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Real-time implementation of airborne inertial-SLAM

Jonghyuk Kim[a,*], Salah Sukkarieh[b]

[a] College of Engineering and Computer Science, The Australian National University, ACT 0200, Australia
[b] ARC Center of Excellence for Autonomous Systems, The University of Sydney, NSW 2006, Australia

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Abstract

This paper addresses some challenges to the real-time implementation of Simultaneous Localisation and Mapping (SLAM) on a UAV platform. When compared to the implementation of SLAM in 2D environments, airborne implementation imposes several difficulties in terms of computational complexity and loop closure, with high nonlinearity in both vehicle dynamics and observations. An implementation of airborne SLAM is formulated to relieve this computational complexity in both *direct* and *indirect* ways. Our implementation is based on an Extended Kalman Filter (EKF), which fuses data from an Inertial Measurement Unit (IMU) with data from a passive vision system. Real-time results from flight trials are provided.

Keywords: Airborne SLAM; Inertial Measurement Unit (IMU); Vision; UAV

1. Introduction

Unmanned Aerial Vehicles (UAVs) have attracted much attention from robotics researchers in both civilian and defense industries over the past few years. They can perform various tasks in highly dangerous environments, where access by human operators or from ground vehicles are limited. There is a broad spectrum of applications, ranging across academic research, resource monitoring, search and rescue, bush fire monitoring and information gathering. Advances in cost effective inertial sensors and accurate navigation aids, such as the Global Navigation Satellite System (GNSS), have been key determinants of the feasibility of UAV systems. By fusing information from an Inertial Measurement Unit (IMU) with that from GNSS, a 6DoF vehicle state can be reconstructed, which is a crucial step for guidance and flight control [1,2].

In many robotics applications however, the vehicle needs to perform a task within environments where GNSS information may not be available, such as indoors, in forests, underground, or other such locations where GNSS is naturally denied. In such cases, autonomous localisation is required.

Autonomous localisation is a process of determining the platform's position without the use of any *a priori* information external to the platform except for what the platform senses about its environment; that is, the determination of the platform's position and attitude without the use of predefined maps or any purpose-built infrastructure. This is also known as Simultaneous Localisation and Mapping (SLAM), as introduced by [3], where the vehicle has a capability for online map building, while simultaneously utilising the generated map to estimate and correct errors in the navigation solution obtained.

There have been significant advances in SLAM research over recent years in terms of its real-time deployment and implementation on land, and in underwater applications. Most efforts have concentrated around reducing the computational complexity of SLAM. For example, large-scale maps are partitioned into small amenable maps [4,5] and [6] introduced the hierarchical sub-map method. The sparse nature of the SLAM information filter has also been extensively investigated and implemented [7]. In parallel to these efforts, there have been attempts to develop SLAM for 3D environments, for example: the use of rotating laser range finders in mining applications [8], and the use of stereo vision systems for low-dynamic aerial vehicles [9]. However, in these applications, the 3D implementation is limited to the use of low-dynamic

* Corresponding author.
E-mail address: jonghyuk.kim@anu.edu.au (J. Kim).

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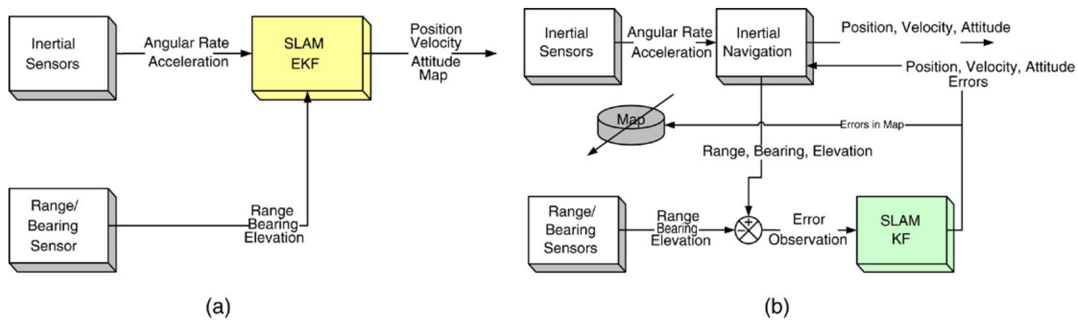

Fig. 1. (a) The direct 6DoF SLAM structure, which estimates the vehicle position, velocity and attitude along with observed feature locations, and (b) the indirect 6DoF SLAM structure, which uses the error state of the INS and map model, and estimates the errors in the vehicle states and map.

vehicles, due to the extensive processing needed for 3D mapping.

