example of how Kriging can treat clusters of data points as a single data point. Bohling asserts that the covariances of the measurements and their assigned Kriging weights are entirely dictated by their locations and their corresponding covariance model rather than their measurement values [20]. Selecting which neighboring data points to use when computing an interpolated estimate is at least as influential as the choice of interpolation method itself [20]. A search algorithm like k-nearest neighbors, described in [21], can be used in conjunction with Kriging to select which data points are used for each estimate.

B. SEMIVARIOGRAM CONSTRUCTION AND ANALYSIS

In the previous section, an equation was presented to scale spatial measurements and calculate an optimal estimate at a desired location. The function used to scale the

measurements is known as a semivariogram. The semivariogram is a representation of the dissimilarity of measurements as a function of distance, quantified by semivariance. Considering a set of measurements of the same random variable taken at various distances apart from one another, the separation distances between each measurement are typically known as “lag” distances [19]. These lag distances are often divided into bins encompassing a range of lag distances whose size are dictated either by a specified number of bins or by a “lag tolerance” [19]. Once the collected measurements have been sorted into lag distance bins, the average semivariance for the measurement pairs in each bin is computed and plotted versus their associated lag distance. A best fit curve through this empirical data is then used to construct a semivariogram model for computing semivariance as a function of distance between measurements. This fitted function is used during the Kriging process to assign weights to measurements taken during the estimation process.

1. Covariance, Correlation, and Semivariance

There are three common statistics examined in the realm of geostatistics: covariance $C(h)$, correlation $\rho(h)$, and semivariance $\gamma(h)$. These statistics can be mathematically defined as [19]

$$C(h) = \frac{1}{N(h)} \sum_{\alpha=1}^{N(h)} z(u_{\alpha}) \cdot z(u_{\alpha} + h) - m_0 \cdot m_{+h} \quad (5.11)$$

$$\rho(h) = \frac{C(h)}{\sqrt{\sigma_0 \cdot \sigma_{+h}}} \quad (5.12)$$

$$\gamma(h) = \frac{1}{2N(h)} \sum_{\alpha=1}^{N(h)} [z(u_{\alpha} + h) - z(u_{\alpha})]^2 \quad (5.13)$$

where u is a vector of (x, y) coordinates at which measurements are taken, $z(u)$ is the random variable of concern as a function of measurement locations, h is the lag distance vector between two given measurement locations, $z(u + h)$ is the lagged version

of the random variable, and $N(h)$ is the number of pairs of measurements separated by h [19]. According to Bohling, it is common to refer to $z(u)$ as the “tail variable” and $z(u+h)$ as the “head variable” when thinking of h as a traditional head-to-tail vector [19]. As a result, m_0 and m_{+h} can be considered to be the means of the random variable at the tail and head, respectively, of each lag distance vector, and σ_0 and σ_{+h} are their corresponding standard deviations [19].

Bohling points out that while covariance and correlation are measures of similarity among pairs of head and tail measurements in a dataset, semivariance is a measurement of dissimilarity among them [19]. Semivariance is the desired statistic for the formulation of the Gaussian process models used in this thesis because semivariograms tend to “filter the influence of a [possible] spatially varying mean” [19]. A plot of semivariance versus lag distance between the measurements of a random variable in a dataset is known as a semivariogram. As Bohling explains, estimating a semivariogram function can be tricky due to the common issue of having irregularly distributed data, which requires the grouping of measurement pairs into lag distance bins. Having larger lag tolerances and bins allows for more pairs of measurements to contribute to the estimation process, but it also reduces the level of detail and resolution provided by the semivariogram [19]. Another key problem usually arises from a lack of measurement pairs at shorter lag distances, even though it is very important to the estimation process that the semivariogram accurately characterize the semivariance at these distances [19].

2. Second-Order Stationarity

The second-order stationarity assumption is significant and calls for the covariance function and semivariance function for a given series of random variable measurements to obey the following [19]

$$C(0) = \text{Cov}(z(u), z(u)) = \text{Var}(z(u)) \quad (5.14)$$

$$\gamma(h) = C(0) - C(h) \quad (5.15)$$

These equations state that the covariance of the measurements at a lag distance of zero should equal the global variance of the random variable of concern, and the semivariogram should essentially “look like the covariance function turned upside down” [19]. However, it is common for deviations from second-order stationarity to occur in practice, leading to problems in the estimation process. According to Bohling, another benefit to using the semivariogram is that it can be applied under a less stringent requirement than second-order stationarity; this requirement is called the intrinsic hypothesis [19]. Under the intrinsic hypothesis, when the initial differences between a pair of measurements are second-order stationary, the semivariogram may be used even though the covariance function would otherwise be undefined [19].

3. Characteristics of the Semivariogram

There are three primary characteristics of the semivariogram that are of interest: the sill, the range, and the nugget as shown in Figure 24.

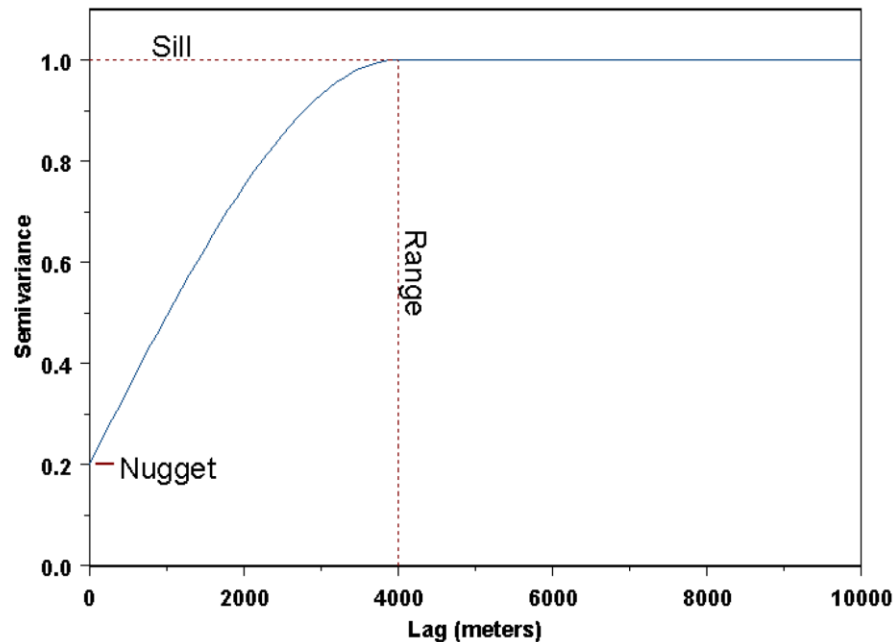


Figure 24. Semivariogram characteristics. Source: [19].

The sill is defined as the semivariance value at which the semivariogram plateaus [19]. The range is the lag distance at which the sill value occurs and the point at which autocorrelation at greater lag distances presumably approaches zero [19]. The nugget describes the dissimilarity in the data at very small lag distances, which are typically smaller than the spacing between measurements [19].

4. Modeling the Empirical Semivariogram

The empirical semivariogram produces a plot of data that represents the dissimilarity of measurements as a function of the lag distance between them. In order to use an empirical semivariogram to scale measurements in the Kriging process and produce estimates of a random variable at unknown locations, its characteristics must first be summarized by an analytic expression. This step is necessary because the optimal spatial interpolation algorithm requires values for lag distances not present in the empirical semivariogram, and they must be positive semidefinite such that the Kriging equations are non-singular and solvable [19]. Modeling a semivariogram is typically done by fitting a curve to it. According to Bohling, these curves are typically selected from a group of functions that are known to be acceptable [19]. The two semivariogram models used in this thesis are the spherical and exponential models, which are defined in Equations (5.16) and Equation (5.17), respectively [19]

$$g(h) = \begin{cases} c \cdot \left(1.5 \left(\frac{h}{a} \right) - 0.5 \left(\frac{h}{a} \right)^3 \right) & \text{if } h \leq a \\ c & \text{otherwise} \end{cases} \quad (5.16)$$

$$g(h) = c \cdot \left(1 - \exp \left(\frac{-3h}{a} \right) \right) \quad (5.17)$$

where h is lag distance, a is the range or practical range, and c is the sill. While the spherical model actually reaches the sill value, the exponential model does not and only approaches it asymptotically by reaching 95% of the sill value at the practical range specified by a [19]. As explained by Bohling, both models appear to be linear near the origin, which proves to be better for representing data pairs with greater levels of variability

at shorter lag distances [19]. Additionally, each is considered a “transition model” with a finite sill and a corresponding covariance function defined by $\text{Cov}(h) = c - g(h)$ [19]. It is also acceptable to use linear combinations of licit models to produce more complex models, but only singular models are used for this thesis [19].

The overall process of fitting a model to an empirical semivariogram is not straightforward and requires a degree of finesse. Bohling acknowledges that there are many different accepted and suggested methodologies and protocols, but the approach chosen will ultimately depend upon the judgment of the individual fitting the model [19]. In some cases, it is possible for a random variable to show different autocorrelation depending on the relative bearing between measurements [19]. This requires an anisotropic variogram [19]. However, when using Kriging techniques to estimate the SNR field generated by two ground nodes, the SNR fields are assumed to be spatially homogeneous, omnidirectional, isotropic processes. Much like the output of the Friis transmission model, the degradation of SNR as a function of distance and the autocorrelation of the measurements are uniform—regardless of bearing to the node and the relative bearing between measurements [19]. This is a fundamental assumption for this thesis. An alternative method of modeling the SNR field would represent SNR fields based on polar coordinates instead of the cartesian approach used in this thesis. Due to time constraints, this method can be explored in future work.

C. KRIGING USING EXPERIMENTAL DATA

1. Detrending Data

In cases where the empirical semivariogram climbs steadily beyond the global variance value of the dataset, this is “indicative of a significant spatial trend in the variable, resulting in a negative correlation between variables separated by large lags” [19]. This was the case with the SNR measurement data collected during field experiments, especially data collected over large distances in Yuma, AZ. Rather than simply ignoring the problem and using a poor variogram fit, this can be dealt with by removing a first-order trend from the data and working with the resulting detrended measurement values. This approach is known as “Kriging with a trend” [20]. After the estimation process is complete, the trend

can be added back to the estimated values. The detrending of SNR data collected from two wireless nodes during experiments conducted in Yuma, AZ is illustrated in Figure 25. The results show a maximum variability in the measurements of about 10 dB.

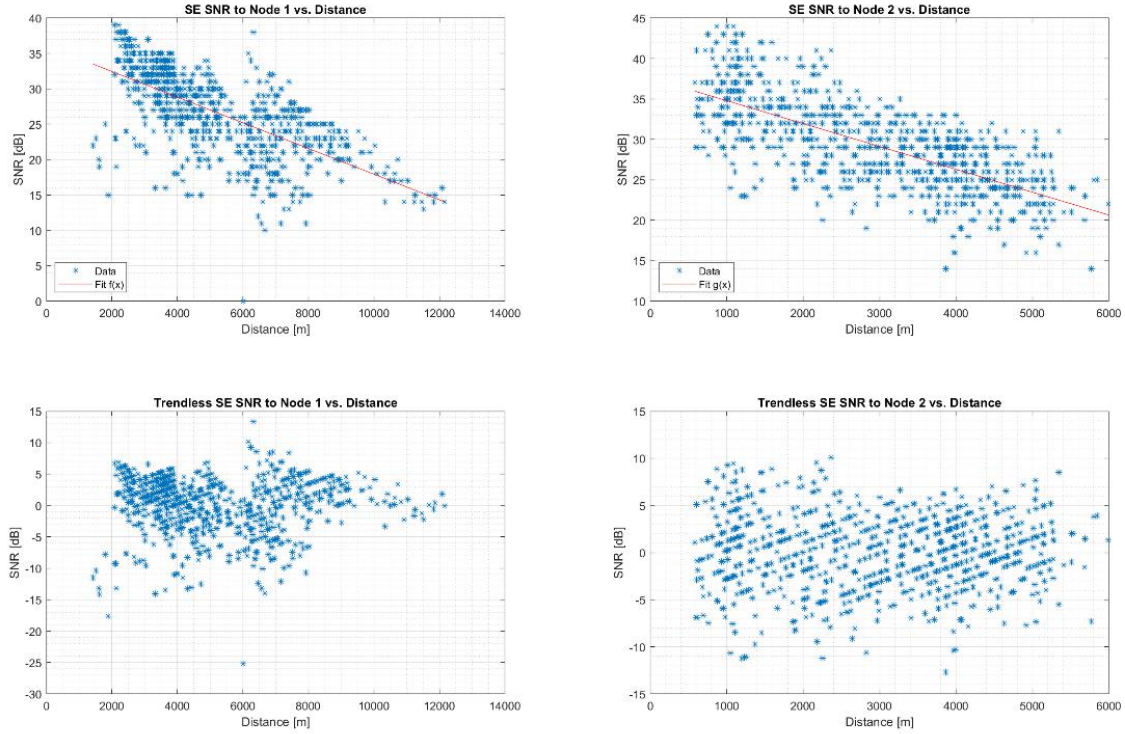


Figure 25. Removal of 1st order distance trend from collected SNR data

2. Full Flight Path

Data collected along the full flight path of the UAV during field testing in Yuma, AZ can be used to produce Kriging estimates of the SNR fields generated by the two wireless ground nodes. First, the collected data is sorted into lag distance bins based on the distance between each possible pair of measurements in the dataset. For this analysis, the maximum distance between possible pairs of measurements was capped at 2,000 meters. This effectively limits the number of pairs of measurements whose associated variability can influence the estimated value at a desired location. Although measurement pairs with lag distances over 7,000 meters exist, it is ill-advisable to use these pairs (and their associated variability) to influence the value of local estimates at much smaller ranges.

Each pair of measurements has an associated semivariance value describing the dissimilarity in the data. The result is a binned variogram cloud for each node as shown in Figure 26 and Figure 27. Upon initial inspection, there is a greater level of dissimilarity and variability in the ScanEagle's SNR measurements from Ground Node 1 than is present in its SNR measurements from Ground Node 2. This is likely due to the fact that the ScanEagle spent a significant amount of time flying above and around Ground Node 2, while the closest it flew to Ground Node 1 occurred along an orbit centered on the midpoint between the two ground nodes.

