Chapter 1

Introduction

Generating an accurate and high precision model of its surrounding environment to indicate hazard features is an important issue for any autonomous vehicle. Knowing its own location in the map is essentialfor the vehicle to navigate and avoidobstacle autonomously.

In many applications, the mobile robot has a priori map. The given priori map may be sufficient for localization purpose, but generally do not have the resolution required for obstacle detection. Ground vehicles need to deal with temporary added road block and parked cars. Arial vehicles may not have a high enough resolution map that indicates tall trees, steep hills or electrical towers. In addition, useable map do not always exist. Without maps or externally referenced pose information, the robot must produce its own map and concurrently localize itself within the map. This problem is referred to as the simultaneous localization and mapping (SLAM).

Traditional 2D SLAM algorithms are well established in the past decade [ref]. A SLAM algorithm typically utilises measurements from several types of sensor which can be divided into two groups, those that provide vehicles pose and orientation measurement, such as wheel odometry, GPS, or IMU; and those that provide landmark bearing and range, measurement, such as radar, sonar, laser range finder. In recent years, optical sensors are actively being incorporated into SLAM algorithm and successfully used in ground vehicle navigation [ref]. For aerial vehicles, the experiments are mostly limited to simulation, and results with realistic aerial video data are unavailable.

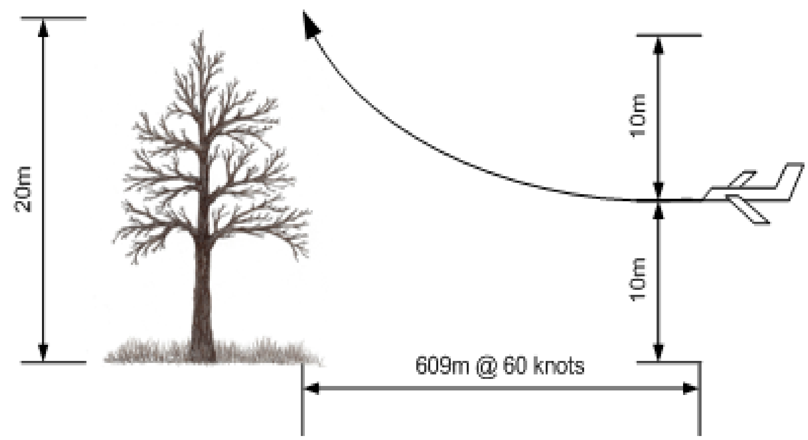
1.1 Problem Statement

Obstacle detection has received a lot of research interest in recent years. Various algorithms were developed for ground, under water and aerial vehicle using different sensor such as sonar, radar, LIDAR, and vision. Most research focus on utilizing with only one sensor. Yet, research shows that using multiple sensors produces a better measurement than single sensor [reference in proposal]. With various sensors readily available on most UAV navigation hardware; such as accelerometers, gyroscope, GPS receiver, altimeter, etc., fully utilizing these sensors to aid the main OD sensor helps to improve the accuracy and robustness of the range measurement, especially in harsh flying condition.

This thesis focuses on developing anobstacle detection system by using a SLAM algorithm as a sensor fusion framework for medium size UAV conduction low altitude terrain following flight in natural environment.The obstacles are static objects on ground, and moving objects are not considered. Research presented in this thesis contributes to the project of developing a mid size UAV to perform geological survey, carried out by Carleton in collaborated with Sander Geophysis Ltd., an Ottawa based company specialized in high precision geophysical survey. Toachieve high resolution data acquisition, the UAV must be able to perform terrain following flight with altitude from ground as low as 10 meters at speed ranging from 60 knots (30 m/s) to 100 knots (51.4 m/s). The rate of climb for the UAV is specified to 400ft of vertical rise per minutes (122 meters per minutes). A quick analysis on the UAV specification and aerodynamic behavior reveals the requirement of a practical obstacle detection system. Assuming a tree height of 20 meters, which is the average height for oak or pine, to allow for enough time to avoid obstacle, the UAV must be able to detect the threat at least 610 meters away from it (). This analysis indicates that the obstacle detection must be able to map object up to a few thousands away from the UAV.

Figure 1 Case study for obstacle detection requirement

Although digital terrain map are generally available for flight path planning and in flight navigation, it does not have the resolution to indicate all hazardous obstacle such as tall trees, steep hills, or man-made tall objects. The obstacle detection and avoidance system must be in place to detect discrete threat, and operate automatically with minimum intervene from the operator.



1.2 Contributions

The thesis reviews the properties and consistency of a typical Extended Kalman Filter (EKF) based SLAM algorithm, and discusses the advantage and limitation of vision based SLAM method. The analysis motivates the development of an improved method by fusing multiple sensors into a mono vision EKF based SLAM framework.

Using a monocular vision for mapping is a bearing only SLAM problem. The measurement is through projection, which loses information about the relative position of the feature since the range is unknown. Without camera motion measurements, map created by monocular vision can be scaled arbitrarily. For a SLAM application in aerial scenario, camera vibration and sudden movement is common when aircraft is hit by cross wind, which can cause the lost of tracked features. A recursive EKF based SLAM algorithm is described in this thesis. The method utilizes sensor onboard the UAV to provide motion measurement of the camera, and improve the robustness of the algorithm under rough flying condition. Real aerial data were collected to test the performance and accuracy of the algorithm in a scenario similar to the one where the UAV will be eventually deployed. The preliminary result of the test flight was published in []. This paper is one of the first ones in the field that successfully applying monocular vision SLAM in large scale aerial application. A more thorough analysis on the behavior of the algorithm and its error is presented in this thesis.Furthermore, a number of baseline separations for the cameraare tested to optimize the performance and computation cost of the algorithm.

1.3 Organization

The thesis is organized as follows:

- Chapter 2 presents an overview on sensors, computer vision algorithms, SLAM algorithm related to obstacle detection and range measurement.
- Chapter 3 describes the detail implementation of the proposed multi-sensory monocular SLAM algorithm.
- Chapter 4 describes camera calibration procedure, equipments setup for the aerial data collection, and data preparation steps.
- Chapter 5 presents detail analysis on the performance of the algorithm. Convergence and consistency of the algorithm is discussed in section and . Error analysis compared to ground truth data is presented in and . The effect of using multiple sensors in improving the robustness is discussed in . At last, the camera baseline optimization is given in .