PostDoc Project:

Multi Sensor Image-Based Navigation

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Abstract

Aerial navigation in GNSS contested environments is a challenge for both manned and unmanned aircraft. This research project aims to study and develop technologies and algorithms to address the problem of aerial navigation without relying on GNSS, focusing in image-based navigation with multi-sensor fusion in order to get a precise localization of the aircraft. The proposal application to be used in this research project is related to an aerial transport of goods in a remote area (challenging environment and low risk area), using real-time embedded processing of images and data from other sensors to improve the aircraft localization, without using GNSS data.

1 Project Background

The Global Navigation Satellite System (GNSS) is the major source for position, navigation and timing (PNT) applications. Almost all navigation applications (military and civil) rely only on GNSS for PNT. However, GNSS is susceptible to interference (both intentional and unintentional) making the navigation within affected areas hard to perform or even infeasible. Furthermore, the general applicability of GNSS is further limited as the accuracy and availability can be seriously compromised in an urban environment and environments without a clear view of the sky. Hence, capability to navigate without GNSS capability becomes key element to guarantee airworthiness for current and future navigation applications.

1.1 Research Front

Finding alternatives to GNSS for positioning and navigation has been a longstanding goal, which has of lately intensified with the increase of autonomous vehicles intended to work in GNSS denied or compromised environments. The core of the GNSS complements usually consists of an Inertial Navigation System (INS), which use an Inertial Measurement Unit (IMU), comprising triads of accelerometers, gyroscopes, and magnetic field sensors. INSs are based on the idea of dead reckoning, i.e., double integrating accelerations to obtain position, which cause the position to drift proportional to the cubed time. High-quality sensors can slow down this degradation, but these sensors are expensive, often bulky, and can only slow down the error accumulation [18, 19]. To truly resolve the problem, additional sources of information are needed to completely remove the drift. Depending on availability, different sensing modalities have been considered.

Maps is one source of additional information that has been used. The fundamental idea is to observe the environment, and compare it to a map, and this way limit the INS drift. This is often denoted terrain navigation. Similar ideas have been exploited for aircraft, ships, car, and underwater vehicle navigation utilizing elevation maps, sea charts, and road networks [1, 5, 6, 9]. Though effective, these methods require accurate maps of the area of operation, which can be costly or even impossible to acquire for some missions. In aviation the maps often consist of known radio sources, e.g., dedicated radio beacons (VOR, DME and Loran-C) [14] or signals of opportunity (SoOP) [8, 14]. The former is easier to use, but infrastructure needs to be installed for the purpose, whereas the later use digital and analog television signals, AM radio signals which were not primarily intended for navigation and require mapping of the area ahead of time. Usually these methods require being able to determine the angle of arrival of the signals, which can be limiting for small aircraft.

Today, advances in technology and reduced costs have made imaging sensors available in aircraft of all sizes. This combined with ever increasing computational power, has led to increased interest in using images data as standalone solution or to support INSs [2–4, 16, 17]. Two principles exist, either to match the images of the terrain below the aircraft (or landmarks in them) to determine the location given a map as described above [15], or in different ways use sequential images to estimate motion (visual odometry) [7, 10, 12, 20]. A limiting factor of the map-based methods is the acquisition of the map. Visual odometry on the other hand is map-free but can only limits the drift not completely stop it.

2 Project Description

The main objective of this project is to study and develop technologies related to image-processing and sensor fusion for aerial navigation in a GNSS denied environment. In summary, use image-processing to get a measurement of the aircraft position and combine this measurement with INS to perform the INS fix, instead of the GNSS data. The aforementioned techniques have been studied before e.g., [3, 4, 15]. This project aims to use some recent development in the area of Machine Learning, which has been very successful in the area of image processing and analysis [13]. In particular, methods based on Neural Networks will be used in order to obtain measurements of the platform's movement based on the dense optical flow in the images e.g., [11]. Optical flow is an alternative to sparse feature/point based image motion tracking (used for visual odometry) and which is more resilient to wrong data association, as an example. The downside of the optical flow is its computational cost (compared to the sparse methods) prohibiting the real-time usage, and use of Neural Networks is a promising way forward to solve the real-time issue. The project will look deeper into these methods and how they can be integrated into the whole sensor fusion based localization system.

The project is a collaboration between Linköping university and Saab AB (Swedish aircraft manufacturer), where Saab's role is to provide relevant scenarios and data. After an initial phase for use case, scenario and requirements definition, some flight tests will be performed to obtain a set of real data (images and flight data) to be used throughout the development phase. Besides images and flight data, the GPS data will be also collected, but it will be used for comparison purposes only (ground truth). The algorithms and techniques developed in this project will be tested and validated using this data.

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