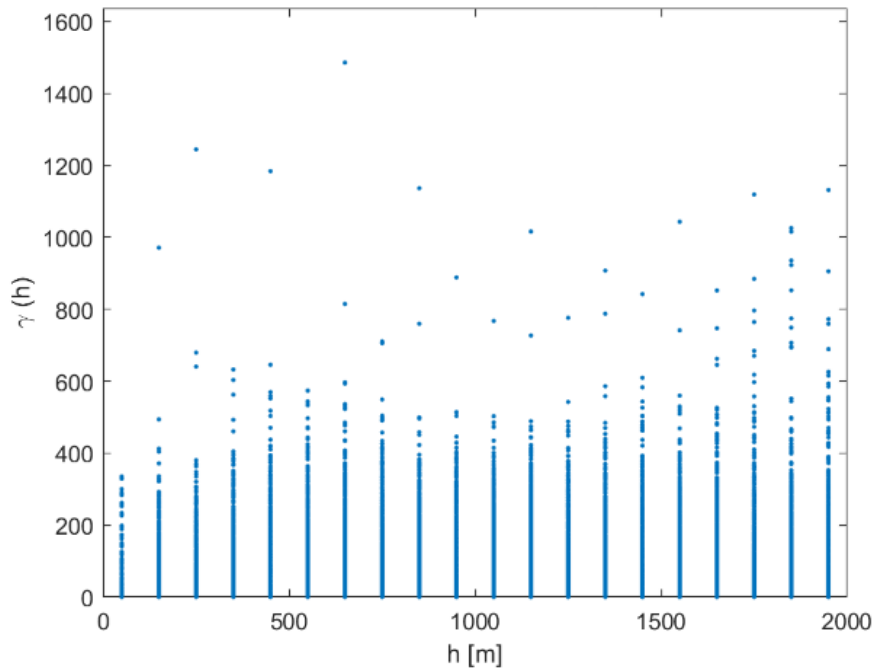


Figure 26. Binned variogram cloud of SNR data for Node 1

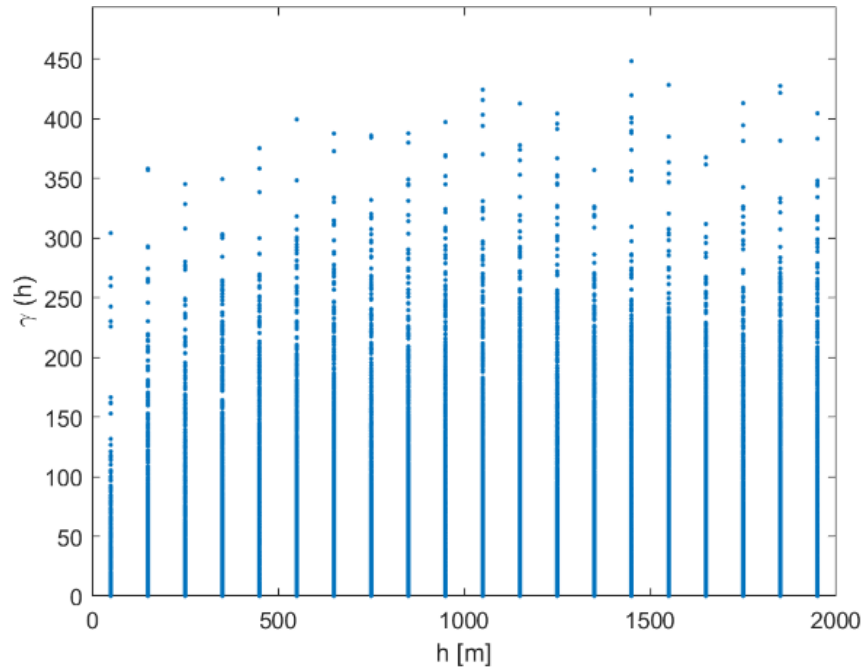


Figure 27. Binned variogram cloud of SNR data for Node 2

Once the data has been sorted into lag distance bins, the semivariance values within each bin are averaged to produce an overall semivariance for each bin. This results in an empirical semivariogram as shown in Figure 28 and Figure 29. These results clearly show a greater level of dissimilarity and variability associated with the data from Ground Node 1 as compared to the data from Ground Node 2.

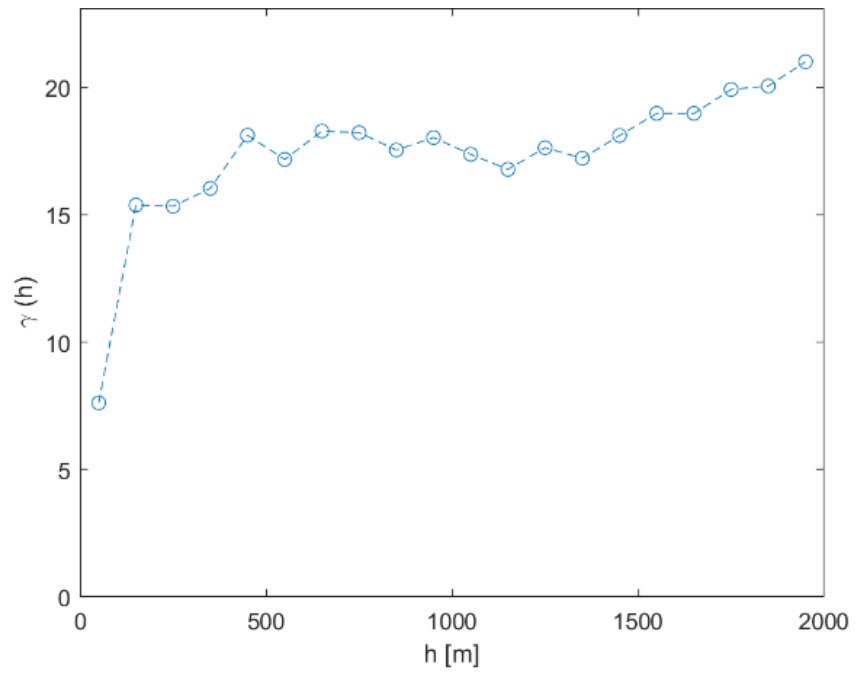


Figure 28. Empirical semivariogram of SNR data for Node 1

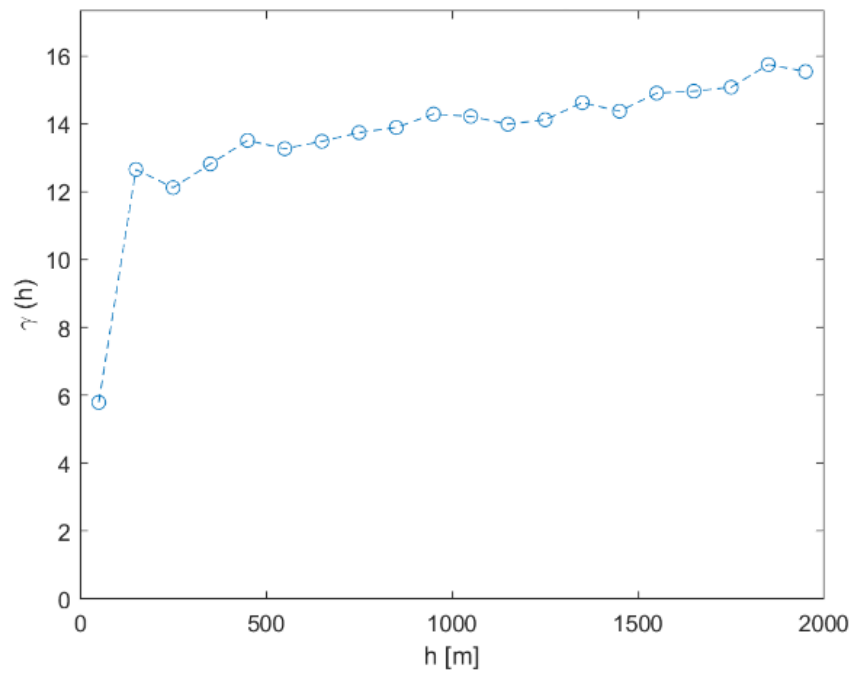


Figure 29. Empirical semivariogram of SNR data for Node 2

Once the empirical semivariogram is constructed, a variogram fit can be applied to create a Gaussian process model describing the variability and uncertainty of the system. A spherical variogram model was chosen and its nugget semivariance was initialized to the minimum semivariance value present in the empirical semivariogram. The resulting variogram model can then be used in the Kriging process with actual measurements to estimate SNR values at other desired locations. Variogram fits for the data collected in Yuma, AZ are presented in Figure 30 and Figure 31.

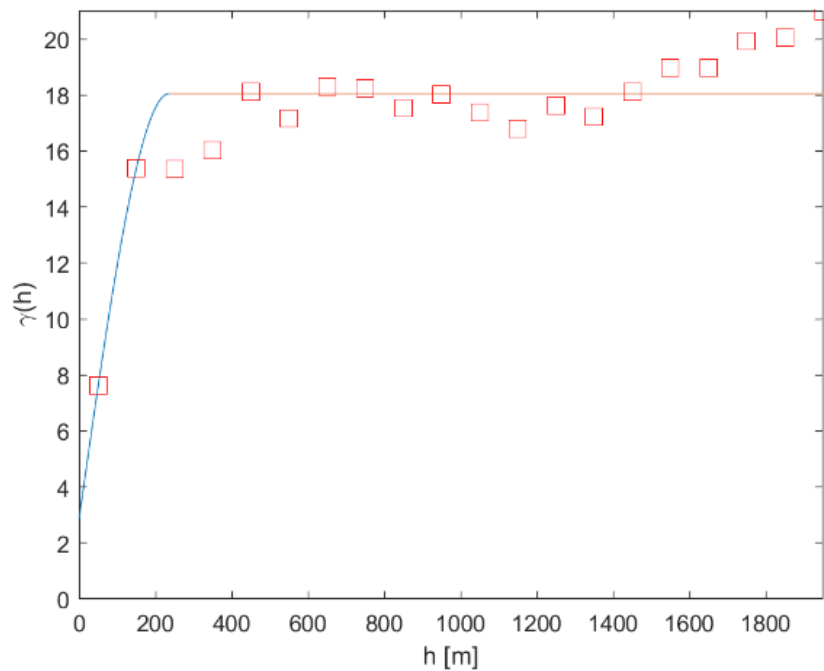


Figure 30. Variogram fit of SNR data for Node 1

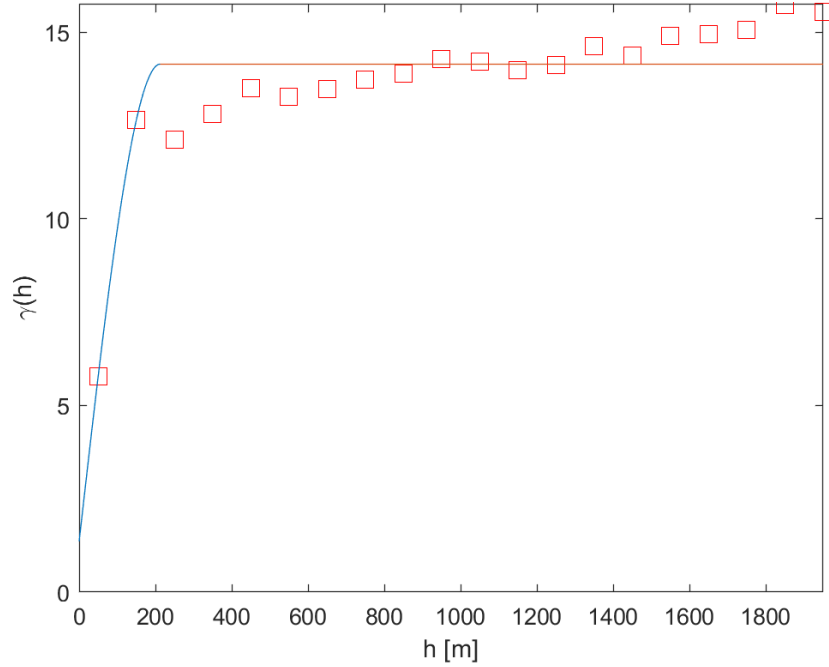


Figure 31. Variogram fit of SNR data for Node 2

3. Comparison to Friis Transmission Model Assumption

Once a variogram fit has been constructed to model the autocorrelation of the SNR data, it can be used to estimate values for this random variable in locations at which SNR measurements have not been taken using Kriging techniques. For this thesis, a Kriging estimate of the discretized SNR field for each ground node encompassing the entire operational area in Yuma was computed from experimental data. The SNR fields estimated via Kriging are illustrated in Figure 32. For comparison, the SNR fields computed according to the Friis transmission model are presented in Figure 33.

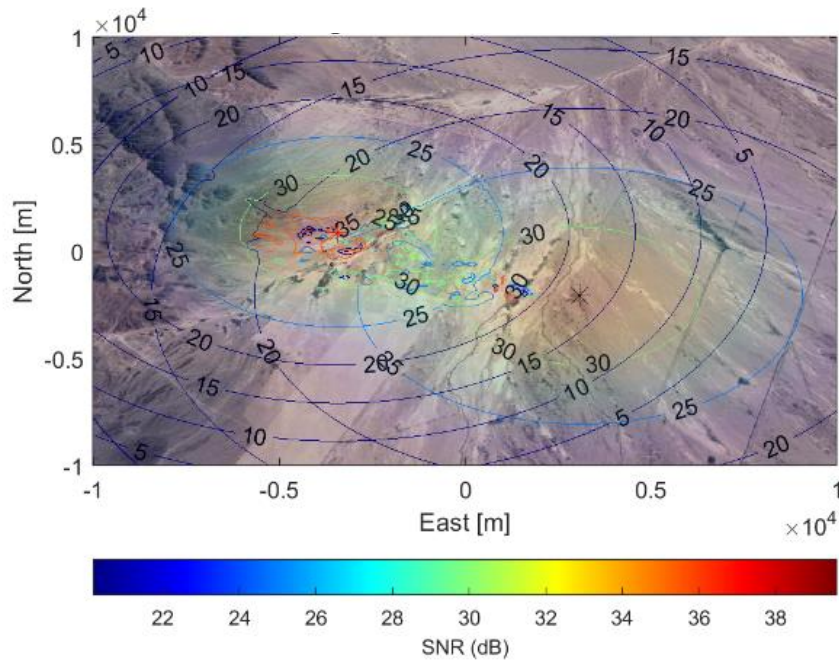


Figure 32. Kriging Estimate of SNR fields

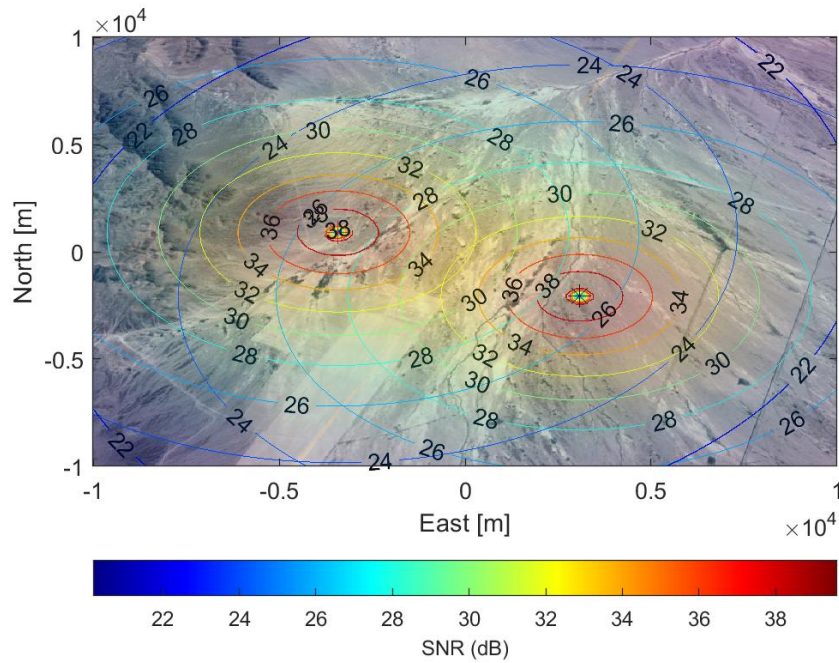


Figure 33. SNR fields computed from Friis transmission model

The SNR fields computed from the Friis transmission model are far more optimistic than the Kriging estimate computed from actual SNR data, in terms of SNR degradation as a function of distance. However, as mentioned previously, the ScanEagle spent a significant amount of time flying above Ground Node 2 as opposed to Ground Node 1, so fewer measurements were collected in close proximity to Ground Node 1. As a result, the Kriging estimate of the SNR field for Ground Node 1 is not as refined or accurate compared to that of Ground Node 2. This is also reflected by greater dissimilarity and semivariance in the empirical semivariogram for Ground Node 1 depicted in Figure 28 and Figure 30. The difference between the Kriging estimate and the Friis transmission model becomes even more apparent when examining the intersection of the two resulting SNR fields, as shown in Figure 34 and Figure 35.