For airborne applications, to the best of our knowledge there have been only three attempts up to now: SLAM on a blimp-type (thus low-dynamic) platform using a stereo vision system [9]; inertial SLAM in a laboratory environment [10]; and SLAM on a fixed-wing UAV with inertial sensors and a single vision system by the present authors [11].

In this paper, we will provide a real-time implementation of airborne SLAM as an extension of our previous work. The challenge in airborne deployment of SLAM lies in the complexity of the dead-reckoning process involved and its fast-drifting error. If we look at how the localisation system for an airborne vehicle has been formulated in the past, the core sensing device has been an IMU. This unit measures the acceleration and rotation rate of a platform with high update rates, which can then be transformed and processed to provide its position, velocity and attitude, resulting in an Inertial Navigation System (INS) [12,13]. The data presented by the INS are fed to the guidance and control system to achieve further autonomy. Inertial navigation is significant in that it only measures dynamical quantity, and is thus independent of platform kinematics. The navigational solution provided by INS, however, drifts with time, as in most other dead-reckoning systems. However, the drift rate of the inertial position is typically a cubic function of time, which makes the development of any inertially based SLAM a challenge. Even small errors in gyros will be accumulated in angle estimates (roll and pitch), which in turn misrepresent gravitational acceleration as the vehicle acceleration, thus resulting in quadratic velocity (and cubic position) errors. Therefore, the INS requires reliable and effective supplementary information to constrain these errors. In this paper, we will provide results from a real-time airborne SLAM based on an Extended Kalman Filter (EKF), which fuses information obtained from a vision system with the information from the INS.

In Section 2, we will present our airborne SLAM algorithm based on two different approaches, direct and indirect, and discuss the benefits of both. Sections 3 and 4 will provide details of the real-time SLAM implementation and flight test results. Section 5 provides a conclusion, with directions for future work.

2. Airborne SLAM formulation

SLAM has been formulated *directly* for nonlinear dynamic and observation models, using an EKF. In inertial navigation applications however, SLAM can also be formulated *indirectly* for linearised error dynamic/observation models, using a linear Kalman Filter (KF). This indirect formulation has several benefits over the direct formulation. Fig. 1 compares these two SLAM structures. In both cases, an IMU provides the acceleration and angular velocity of the vehicle. The observation sensor provides the range, bearing and elevation of observed features. In *direct* form, the filter accepts raw data from the IMU and passes this into a nonlinear 6DoF model, and the EKF proceeds through the process of predicting and updating the states of the vehicle and feature locations.

In an *indirect* implementation however, the inertial loop is separated from the filter; thus, the inertial navigation equations transform the raw inertial data to position, velocity and attitude measurements outside of the filter with sufficiently high rates. The state dynamic model in KF is an error model of both the vehicle and the observed features. When an observation occurs, a predicted observation is also generated, which is based on the current location of the vehicle and location of the feature as indicated by the map. The difference between the predicted and actual observations is passed to the KF as an observed error. The KF uses this to estimate the inertial and feature errors. The estimated errors from the filter are then fed back to the INS and map to make further corrections.

Although the heart of the SLAM algorithm is exactly the same, the main benefits of this indirect structure can be summarised as follows [14]:

- The system becomes more tractable for real-time processing. The main INS loop can provide continuous navigation data within fixed time intervals. The SLAM update cycle, whose computation time increases with map size, will not disrupt the main INS loop, and time propagation algorithms can be used to match information at appropriate times.
- The SLAM prediction cycle can exploit the low-dynamic characteristics of INS errors. As a result, the rate of the prediction cycle can be much lower than that of the direct filter. The more accurate the IMU, the less frequently the prediction cycle has to run.