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WHERE CONCEPTS BECOME REALITY

2025/26 Interdepartmental Final Year Project Interim Report

Intelligent UAV Systems for GNSS-Based Remote Sensing on Vegetation

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Contents

1 Abstract

Placeholder text

2 Introduction

Vegetation is a critical asset to the environment and the human civilization. Not only does vegetation produce essential societal resources, but its distribution and productivity also greatly impacts the terrestrial ecosystems and the global climate [1]. Therefore, the continuous and accurate monitoring of vegetation is essential for sustainable resource management [2], ecosystem preservation [3], and climate change modeling [1].

Traditionally, methods of vegetation monitoring involved manual field assessments of site characteristics, extracting vegetation condition indicators such as species composition, geometrical structure, and biochemical activities [4]. However, the accuracy and efficiency of such monitoring methods are highly dependent on the available expertise and resources, as the site assessments often required the assessor to possess reasonable levels of field knowledge prior to surveying [5]. To address the limitations of manual assessments and to accommodate for the increasing large-scale monitoring demands, remote sensing systems emerged as an essential tool for ecological monitoring [6].

Remote sensing refers to the acquisition of an object's information through measurements obtained without coming into direct contact with said object, effectively minimizing the need for manual involvement on-site [7]. Specifically, remote sensing relies on information derived from different measurements of energy reflected from the object of interest [7]. In the context of surveying terrestrial vegetation, the remote sensing methods could be classified into two categories based on the distance between the target object and the measurement sensor: 1) space-borne and 2) airborne remote sensing. Space-borne remote sensing involves the use of instruments onboard orbiting satellites, including spectral and hyperspectral cameras [8], synthetic aperture radar (SAR) [9], and space-borne Light Detection And Ranging (LiDAR) sensors [10]. Due to the wide coverage and availability of space-borne data, large-scale terrestrial changes over time could be captured, enabling the continuous monitoring of macro-scale ecosystems [11]. Compared to space-borne systems, airborne remote sensing can provide significantly improved

spatial resolution and assessment flexibility through the integration of sensors onboard manned aircraft or unmanned aerial vehicles (UAVs) [11]. Although limited by coverage area, airborne remote sensing can provide timely information for addressing regional emergencies such as pest [12] or wildfire [13] outspreads since the systems could be deployed on-demand. In UAV-based remote sensing particularly, this temporal flexibility is further complemented with the benefit of low operational cost, rendering it an ideal platform for monitoring regional and urban vegetation [14].

Conventionally, UAV remote sensing platforms carry similar instruments to that of other remote sensing systems, including radar, LiDAR, and multi-spectral or hyperspectral imagery sensors [14]. However, while imaging instruments are susceptible to the influence of lighting and weather [15], LiDAR devices tend to face difficulties penetrating through dense canopy [16]. Therefore, it is critical to explore a robust sensing technique that is suitable for UAVs in terms of payload and power consumption to complement the existing instruments. Recently, the technique of Global Navigation Satellite System Reflectometry (GNSS-R) is receiving increasing interest in the field of remote sensing. GNSS-R exploits the L-band signals transmitted from Global Navigation Satellite Systems (GNSS) that are then scattered on different terrain surfaces of the Earth [17]. Then, the reception of reflected GNSS signals can provide information regarding the properties of the signal reflector on land [17]. As signals of opportunity conventionally dedicated to Positioning, Navigation, and Timing (PNT) applications, GNSS is capable of providing real-time measurements regardless of time, location, and weather [17]. Additionally, as a bi-static system where signal transmitters are separated from receivers, GNSS-R is exempt from the need of dedicated transmitter-receiver instruments that are crucial to mono-static radar systems [18]. Instead, any consumer-grade receivers capable of receiving reflected GNSS signals could be used for GNSS-R remote sensing, further demonstrating GNSS-R's applicability onboard low-cost remote sensing systems such as an UAV.

May need some intro for path planning and lidar here. The above is from Louise's project proposal, so need further editing. (Also need to mention the full name of SLAM somewhere)

In this project, the technique of GNSS-R will be integrated onto an UAV platform to achieve an intelligent and structured remote sensing system for vegetation monitoring. The main objec-

tives of this project are as follows:

1. To introduce an autonomous path planning framework onboard the UAV platform for optimized GNSS-R remote sensing.

2. To analyze and model the correlations between signal propagation parameters retrieved through GNSS-R and ground vegetation conditions.

3. To classify signals reflected by vegetation and predict vegetation parameters based on raw GNSS data using machine learning-based approach.

4. To establish a detailed 3D canopy map using LiDAR-based SLAM, providing a spatial validation reference for the 2D vegetation features detected by GNSS-R.

This report is structured as follows: Section 3 reviews contemporary research in UAV path planning, GNSS-R, machine learning, and LiDAR SLAM, while Section 4 outlines the project's methodologies. The subsequent sections cover the experiments conducted (Section 5), a discussion of current results (Section 6), and the project conclusions (Section 7). Finally, Section 8 explores future work, and Section 9 summarizes project management details.

3   Literature Review

To achieve the project objectives, this literature review comprehensively examines the contemporary research in four domains, each associated with one project objective. First, existing path planning methodologies are reviewed to . . . Subsequently, the existing techniques of GNSS-R are explored, with a focus on its prior applications in vegetation parameter retrieval. Then, machine learning . . . Finally, LiDAR-based SLAM techniques . . . Consequently, this review identifies the existing gaps in each domain for the objective of vegetation monitoring, which will inform the integrated project methodologies.