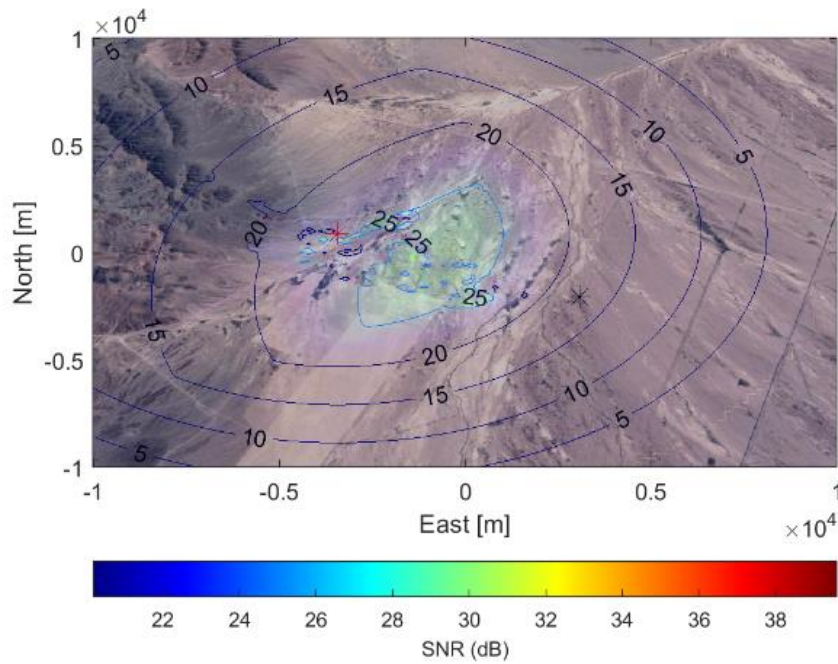


Figure 34. Kriging estimate of SNR field intersection

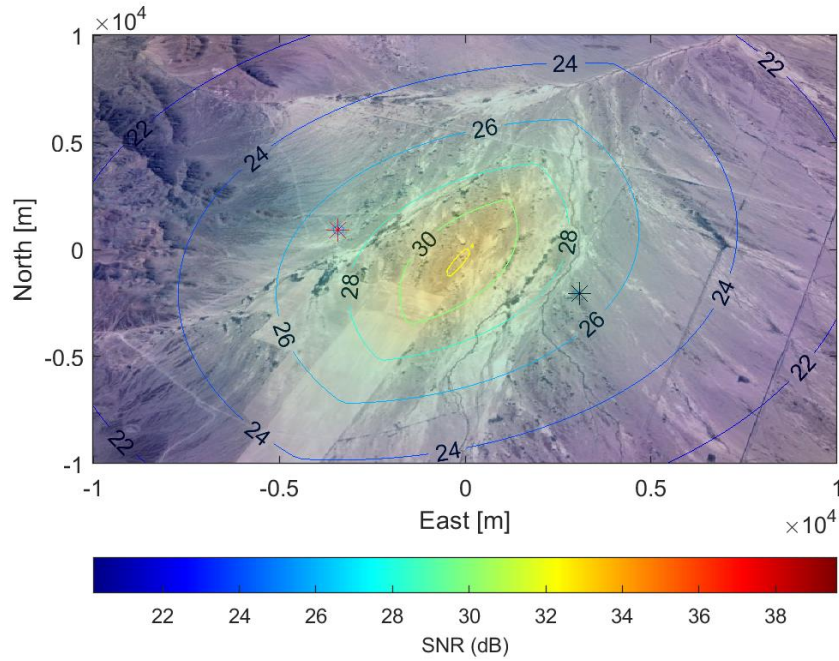


Figure 35. SNR field intersection computed from Friis model

The difference between the two SNR field intersections is significant. A UAV using a real-time estimation algorithm, with an initial expectation based on the Friis transmission model, would likely have a much smaller region in which extremum seeking guidance is actually reliable, illustrated by the Kriging estimate in Figure 34.

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VI. INFORMATION THEORETIC PATH PLANNING WITH SYNCHRONOUS KRIGING

In this chapter, we introduce a method for calculating a local trajectory for the UAV to determine the optimal loitering position for bridging communications between two ground radios. The method utilizes the uncertainty of SNR models constructed from measurement data, as well as an energy function to select a path from candidate trajectories. This novel, information theoretic approach evaluates and selects from candidate trajectories based on a defined metric for information gain with respect to the uncertainty associated with the estimated SNR fields for two ground nodes.

A. PATH PLANNING OBJECTIVE

Equation Chapter 6 Section 1The autonomous exploration of an uncertain area is a challenging problem because the vehicle knows little more than an initial assumption of the environment, and it must effectively predict how measurements along potential trajectories will help reduce the uncertainty in its map [22]. As Charrow et al. describe it, the vehicle must face an “exploitation-exploration trade-off” in which it must decide whether to locally improve the map by refining its understanding of a particular region or to explore other uncertain regions of the environment [22]. The UAV must determine both where to collect measurements and how to get there [18]. There are many challenges associated with this mission, particularly for a UAV, including its dynamic constraints and limited flight time.

The path planning problem for this thesis is to determine a path that best reduces the uncertainty of the SNR models. Given a map of an SNR field at a particular moment in time, the goal for the path planner is to generate paths the vehicle should follow to gather measurements, which can then be used to update the map’s underlying SNR model [22]. The path the vehicle is directed to follow must enable the collection of measurements that will facilitate efficient model updates and reduce uncertainty associated with the SNR map [22]. As explained by Charrow et al., this can be achieved by maximizing the rate of a given information gain metric between a current map and a predicted future map. Within

the context of this thesis, information gain is based on SNR models which are updated using the predicted future measurements that would be gathered along candidate trajectories [22]. The fundamental problem is optimally selecting these paths given an appropriate planning horizon [13].

For our problem, we expect that the area of greatest potential information gain is the region of intersection between the two SNR fields generated by each ground node. We first assume an a priori probabilistic model of the SNR field. This model is a Gaussian random variable over a lattice field whereby each grid cell is represented by a mean and variance. Additionally, we utilize a probabilistic semivariogram model for each node.

The UAV is then able to collect measurements of the SNR field along its flight path for the purpose of updating its underlying model. As more measurements are collected, the two semivariograms are updated and their associated uncertainty bands are reduced. Candidate paths do not need to be determined in advance but can be generated from adaptive sampling techniques and chosen in response to both direct measurements and predictive measurements based on a measurement model of the SNR environment [13].

B. CANDIDATE TRAJECTORY GENERATION

A set of local candidate trajectories generated by constant heading rates can be simply computed from the position and orientation of the UAV at a given point in time. By specifying a set of feasible criteria that candidate trajectories must meet, i.e., they must not violate dynamic constraints and actuator limits, several potential flight paths can be generated for a specified time horizon into the future. For this problem, we generate seven simple candidate trajectories from the UAV's current pose and a feasible, constant heading rate and constant forward speed of 32 knots for a 50-second time horizon. These candidate trajectories are further discretized at five second intervals to produce a set of future measurement locations as shown in Figure 36.

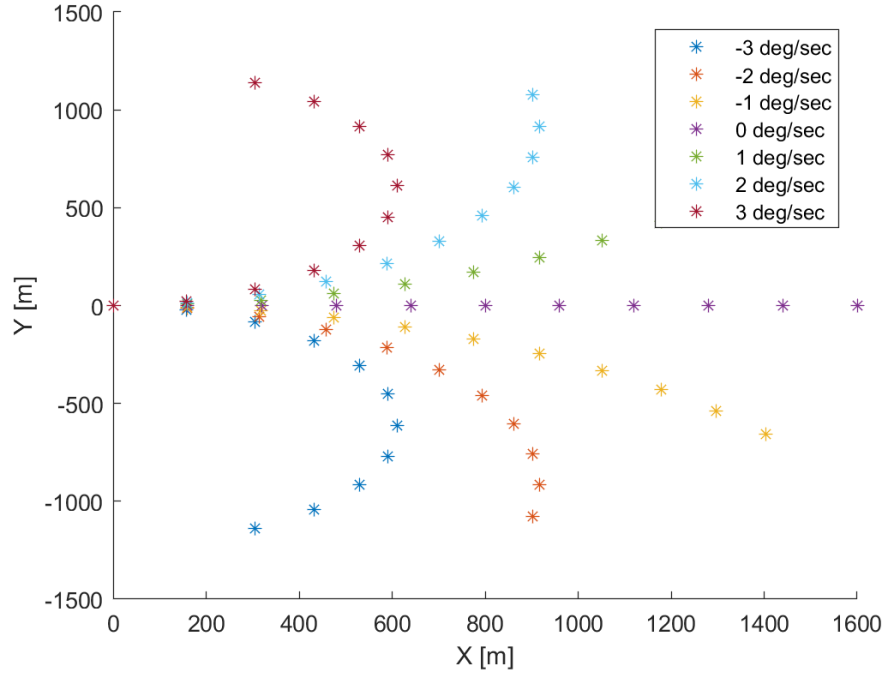


Figure 36. Candidate trajectories at constant heading rates and speed

C. PATH EVALUATION

In order to choose the best path among the locally generated candidate trajectories, each must be evaluated against some metric. This metric should be constructed such that the path with the greatest objective value leads the UAV to appropriately explore uncertain regions of the SNR environment [13]. In other words, regardless of the UAV's location within the operational space, the metric must incentivize the exploration of uncertain regions of the map as well as the thorough discovery of the intersecting region of the SNR fields. This can be done by creating an information-theoretic objective function used to guide the UAV to collect measurements in areas of the SNR map with greater uncertainty [22]. Charrow et al. state that a probabilistic measurement model is required to generate the predicted future measurements [22]. For this thesis, these predicted measurements are needed for guiding the UAV to uncertain areas of the map. Prior work has investigated a multitude of information gain metrics including information entropy, mutual information gain, rate of information gain criterion, and map entropy gradients [22]. According to Charrow et al., each has their own drawbacks that can result in inefficient map exploration

behavior [22]. Ultimately, Charrow et al. explain that “maximizing the rate of information gain is preferable to purely maximizing information, as it enables the [vehicle] to compare the value of actions over different time and length scales” [22]. For this problem, the value of a path is determined by both its anticipated information gain for both nodes’ SNR models, and the change in energy, defined by the slope of the SNR fields, along the path. Therefore, we will define an objective function which ensures that selected trajectories satisfy the dynamic constraints of the vehicle, maximizes information gain, and uses an energy function to prioritize exploration at the intersection of the ground nodes’ SNR fields. The net effect is an objective function that creates an incentive for the UAV to discover the optimal loitering point between ground nodes.

1. Information Gain Metric

When evaluating candidate trajectories, one objective is determining which trajectory will afford the greatest information gain. In order to define information gain in the context of this problem, it is necessary to first define the foundational concept of information entropy. Information entropy, H , describes the uncertainty associated with a given random variable, X , representing “the expectation of the information that each value of the random variable carries” [23]. For a scenario in which X can be any value x from a set of possible values, χ , and $p(x)$ is the probability of X equaling x , the information entropy of X can be described as [23]

$$H(x) = E_x [I(x)] = -\sum_{x \in \chi} p(x) \log p(x) \quad (6.1)$$

where $I(x)$ is the “self information” of x , defined as $I(x) = \log p(x)$. This quantity represents the “entropy contribution carried by each value of x ” [23].

For this path planning problem, we selected Kullback-Leibler divergence as our information gain metric. Also known as Kullback-Leibler distance, this metric is defined as the distance between probability distributions. The computed distance can also be used to measure inefficiency between an assumed probabilistic model, $q(x)$, and what is discovered through measurements to be an actual probability, $p(x)$, for a given random

variable [23]. For this problem, we make the assumption that the SNR values for each ground node, computed at each discretized grid location, are single, independent random variables. Additionally, we assume that $q(x)$ describes the most current assumed variance models for the SNR maps generated by two ground nodes, and $p(x)$ describes the actual, updated models based on accumulated measurements. Assuming a) that the initial distribution of potential values x for random variable X is given by $q(x)$; and b) that the actual distribution, based on measurements, is $p(x)$; then the distance between these two distributions, the Kullback-Leibler divergence, can be mathematically defined as [23]

$$D_{KL}(p(x) \parallel q(x)) = \sum_{x \in X} -p(x) \log q(x) - (-p(x) \log p(x)) = \sum_{x \in X} p(x) \log \frac{p(x)}{q(x)} \quad (6.2)$$

This definition can then be expanded to determine the Kullback-Leibler divergence between two univariate Gaussian distributions, each defined by a mean, μ , and a variance, σ , where $q(x) = N_{\mu_2, \sigma_2}(x)$ and $p(x) = N_{\mu_1, \sigma_1}(x)$ [24] [25].

By definition [24] [25]

$$\begin{aligned} \sum_{x \in X} p(x) \log(p(x)) &= -\frac{1}{2} (1 + \log(2\pi\sigma_1^2)) \\ \sum_{x \in X} p(x) \log(q(x)) &= -\frac{1}{2} \log(2\pi\sigma_2^2) + \frac{\sigma_1^2 + (\mu_1 - \mu_2)^2}{2\sigma_2^2} \end{aligned} \quad (6.3)$$

Therefore, the definition for Kullback-Leibler divergence can again be rewritten in terms of the means and variances of the two distributions as [24] [25]

$$\begin{aligned} D_{KL}(p(x) \parallel q(x)) &= \frac{1}{2} \log(2\pi\sigma_2^2) + \frac{\sigma_1^2 + (\mu_1 - \mu_2)^2}{2\sigma_2^2} - \frac{1}{2} (1 + \log(2\pi\sigma_1^2)) \\ &= \log\left(\frac{\sigma_2}{\sigma_1}\right) + \frac{\sigma_1^2 + (\mu_1 - \mu_2)^2}{2\sigma_2^2} - \frac{1}{2} \end{aligned} \quad (6.4)$$

This value quantifies the difference between our initial assumption of the SNR distribution and the distribution calculated from accumulated measurements of the random variable [23]. By accumulating SNR measurements for each ground node, and updating their assumed probability distribution, each measurement has a quantifiable value in terms of the information gain it provides about the random variable [23]. Therefore, by evaluating the Kullback-Leibler divergence between the current assumed Gaussian process model and an updated Gaussian process model based on predicted measurements computed using a measurement model of the random variable, the predicted information gain along each candidate UAV trajectory can be evaluated. In order to optimally explore the map and reduce its uncertainty, the candidate trajectory with the greatest predicted information gain can then be chosen.

2. Energy Metric

In addition to determining the trajectory with the greatest information gain, a second objective is to determine which candidate trajectory affords the greatest change in energy. The energy metric in this path planning problem is based on electromagnetic energy associated with SNR. Specifically, the energy value along a candidate trajectory is computed as the absolute change in SNR magnitude with respect to path length for the intersection of the two SNR fields. The intersection of the two SNR fields, $E_{Intersection}$, is simply computed as

$$E_{Intersection} = \min(Field1\ SNR, Field2\ SNR) \quad (6.5)$$

The energy gain computed along a particular segment of a trajectory is then computed as

$$\left| \frac{dE_{Intersection}}{dx} \right| = \left| \frac{E_2 - E_1}{\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}} \right| \quad (6.6)$$

where E_1 and E_2 are SNR values for the intersection of two SNR fields computed at two discretized grid locations along a particular segment of a candidate trajectory, and

$\left| \frac{dE_{Intersection}}{dx} \right|$ is the absolute change in SNR magnitude for the intersection over the course of that trajectory segment.

When examining the SNR fields generated by two ground nodes, the net energy value computed from both fields is the greatest in the intersecting region where the slope of the combined change in SNR over distance for both nodes is greatest. This is also realized by examining the intersection of the two fields, whose slope is greatest around its peak. Therefore, when this metric is combined with information gain, the UAV will not only choose the path that will afford the greatest amount of information gain, but it will also be inclined to choose the path that guides it towards the intersecting region of the ground nodes' SNR fields. Discovering this region is one of the steady-state goals for this path planner, once exploration has sufficiently reduced the uncertainty in the underlying SNR models.

3. Information-Theoretic Objective Function

Considering both information gain and energy change as well as feasibility with regards to UAV dynamics, the resulting information-theoretic objective function used to evaluate candidate trajectories is defined as

$$J = \sum_{t=0}^{t=t_f} k_{IG} (D_{KL,Node1} + D_{KL,Node2}) + k_E \left| \frac{dE_{Intersection}}{dx} \right| \quad (6.7)$$

where k_{IG} and k_E are gains associated with the information gain and change in energy along a candidate trajectory segment. The variables $D_{KL,Node1}$ and $D_{KL,Node2}$ are the predicted information gains for each SNR field based on predicted measurements taken while traveling between two discretized grid locations along a particular segment of the candidate trajectory. These grid locations are used to compute updated SNR maps for each node along each candidate trajectory segment. The values computed for energy and information gain are then summed along the entire length of each candidate trajectory to compute the objective function J for each one. The candidate trajectory with the greatest objective value is selected for execution.

As the UAV travels and collects measurements, the Gaussian process model used for computing the predicted information gain is updated prior to the next generation of candidate trajectories. As a result, the next set of paths to choose from are generated in response to newly acquired SNR measurements [13]. This is important for the UAV to prioritize flying over unexplored, uncertain regions of the map as opposed to areas that have already been explored and whose uncertainty has already been reduced.

Due to the nature of the summed computation for path value, path selection is subject to scaling issues regarding path length. A feasible candidate trajectory that is longer is likely to have a larger sum of energy change and information gain value and therefore is more likely to be selected as the candidate trajectory, even if another path has greater value for its length scale. A candidate for future work is to modify the objective function to normalize for the path length of each candidate trajectory.

D. LOCAL VS. GLOBAL PLANNING

The planning horizon is an important consideration for path planning, as candidate paths are computed by projecting a turn rate command over a discrete period of time. When the time horizon is short, the plan represents a short trajectory that is feasible with respect to the UAV dynamics. These paths can be locally optimal, yet potentially fail to achieve long-term objectives. Conversely, a long time horizon produces a longer trajectory that may be more computationally difficult to evaluate in real-time and might be optimal only with respect to the current condition of the map.

For this problem this problem, we define the final state of a global planner not by a location, but by a sufficient reduction in uncertainty associated with the SNR map around the intersecting region of the ground nodes' SNR fields. Therefore, a global planner may produce paths consistent with those flown during field experiments to explore the entirety of the map and place greater emphasis on the intersecting region. However, a globally planned trajectory may be inefficient in reducing the uncertainty of the map. A globally planned trajectory may be chosen based on an anticipated value, but it will not provide you any additional insight beyond the initial expectation. According to Charrow et al., global exploration strategies often cause vehicles to remain distant from uncertain regions of the

map [22]. While they avoid the possibility of vehicles getting stuck in local minima that may appear optimal based on the path planning cost function used, they are computationally expensive to generate [22]. Once a global path has been generated, the UAV will continue to follow it, only adapting to changing situations if the global path is periodically re-planned based on accumulated measurements. Furthermore, a global path may have redundancies in which the UAV flies over certain regions of the map more than once. Redundant measurements in regions already explored (i.e., whose uncertainty has already been reduced) provides less value than measurements taken in unexplored regions.

On the other hand, local path planning generates paths for relatively short time horizons into the future. In near-real-time, measurements are taken as the vehicle follows a chosen path. As the path nears completion, those measurements can be used to inform and improve the Gaussian process model of the SNR environment. The updated model can then be used to predict the objective value for the next set of candidate trajectories, which aids the selection of the next path. As a result, the path planner will prioritize paths with greater value, and in turn, will more likely select paths which will enable the vehicle to take measurements in unexplored regions of the map. In general, locally generated paths will remain closer to uncertain regions of the map, but they make vehicles more susceptible to local minima [22]. The primary drawback associated with local path planning is its limited planning horizon. Since paths are generated, measurements are taken, and the model is updated locally, a local planner can induce behaviors that may be inconsistent with long-term mission objectives, in our case reducing SNR map uncertainty and discovering the intersecting region. For this problem, a local path planner is implemented. However, future work should consider the implementation of a local-global dual planning approach, as discussed in [9] and [22]. In general, this approach utilizes a local planner to routinely monitor a vehicle's path. Whenever the vehicle becomes trapped by local minima, the global planner generates a new path for the vehicle to escape in accordance with the final goal.

E. UPDATING THE GAUSSIAN PROCESS MODEL

As discussed in Chapter V, a Gaussian process model based on accumulated measurements can be used to compute refined estimates of SNR values at desired locations and reduce the overall uncertainty of an SNR map. The key to this approach is the ability to update the models as measurements are collected. Traditionally, Kriging techniques utilize a batch process in which measurements are collected in bulk and estimates at desired locations are computed off-line. However, the approach described in this thesis requires updates in near real-time, much like the process described in [26], to guide the UAV to explore and discover the optimal loitering location. For this thesis, we perform localized model updates after taking a specified number (approximately ten) of measurements along each trajectory segment. This takes place prior to choosing the next trajectory segment. This process incentivizes the exploration of uncertain regions of the map so that the UAV does not consistently fly over the same, previously sampled areas.

Our process begins with an initial map of mean SNR values for two ground nodes based on the Friis transmission model assumption. In order to account for unmodeled environmental noise, obstructions, or other attenuation factors, we apply a variance with some random variability as an upper and lower bound on the mean SNR values. In this manner, we quantify the uncertainty associated with our *a priori* assumption. The resulting mean SNR fields and their added variability are illustrated in Figure 37, Figure 38, Figure 39, and Figure 40.

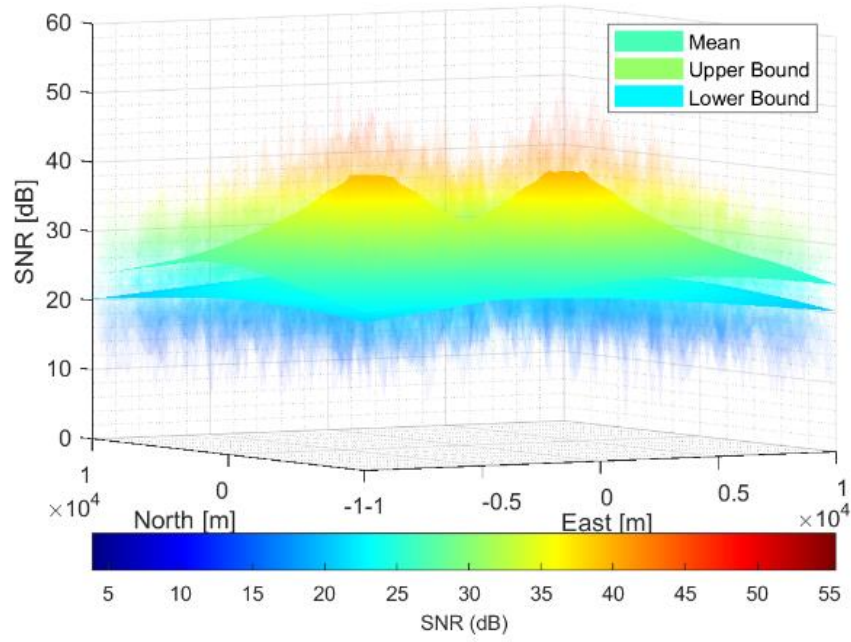


Figure 37. Friis model assumption with added uncertainty bounds

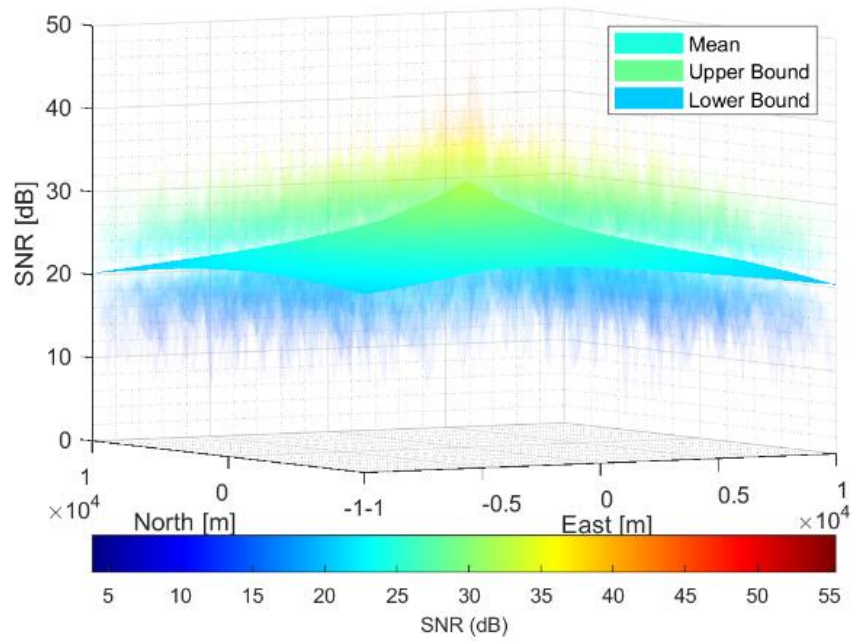


Figure 38. Friis model of intersection with added uncertainty bounds

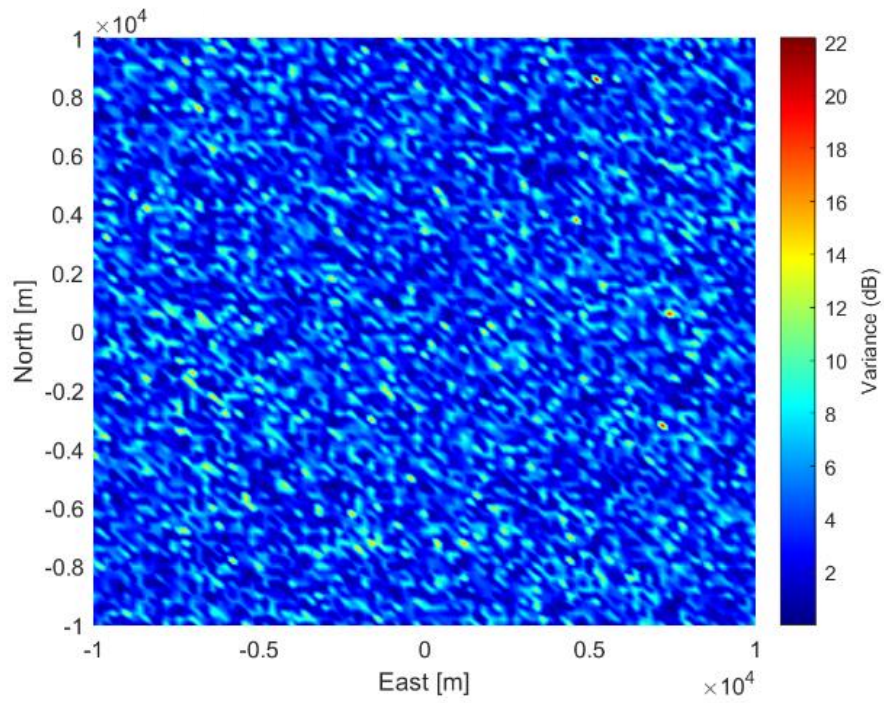


Figure 39. Initial variance map assigned to Node 1

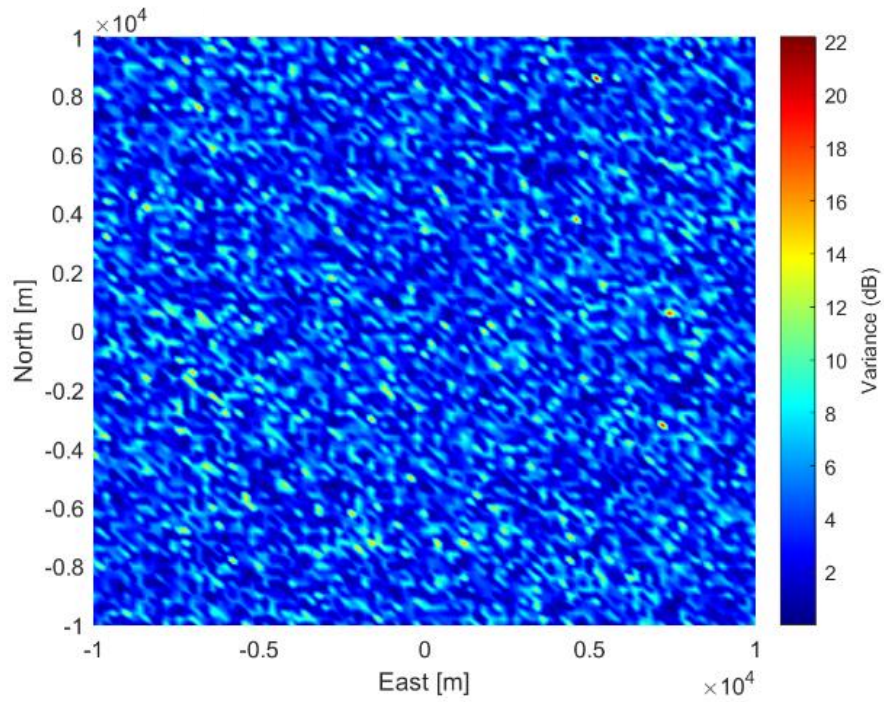


Figure 40. Initial variance map assigned to Node 2

Once the mean and variance maps are formed, an initial semivariogram and variogram fit are constructed to serve as the Gaussian process model for each node. This is accomplished by sorting pairs of data values with added variance into lag distance bins up to a maximum of 2,000 meters and computing the average semivariance between data points in each bin. A spherical model is used for the Gaussian process model, and its nugget semivariance is initialized to the minimum semivariance value present in the empirical semivariogram based on our simulated data. The resulting initial variograms and fit curves are shown in Figure 41 and Figure 42, showing a fairly high degree of variability and dissimilarity that represents the uncertainty associated with the initial SNR maps based on the Friis transmission model assumption.

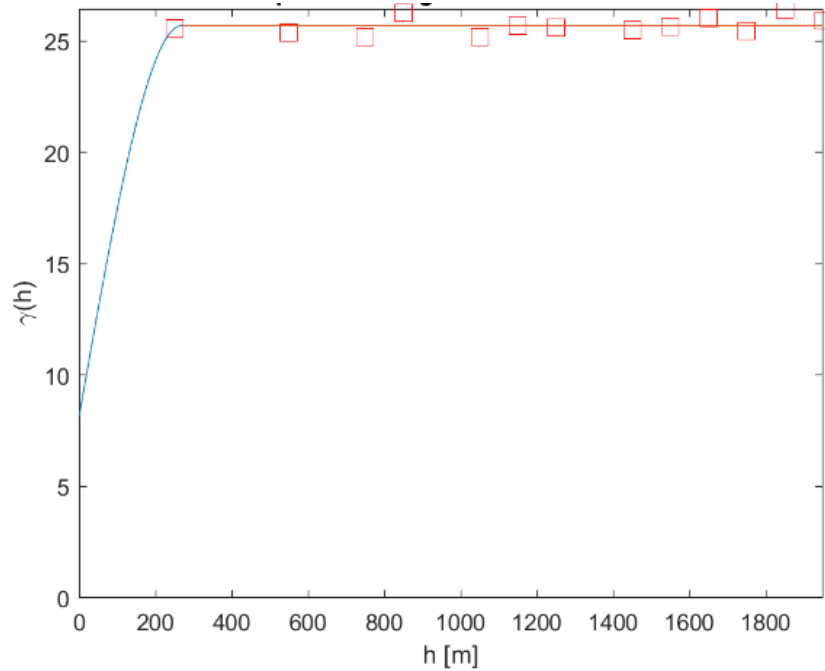


Figure 41. Initial empirical variogram model for Node 1

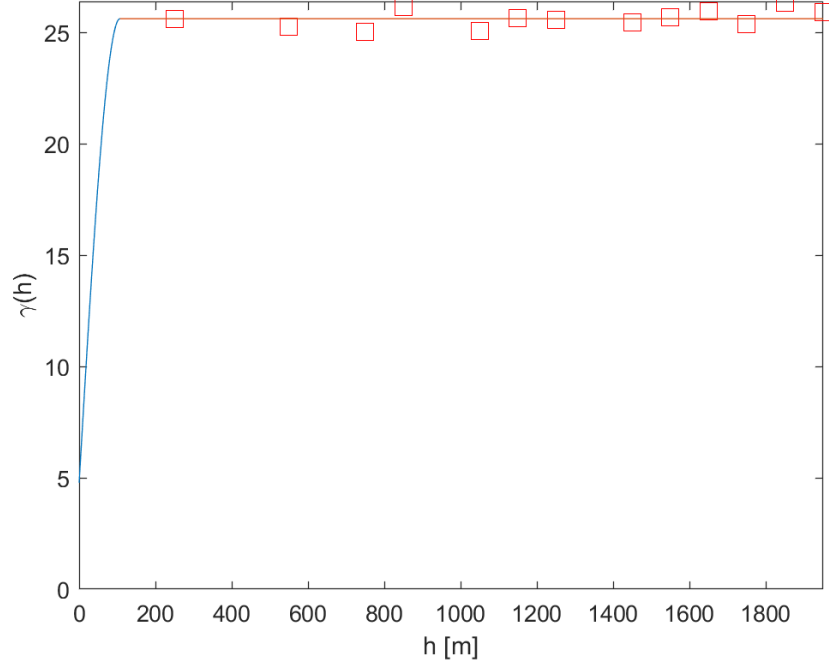


Figure 42. Initial empirical variogram model for Node 2

After the Gaussian process models for each node have been initialized, the first step is to locally plan and evaluate candidate trajectories using the path evaluation function described in Section C.3. Recall that this objective function is based on predicted information gain and change in energy, and it utilizes a measurement model, a Kriged SNR field estimate based on experimental data collected in Yuma, AZ, to compute the overall value of potential map updates for each candidate trajectory. Once an optimal trajectory is chosen, the UAV flies it and simultaneously collects measurements along the way. Once this local trajectory has been completed, the collected SNR measurements are used to update the Gaussian process model. This model is used to locally update the mean and variance maps for each node along and around the trajectory segment most recently completed. In order to update the Gaussian process model, the newly collected measurements must be sorted into the existing lag distance bins and their average semivariance for each bin must be computed. This is done by creating a measurement variogram as shown in Figure 43 and Figure 44. As the UAV continues flying and accumulating measurements, measurement variograms are updated after each local trajectory is completed. Over time, the measurement variogram settles with a sill value less