3.1   Path Planning

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3.2 GNSS-R

The concept of using GNSS-R for remote sensing was first proposed in 1993, where the correlation between direct and scattered GNSS signals were proven promising for the application of ocean altimetry [19]. Today, apart from the originally proposed application, GNSS-R techniques has been extensively used for Earth observations and land information retrieval, including ocean salinity, soil moisture, and ice thickness [20]. However, research on vegetation parameter retrieval remains limited to preliminary analyses [21].

In a previous study, the capabilities of monitoring vegetation through GNSS-R were demonstrated through a theoretical simulation of GNSS scattering characteristics [22]. Furthermore, this study revealed that the sensitivity of GNSS-R signals can be influenced by incidence angle, soil parameters, and tree size, while signals with lower elevation angles and RL polarization (transmission of right-hand circular polarization (RHCP) signal, reception of left-hand circular polarization (LHCP) signal) appeared to be ideal for forest monitoring [22]. In another study, the polarization scattering properties of GNSS-R signals in forest canopies were modeled, where simulations revealed that tree trunk scattering effects would dominate total scattering response, while satellite azimuth angles are significantly correlated to the signal polarization [23].

Aside from simulated approaches, empirical or semi-empirical studies regarding GNSS-R remote sensing of vegetation were also reviewed. In a study by Yueh et al., GNSS-R data onboard the Cyclone GNSS (CYGNSS) satellite were analyzed against the vegetation water content estimated through the satellite-derived Normalized Difference Vegetation Index (NDVI) [24]. The results demonstrated near-linear relationship between vegetation water content and GNSS-R signal attenuation, while the CYGNSS data also suggested the existence of volume scattering within complex forest components [24]. Similarly, another study analyzing GNSS-R data from TechDemoSat-1 demonstrated reduced sensitivity to soil moisture retrieval due to vegetation attenuation, which could be effectively compensated using NDVI data, indicating a correlation between signal attenuation and vegetation water content [25]. Additionally, the interference pattern between direct and reflected GNSS signals from the Earth's surface was used in estimating vegetation height and land topography [20]. Through using a Soil Moisture Interference-pattern GNSS Observations at L-band (SMIGOL) reflectometer, the instantaneous

power of the direct and reflected signals were coherently added, in which the resulting power oscillations present notches that are correlated to vegetation layer thickness and the reflection geometry [20]. As a result, an RMSE of 3-5 cm in estimating the height of vegetation with simple geometrical structures (barley and wheat) could be achieved [20]. Yet, despite the effort in prior studies, the use of GNSS-R techniques in vegetation remote sensing and monitoring is far from developed. Most importantly, existing research relies heavily on space-borne or static ground-based platforms, while the use of high spatial resolution and flexibility platforms - such as an UAV - remains underexplored. Therefore, it is critical to develop a systematic framework for an UAV-based GNSS-R system, in which correlations between GNSS-R signal features and vegetation condition parameters are comprehensively assessed and modeled. Additionally, with adequate dataset size, the GNSS-R framework could be complemented by machine learning-based modelling approaches, further enhancing the system robustness. <mark>Connection to ML part</mark>

3.3 Machine Learning

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3.4 LiDAR SLAM

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4 Methodology

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4.1 UAV Platform

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4.2 System Architecture

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4.3 Path Planning

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4.4 GNSS-R

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4.5 Machine Learning

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4.6 LiDAR SLAM

4.6.1 Frontend: LiDAR-Inertial Odometry

For the front end of the modular SLAM system, LiDAR-Inertial Odometry (Fast-LIO) is used to build a map effectively within a short amount of time. To do this, Iterative Extended Kalman Filter (IEKF) is used to fuse the data between IMU and LiDAR point clouds to create an odometry of the environment.

Iterative Extended Kalman Filter (IEKF) follows the core of Bayesian Recursion to estimate the state of the robot through the prediction and measurement update step. In the prediction step, IEKF assumes that the state of the system at time k evolved from the prior state at time $k-1$ is shown as follows:

$$x_k = f(x_{k-1}) + w_{k-1} \tag{1}$$

Where x_k is the state vector containing the terms of interest for the system at time k. The $f(.)$ represents a non-linear state function that is used to forecast current state data from prior state data. We can approximate $w_k - 1$ as $N(0, Q_k)$ where it has a zero-mean Gaussian distribution with covariance matrix Q_k.

The IEKF is initialized with

5 Experiments

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5.1 Experiment Workflow

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5.2 Summary of Experiments Conducted

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5.3 Key Experiment 1

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5.4 Key Experiment 2

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6 Results and Discussion

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6.1 Path Planning

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6.2 GNSS-R

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6.3 Machine Learning

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6.4 LiDAR SLAM

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7 Conclusion

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8 Future Works

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8.1 Path Planning

Placeholder text

8.2 GNSS-R

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8.3 Machine Learning

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8.4 LiDAR SLAM

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9 Project Management

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9.1 Gantt Chart

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9.2 Project Difficulties and Solutions

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9.2.1 Path Planning

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9.2.2 GNSS-R

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9.2.3 Machine Learning

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9.2.4 LiDAR SLAM

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Appendix

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