than that of the initial Gaussian process model. As a result, we observe that our updates to the Gaussian process model reduce its semivariance, ultimately providing a greater reduction in the uncertainty associated with explored regions of the SNR fields over time.

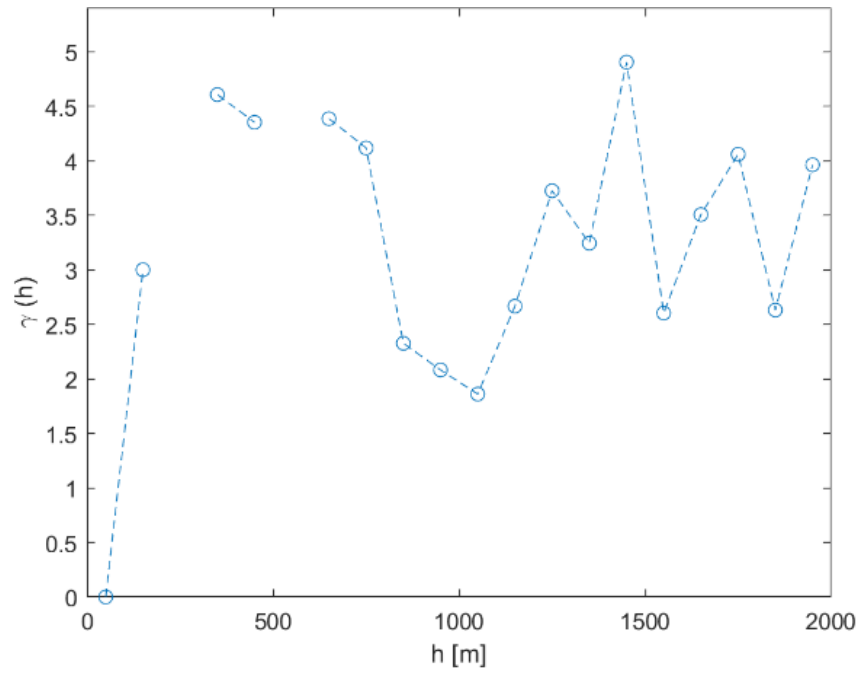


Figure 43. Semivariogram based on SNR measurements for Node 1

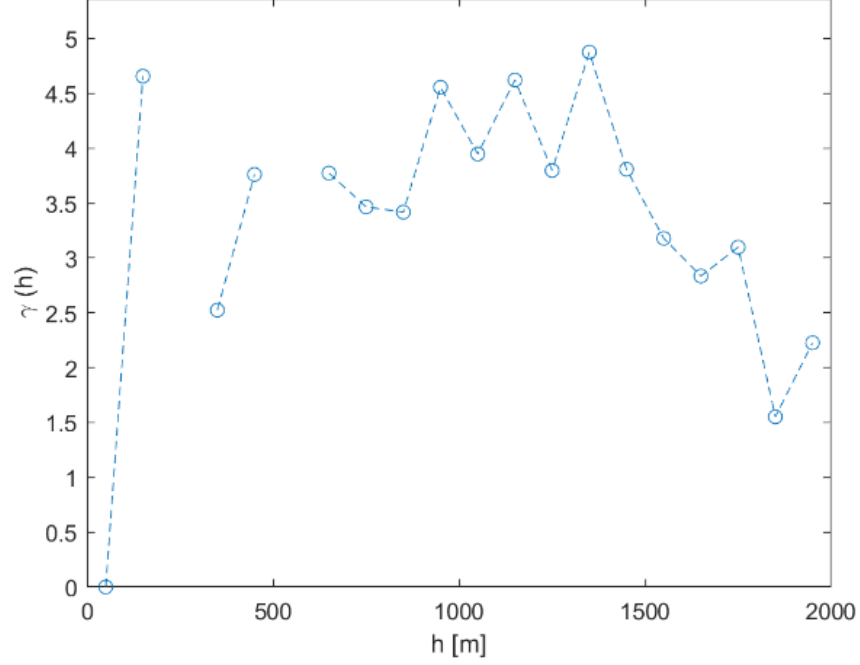


Figure 44. Semivariogram based on SNR measurements for Node 2

The next step is to update the semivariogram model for each node using the current model and the collected measurements. This is done through a Kalman smoothing approach, which computes weights based on variance in the measurements and current model. These weights are used to compute a weighted sum of the semivariance for lag distance bins being updated. This step is necessary because the model is probabilistic in nature and the update is based on measurements taken at future times [10]. For each bin, the updated semivariance is computed as follows:

$$\begin{aligned}
 \gamma_{new}(h) &= k_1 \cdot \gamma_{update}(h) + k_2 \cdot \gamma_{current}(h) \\
 k_1 &= \frac{\sigma_{current}}{(\sigma_{current} + \sigma_{update})} \\
 k_2 &= \frac{\sigma_{update}}{(\sigma_{current} + \sigma_{update})} \\
 \sigma_{current} &= |\gamma_{current}(h) - \mu_{\gamma}(h)|^2 \\
 \sigma_{update} &= |\gamma_{update}(h) - \mu_{\gamma}(h)|^2
 \end{aligned} \tag{6.8}$$

where γ_{new} is the updated semivariance of the Gaussian process model, γ_{update} is the semivariance update based on accumulated measurements, and $\gamma_{current}$ is the current semivariance of the Gaussian process model for a given lag distance bin. The smoothing gains, k_1 and k_2 , are computed based on the variability of the semivariance update σ_{update} and the current semivariance value $\sigma_{current}$ of the Gaussian process model at a particular lag distance with respect to the mean semivariance value, μ_γ . Example results of updated Gaussian process models for each node, are shown in Figure 45 and Figure 46. These results display reduced semivariances and a more accurately fitted nugget variance, when compared to Figure 41 and Figure 42.

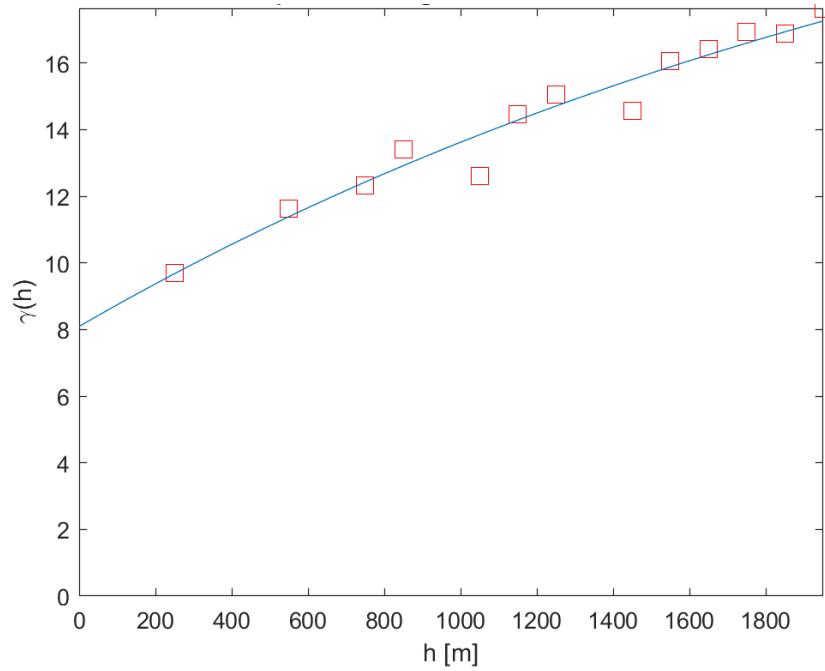


Figure 45. Updated empirical semivariogram model for Node 1

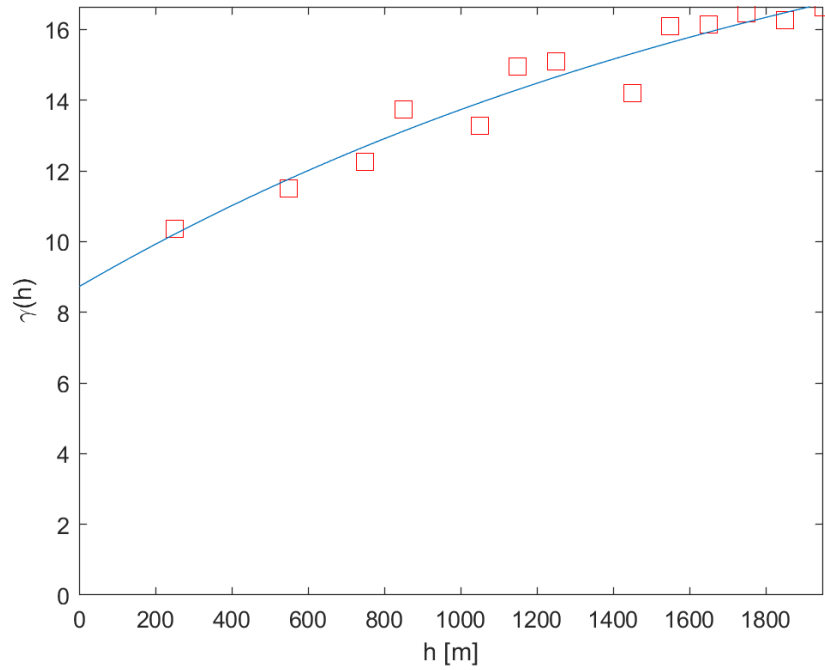


Figure 46. Updated empirical semivariogram model for Node 2

Once the semivariograms are updated, they are used to recompute the mean and variance values in the most recently explored region of the map. This is done by using the Gaussian process models to compute Kriging estimates of the SNR fields at discretized grid locations along and adjacent (within one grid cell) around the most recently flown local trajectory. An example of the local trajectories flown, a local update to the mean intersection map of the SNR fields, and local updates to the variance maps for each ground node is shown in Figure 47, Figure 48, Figure 49, and Figure 50, respectively. The UAV flight is color coded, with dark blue denoted the beginning of its flight path and dark red denoting the most recently traversed portion of its flight path. The fan of candidate trajectories under consideration are shown in blue, with the chosen trajectory highlight in cyan.

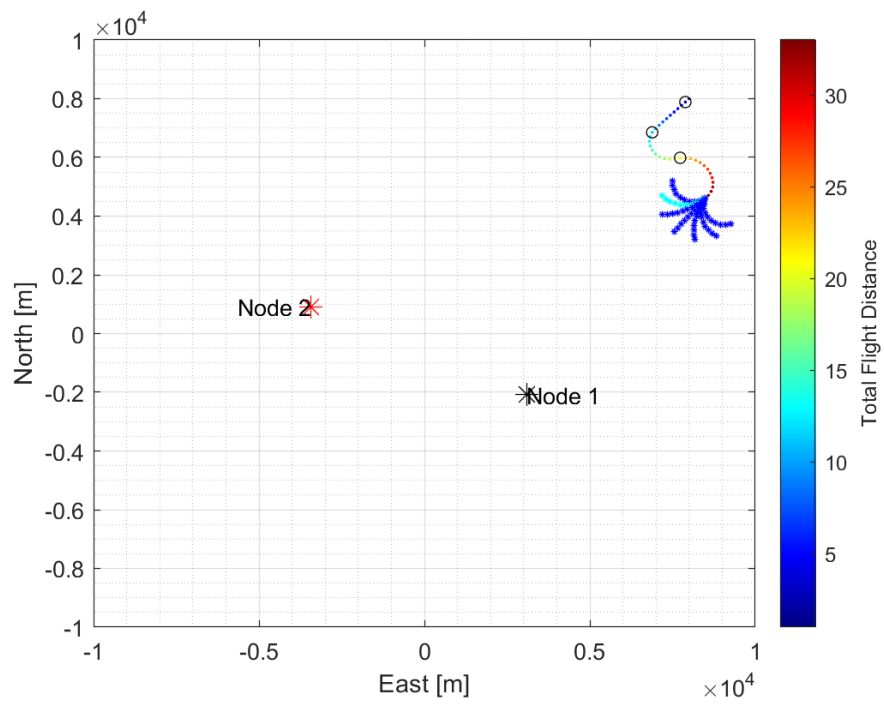


Figure 47. Executed local trajectories

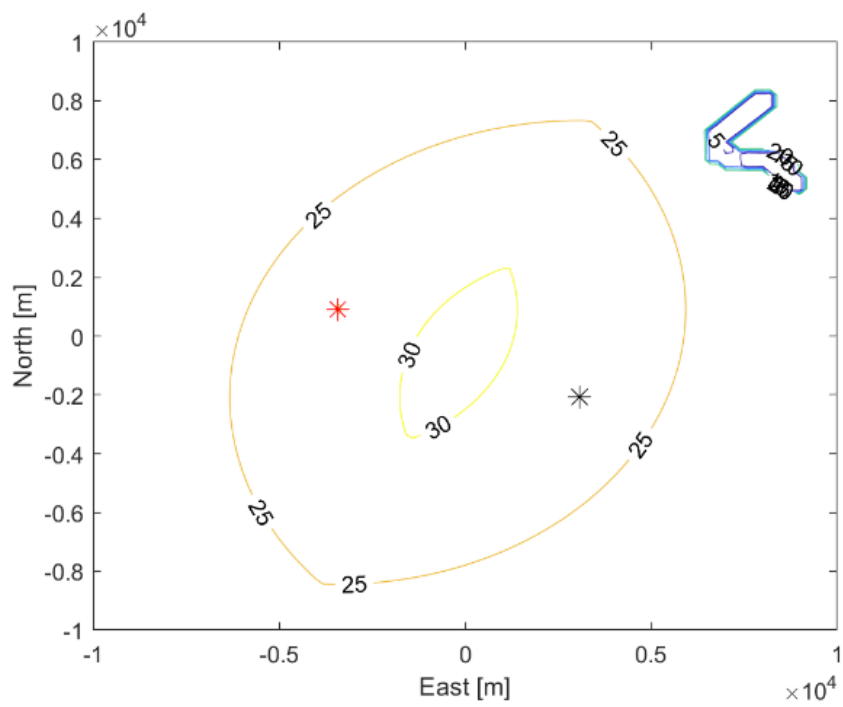


Figure 48. Local update to SNR field intersection

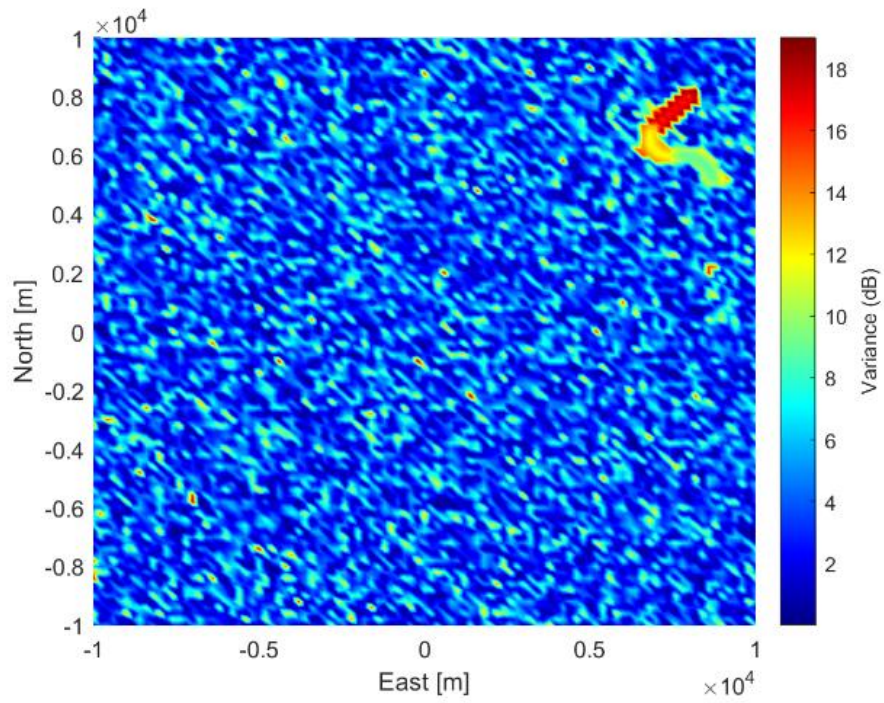


Figure 49. Local update to variance map for Node 1

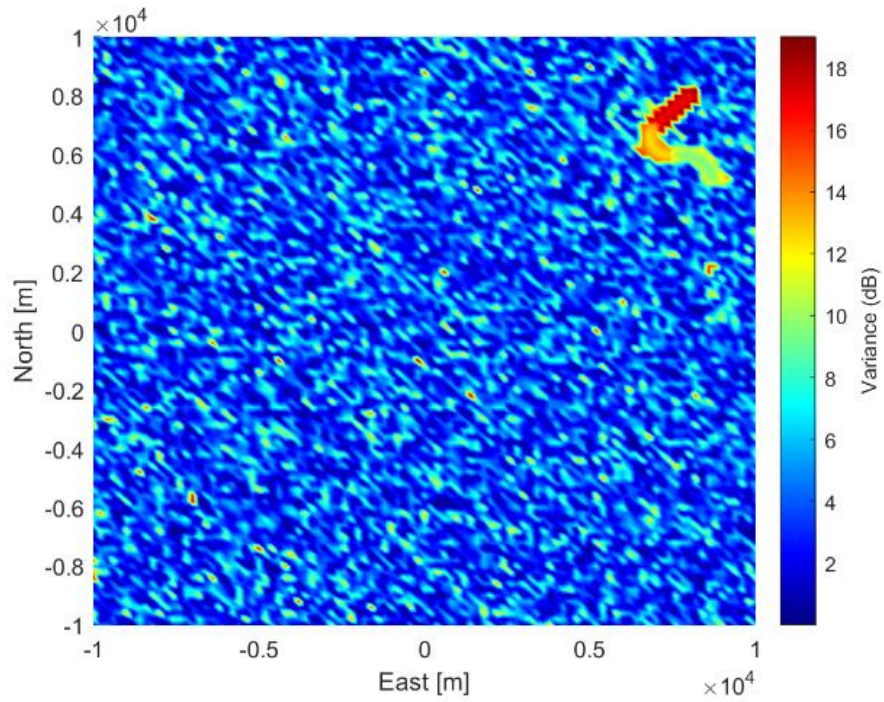


Figure 50. Local update to variance map for Node 2

The updates of the maps are a direct replacement of the previous mean and variance values with the newly computed values at the estimated discretized grid locations of the configuration space. Uncertainty initially increases for the first few trajectory segments due to the high semivariances associated with the Gaussian process models. As these models are updated and their semivariances are gradually reduced over time, however, the map uncertainty improves until both the measurement variograms and the Gaussian process models settle at lower sill semivariance values. After the maps have been updated, the next set of trajectories can be planned and evaluated to determine the next local trajectory the UAV will fly and collect measurements along. This procedure culminates in a near real-time, recursive process. As the UAV flies, the actual information gain computed from Kullback-Leibler divergence is recorded to track information gain over time.

F. RESULTS

Several simulations were run using MATLAB and Simulink with varying gains applied to the information gain and energy change terms of our path evaluation function. Results of these simulations are shown in Figure 51 thru Figure 56. When compared to the initial mean and variance maps for each node shown in Figure 37 thru Figure 40, our simulations produced a significant reduction in both the uncertainty and the mean values near the intersection region of the ground nodes' SNR fields. The reduction in mean can be attributed to the initially optimistic SNR values computed from the Friis transmission model, as compared to the lower estimates computed from the Gaussian process model and gathered measurements. The improvement in the variance can be clearly seen in Figure 55 and Figure 56 as the UAV flight path over the intersection effectively smoothed the variance values for each node.

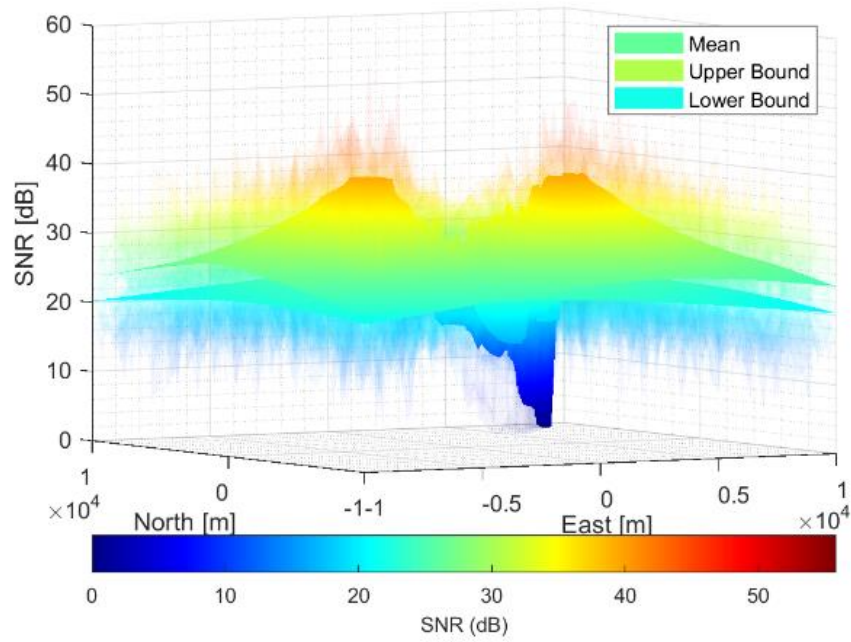


Figure 51. Updated SNR field after UAV exploration (side view)

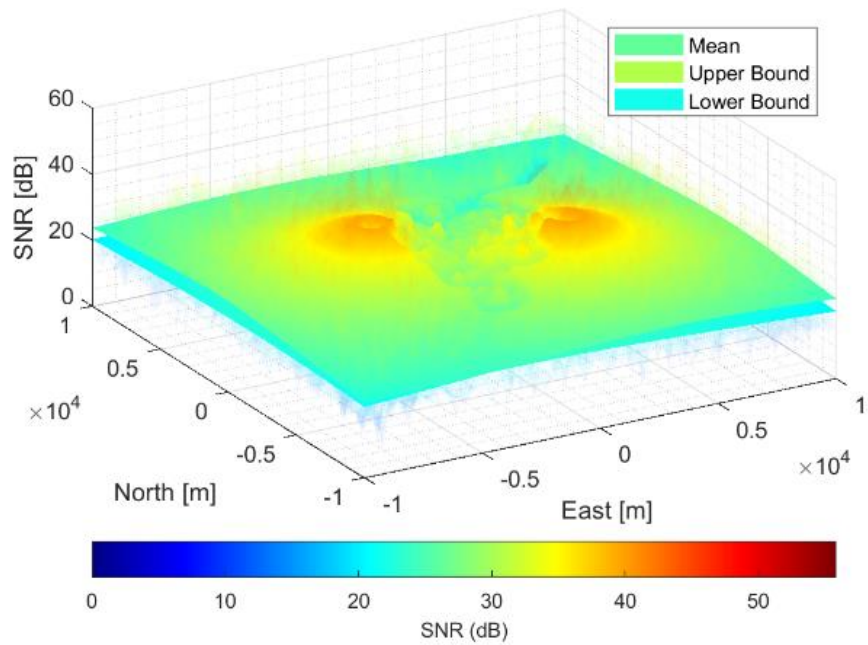


Figure 52. Updated SNR field after UAV exploration (top view)

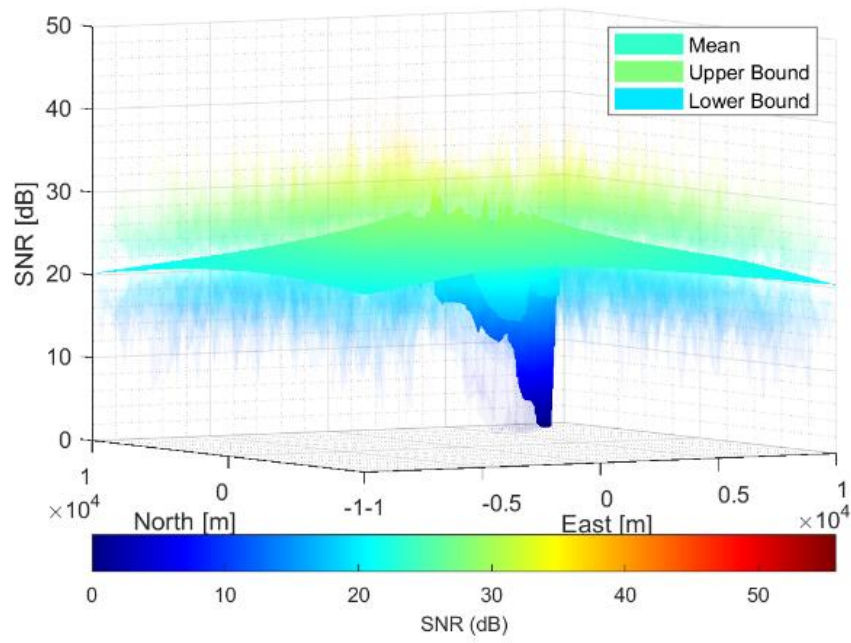


Figure 53. Updated SNR field intersection (side view)

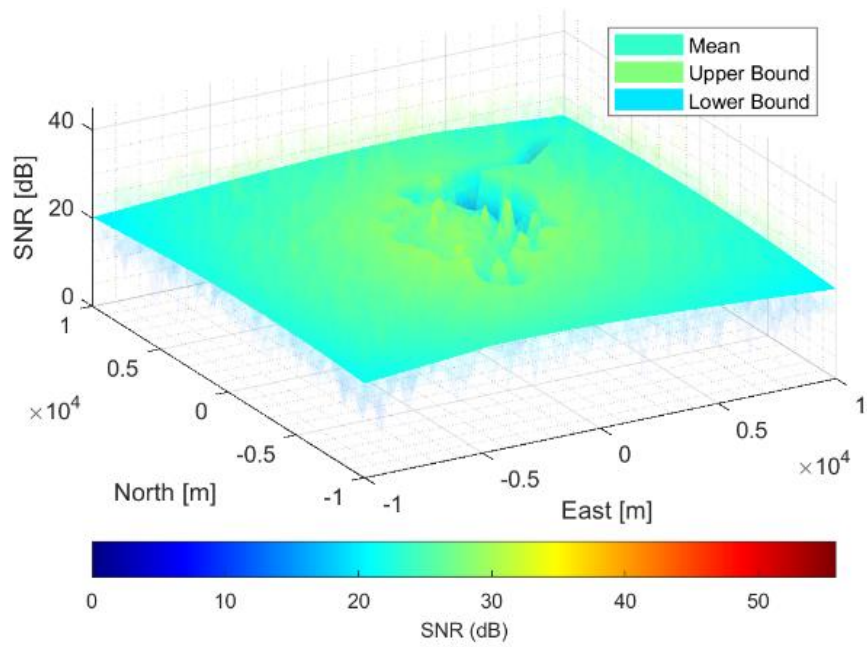


Figure 54. Updated SNR field intersection (top view)

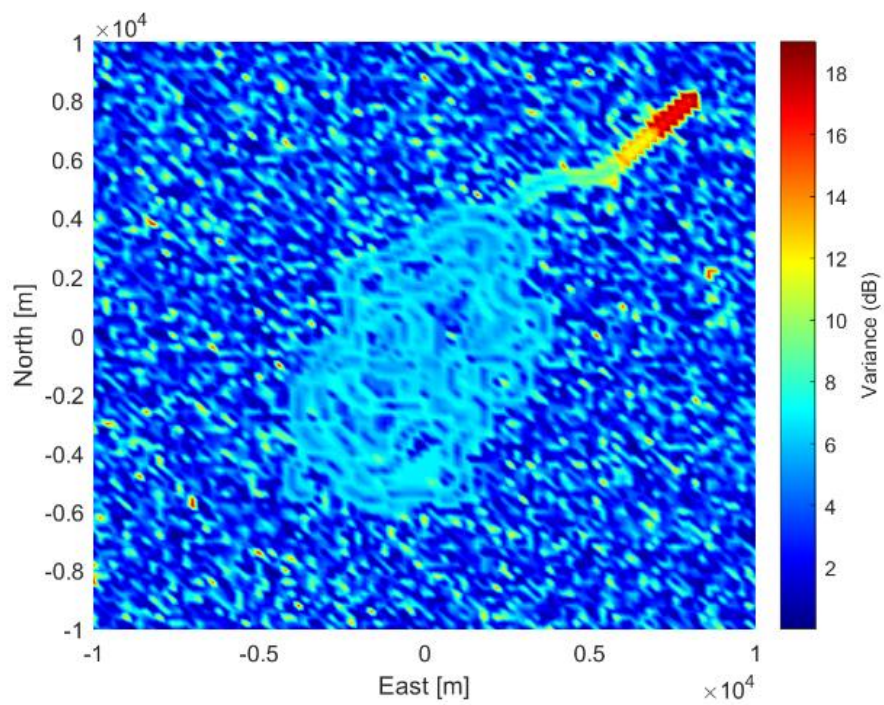


Figure 55. Updated variance map after UAV exploration for Node 1

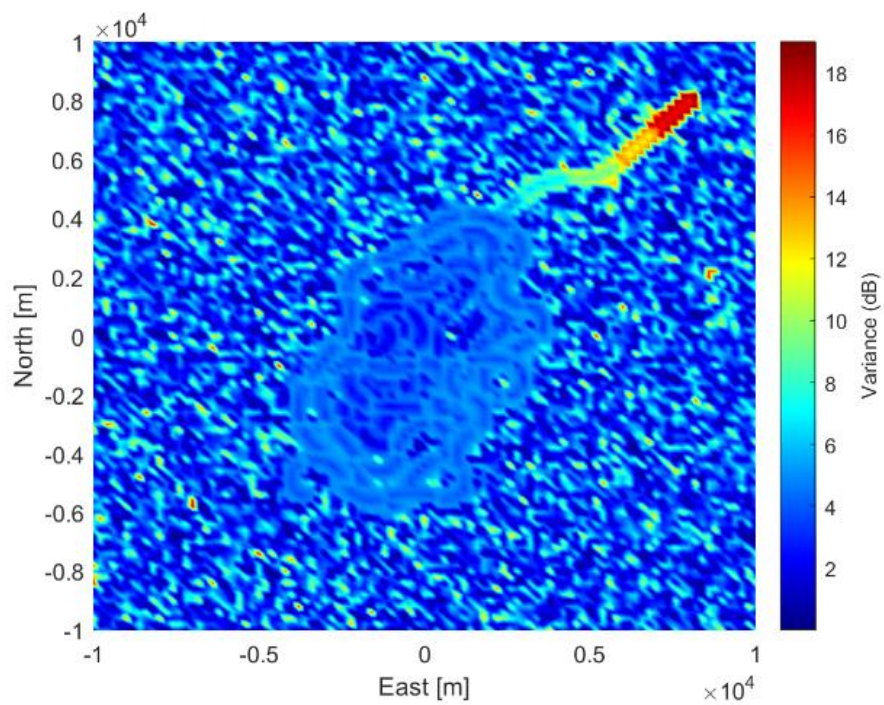


Figure 56. Updated variance map after UAV exploration for Node 2

Upon examining the complete trajectory flown by the UAV, shown in Figure 57, it is clear that the path evaluation function used to select candidate local trajectories was extremely effective at enforcing our primary goals of a) guiding the UAV toward exploration and b) reducing the uncertainty associated with the intersection of the two SNR fields. Because the uncertainty surrounding the intersection region has been sufficiently reduced, the resulting SNR field could be used with confidence by previously developed extremum control algorithms described in [1] and [2] to guide the UAV to loiter about the optimal location for maximizing communications throughput between the two ground nodes.

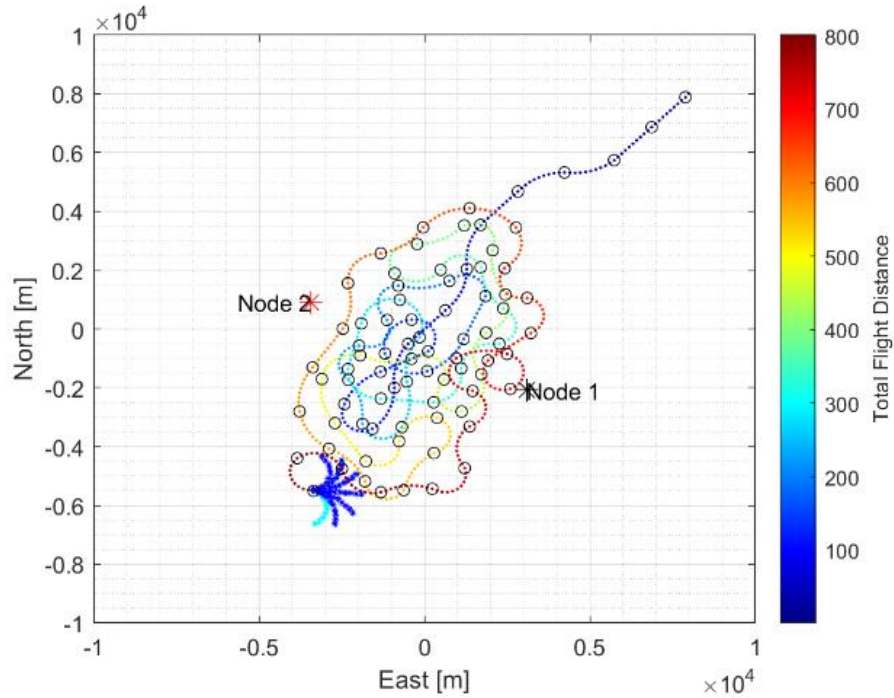


Figure 57. Overall UAV flight path

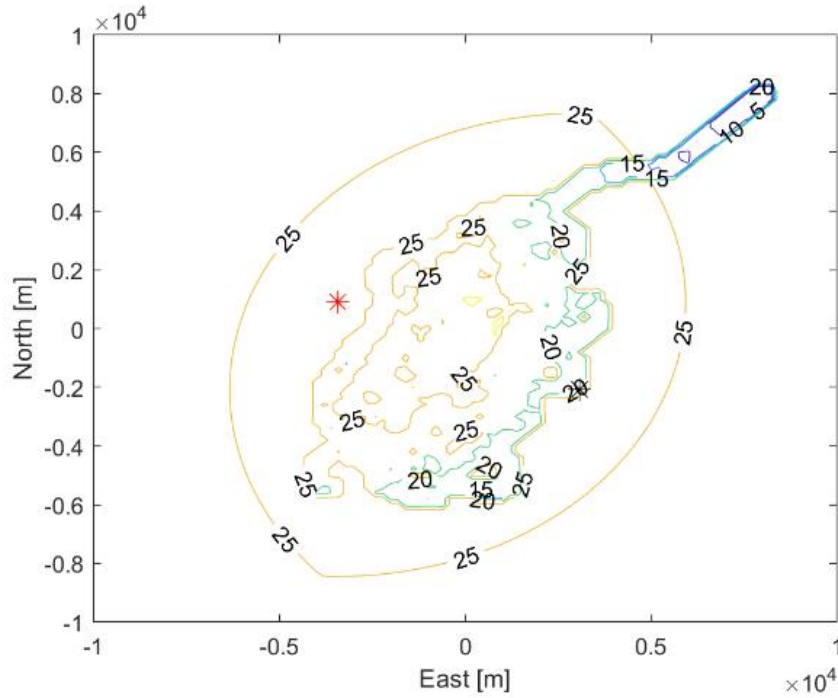


Figure 58. Resulting mean SNR intersection

The resulting measurement semivariograms, shown in Figure 59 and Figure 60, and empirical semivariogram models, shown in Figure 61 and Figure 62, show that the maximum semivariances for both nodes settle around 6 dB. This is significantly lower than the sill value of the initial Gaussian process model variograms, and it shows that the accumulation of measurements to update the Gaussian process models and reduce their associated variability over time was effective.

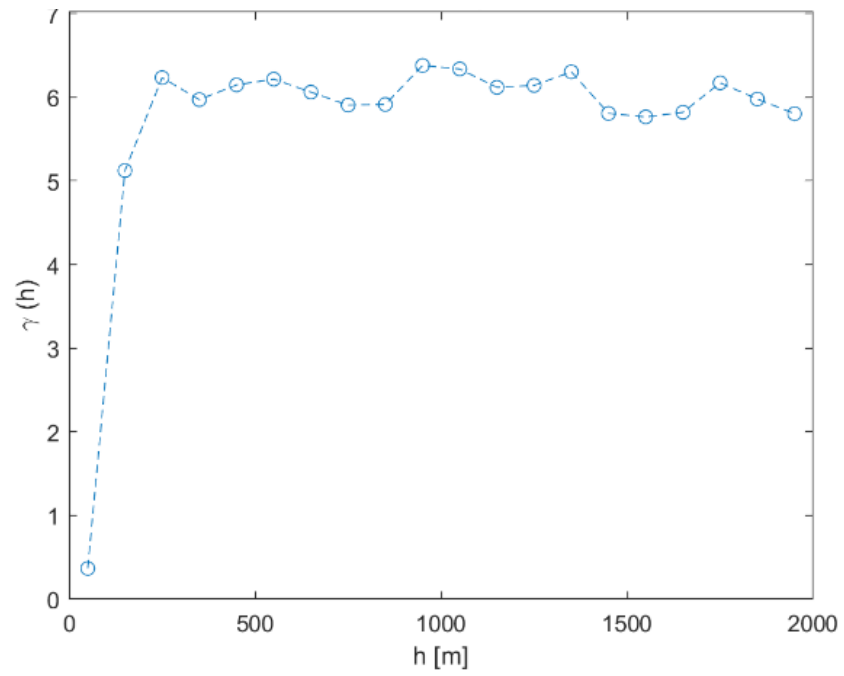


Figure 59. Resulting measurement variogram for Node 1

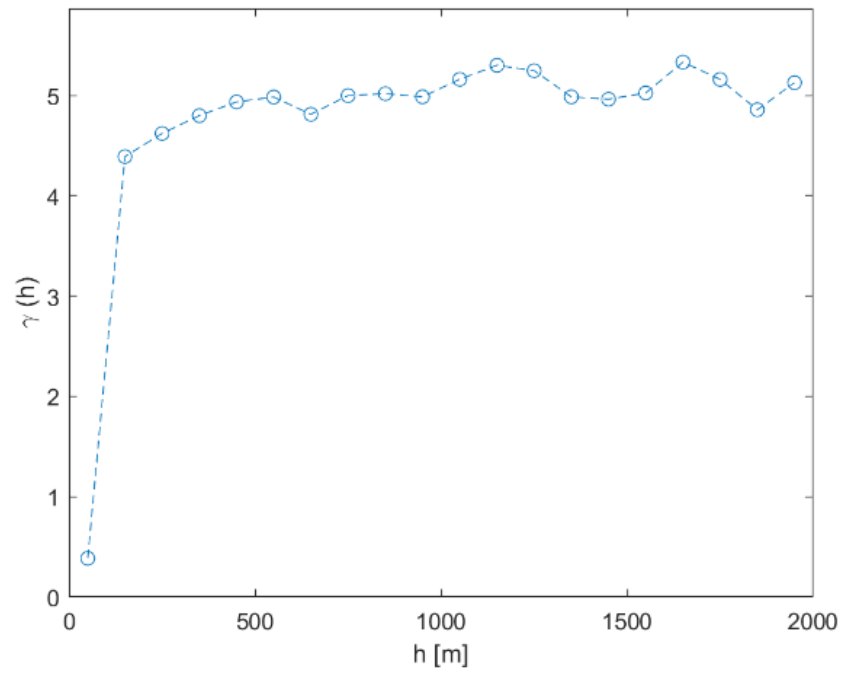


Figure 60. Resulting measurement variogram for Node 2

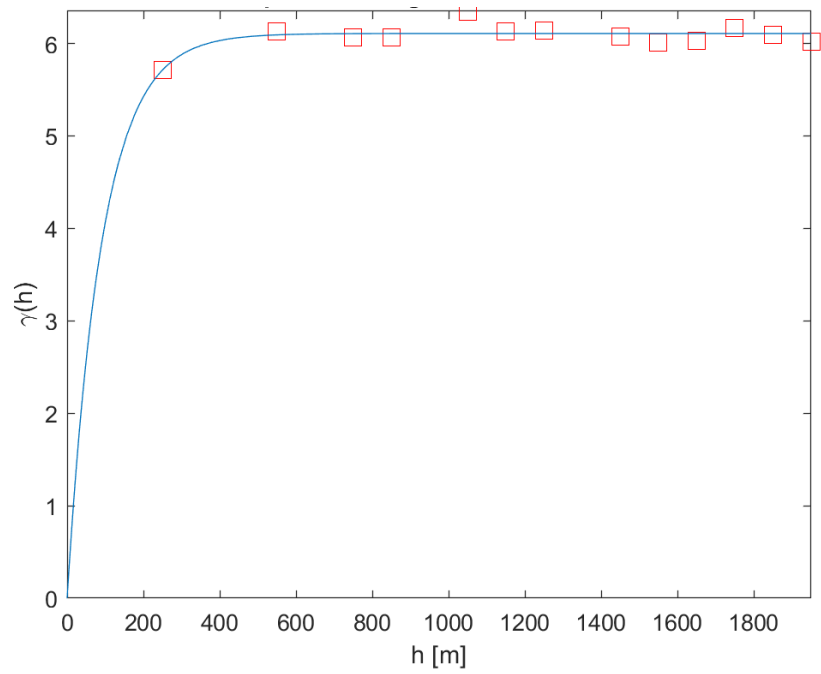


Figure 61. Resulting empirical semivariogram model for Node 1

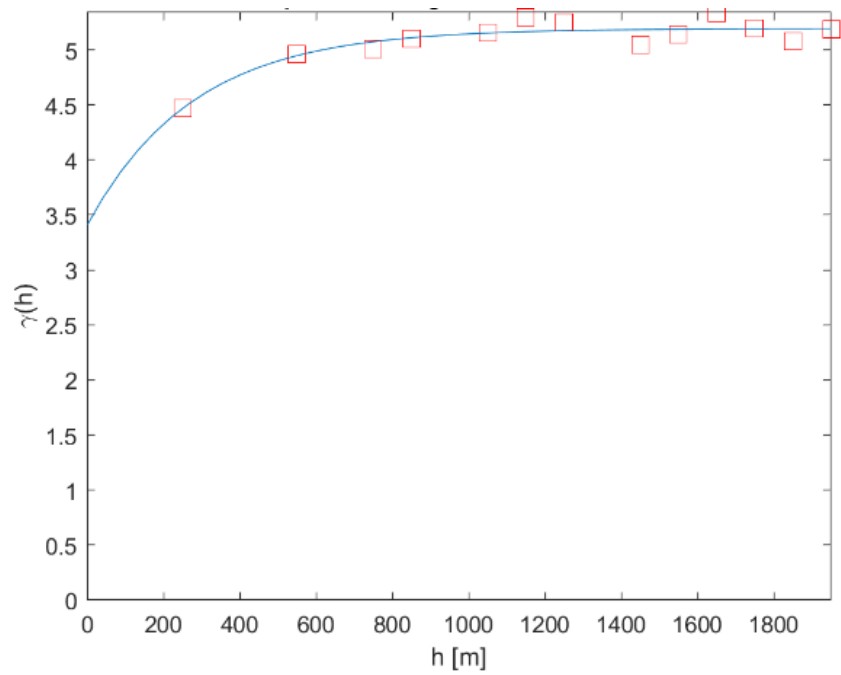


Figure 62. Resulting empirical semivariogram model for Node 2

Finally, Figure 63 and Figure 64 illustrate the resulting accumulated information gain computed from Kullback-Leibler divergence over the course of multiple simulated UAV flights with different k_{IG} and k_E gain values in our objective function. These results show a steady increase for both nodes as the UAV primarily flew over the intersection region during the simulation. Over time, the rate of information gain appeared to decrease in all cases as the UAV explored more of the configuration space. Had the simulation been run longer such that the UAV reduced the uncertainty associated with a majority of the configuration space, we expect that the rate of information gain over time would more visibly reduce, eventually settling to a nearly constant value.

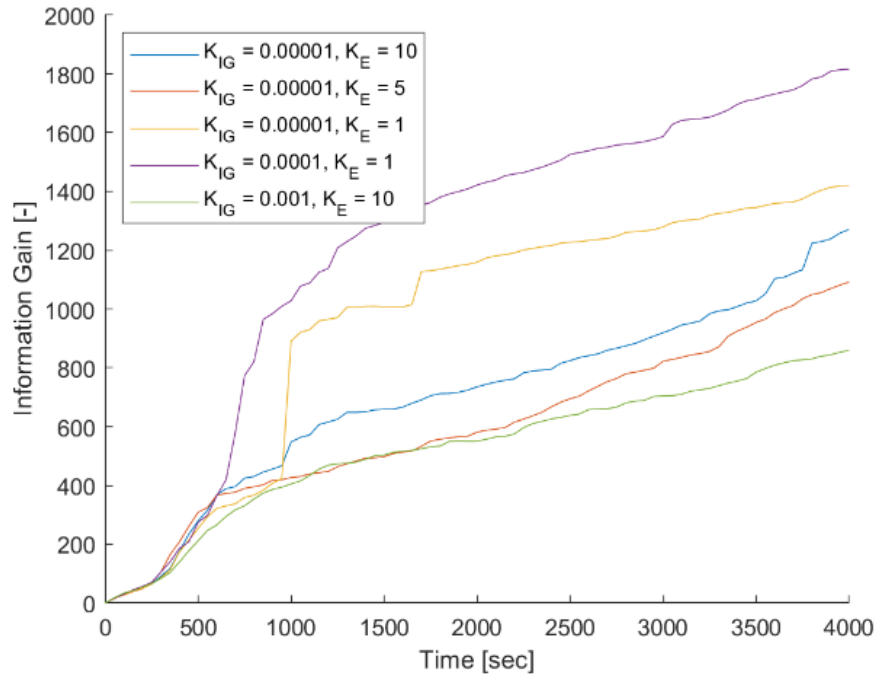


Figure 63. Accumulated information gain during UAV flight for Node 1

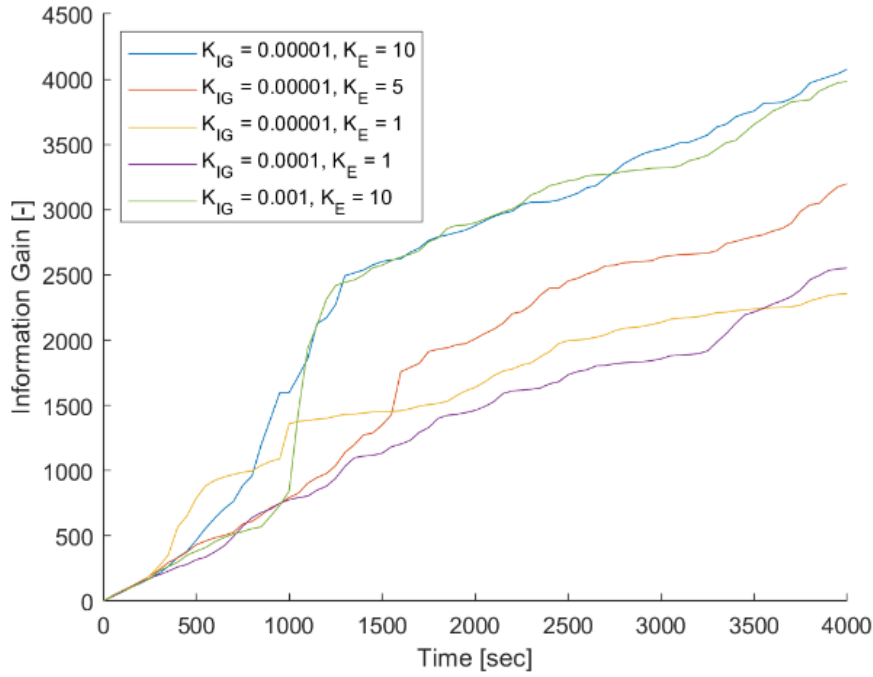


Figure 64. Accumulated information gain during UAV flight for Node 2

The overall information gain for Ground Node 2 was greater than Ground Node 1 in all cases. The first set of gains for the objective function were chosen such that the computed energy and information gain values were weighted equally with the same order of magnitude. The resulting behavior, as shown in Figure 57, resulted in a splining flight path concentrated over the SNR field intersection. As the weighting for energy value was decreased, the UAVs flight behavior became slightly less focused on the intersection region, spreading out and covering a wider area in comparison to the first set of gains. However, the UAVs behavior was a bit more sporadic in achieving this. The executed trajectories were not as clearly concentric in nature, working outward from the peak of the intersection and covering a larger area over time as shown in Figure 57. The sporadic flight behavior and decreased focus on the intersection region continued as the gain for information gain was increased significantly.

Overall, as the weighting for information gain became more significant than the weighting for energy value, the UAV's trajectory deviated more and more from the intersecting region. However, the rate of information gain for Ground Node 1 increased in

comparison with Ground Node 2. This implied that exploring the intersecting region afforded greater overall information gain for Ground Node 2 than Ground Node 1, which was likely a product of how the measurement field was generated from experimental data collected at Yuma Proving Ground. Flying in regions around the intersection provided greater information gain for Ground Node 1 and thus a greater combined information gain. As the weight for information gain increased with respect to the weight for energy value, combined information gain was incentivized over exploring the intersection. Setting both gains to one resulted in extremely erratic, seemingly unstable behavior, but it increased information gain much more than the results shown in Figure 63 and Figure 64. However, the UAV did not spend much time exploring the intersection as intended.

G. SNR MAP CONFIDENCE AND STABILITY

An unanswered question is at what point in time, or at what distance along a UAV flight path, will sufficient confidence in the intersection map be established? Once the map has been explored and its overall uncertainty has been reduced, a sufficiency condition must be determined and met to decide when the UAV has sufficient confidence in the SNR map intersection to use it as an input for extremum control. One possible selection criteria is when the rate of information gain decreases below a pre-selected threshold. Another important consideration is the concavity of the intersection. The intersection of the two SNR maps must be demonstrably concave and positive semidefinite in order to guarantee that the UAV will find and loiter about the optimal peak location during the extremum control phase. The asymptotic stability and concavity of the SNR field intersection region could be proven using a Lyapunov stability function, as described in [14], however this topic is a candidate for future work.

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VII. CONCLUSIONS AND FUTURE WORK

A. CONCLUSIONS

The fundamental assertion posed by this thesis was that the uncertainty surrounding the degradation of SNR as a function of distance must be understood before a spatial model of SNR can be used for control purposes. This thesis successfully addressed the need to accurately model SNR between ground nodes as well as its uncertainty to determine the optimal loitering location. Prior to developing an approach, multiple field experiments were conducted using the ScanEagle UAV and Wave Relay MPU4 and MPU5 radios. Analysis of collected SNR data provided insight into the degradation of SNR as functions of distance and altitude. This thesis successfully developed a methodology for communication optimization that combines elements of machine learning and unmanned system guidance. This methodology for improving the accuracy of an estimated SNR field generated by two ground nodes to be used for extremum seeking control of a UAV is presented.

Our approach leveraged a geostatistical nonlinear optimal spatial estimation technique known as Kriging, to estimate SNR fields with spatially autocorrelated data. Additionally, an information theoretic path planning approach with an objective function, employing Kullback-Leibler divergence as an information gain metric as well as an energy function, to evaluate and select local candidate trajectories is presented. Coupled together, these methodologies enable a UAV to efficiently discover and reduce uncertainty associated with the SNR field between nodes and autonomously determine the optimal loitering location to serve as a communications relay between ground nodes in a wireless network. This represents a novel contribution that is more robust than prior algorithms, since it explicitly considers measurement variability and can adapt to ground node locations and inaccuracies in the assumed Friis transmission model. Such a methodology comprises phase one of a two-phase process used to 1) discover the optimal loitering location with sufficient confidence, and 2) guide the UAV to this location via an extremum control algorithm. Phase two has been described in prior work and is not the subject of this thesis.

The main advantage of our methodology is that it takes into consideration the uncertainty associated with SNR field measurements as a function of distance and altitude and leverages these measurements to improve the SNR field estimates. This has utility for a UAV operating in a previously unknown communications environment. It facilitates efficient discovery of the intersection region without prior information about the ground node locations. This is achieved by simultaneously incentivizing the exploration of uncertain regions of the map and, once discovered, the intersection region of the SNR field. Potential weaknesses of this approach include computational complexity in a near real-time implementation, the susceptibility of local path planning to local minima, and a reliance on several assumptions regarding the optimal spatial estimation process.

B. FUTURE WORK

Future work will focus on implementing the Gaussian process modeling approach developed in this thesis for further experimentation. Simulated results will be verified through field testing and more complex scenarios with an increased number of static and mobile wireless nodes, heterogeneous vehicles, and varying terrain.

1. Expansion of Network Topology

Prior work, both simulated and experimental, has been largely limited to scenarios involving just one UAV and two ground nodes operating in a small wireless mesh network. The primary focus has been developing an approach for the UAV to autonomously discover an SNR field between the two ground nodes with minimal uncertainty and to then use the SNR field as a map to fly toward and loiter about this location for optimal communications relay between the two ground nodes. However, this approach can be generalized to scenarios involving multiple UAVs and a greater number of ground nodes. This would expand the topology of the wireless mesh network and produce an SNR field with much greater complexity. An ontological, distributed information gain approach could be adapted from our current approach. Theoretically, knowledge and information gain could be shared (and accumulated) among all UAVs in the wireless network for the purpose of more rapidly reducing the uncertainty associated with a communications environment.

Such an approach could be adapted to different scenarios involving varying numbers of static and mobile nodes.

2. Obstacle Avoidance

Further development of the path planning methodology presented in this thesis is necessary to incorporate obstacle avoidance. The operating environment for a given scenario is unlikely to mimic that of our Yuma, AZ test location, namely an unobstructed desert plain, without obstacles to communications or vehicle motion. Therefore, an obstacle avoidance methodology should be implemented in order to make our path planning algorithm more robust and generalized. Possible candidate methodologies include the use of A* or rapidly exploring random tree (RRT)* search algorithms to generate heuristic-based, spatially optimal trajectories that avoid collisions with potential obstacles in the operational configuration space. Possible heuristics include Euclidean distance as well as the information gain and energy metrics presented in this thesis.

3. Global Path Planning

In addition to implementing obstacle avoidance, the presented path planning methodology could be further developed to incorporate a global path planner. In conjunction with a local path planner, an optimal global path planner could be used to ensure the UAV's flight path is consistent with long-term goals of both reducing SNR map uncertainty and discovering the location of the SNR peak, while also avoiding local minima. Local minima are an important consideration for scenarios with more than two ground nodes and more than one SNR intersection region. Under this approach, a UAV would generate an initial global path, but predominantly follow frequently generated local paths. At less frequent time intervals, the global path would also be updated to incorporate accumulated measurements and updates to the Gaussian process model, while maintaining progress toward its long-term goal.

4. Real-Time Gaussian Process Modeling & Control

The Gaussian process modeling approaches developed in this thesis are being adapted for real-time implementation onboard a UAV. A ROS process will be developed

to run on the ScanEagle's ODROID CPU during flight, collecting new SNR measurements and UAV state data every second. After several data collection cycles, a Bayesian update of the estimated SNR field in the immediate vicinity of the aircraft will be computed. The estimated SNR field will be used by a local path-planning process, influencing the UAV's flight trajectory for maximizing information gain and efficiently reducing the uncertainty of the SNR map. The optimal flight path for reducing SNR measurement uncertainty is largely unknown, and this must be evaluated based on real-time information gain. Once the map's uncertainty is sufficiently minimized, the UAV will transition to an extremum seeking controller to navigate to the optimal loitering location.

Furthermore, real-time field testing will provide insight into how environmental and vehicle states contribute to measurement uncertainty and affect communication robustness and reliability. An incremental step toward a real-time, onboard implementation would allow the UAV to communicate its SNR measurements to a ground computer that computes Gaussian process updates, determines optimal local trajectories for reducing the SNR map uncertainty, communicates these local trajectories to the UAV, and eventually provides a notification when there is sufficient confidence in the SNR intersection map to begin the extremum control phase. This map can then be shared with the UAV and used in an extremum control algorithm running on the ODROID secondary controller to guide the UAV to the optimal loitering location.

APPENDIX. SIMULINK MODELS

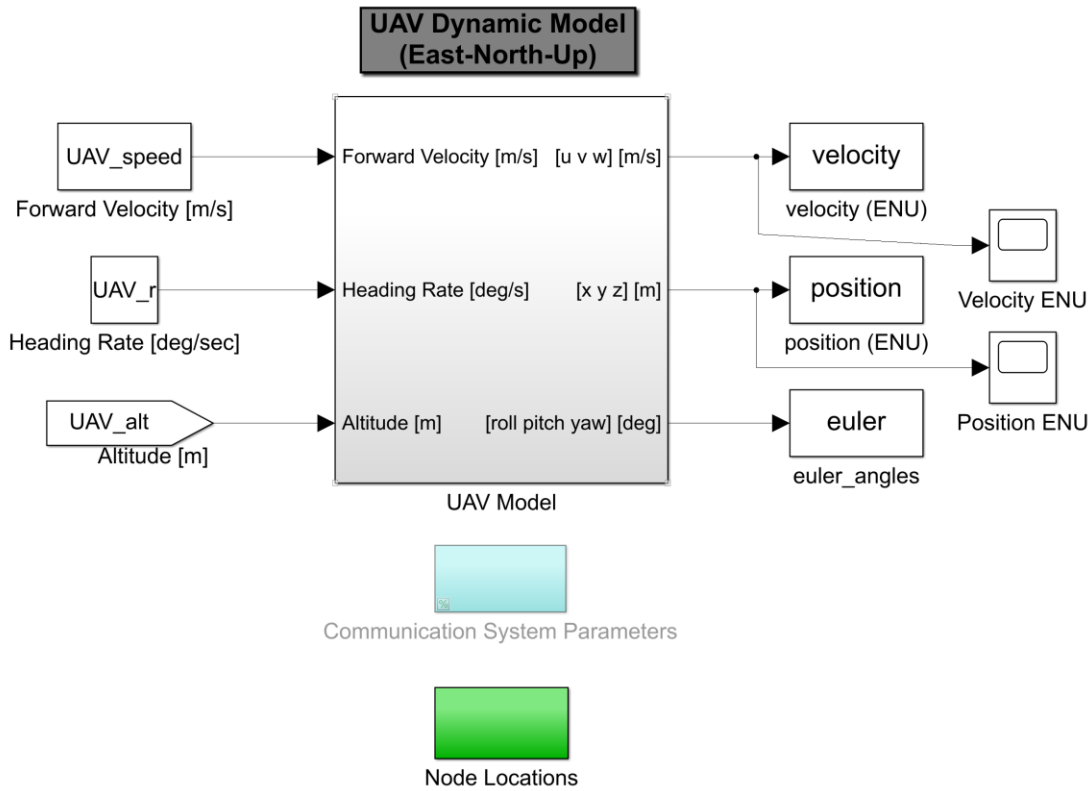


Figure 65. Simulink model of UAV dynamics (outer level)

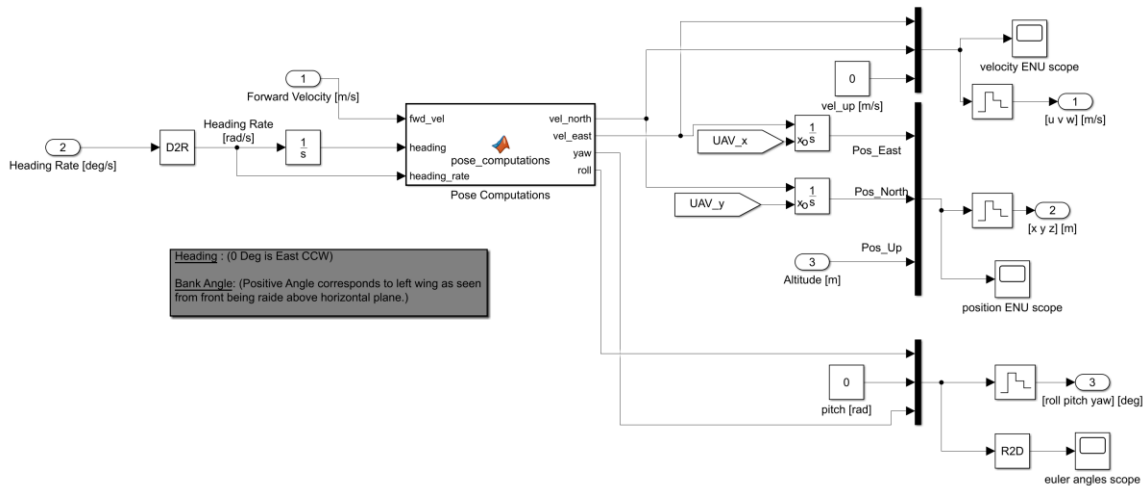


Figure 66. Simulink model of UAV dynamics (inner level)

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