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Aspects on Aircraft Mapping and Navigation System: Theoretical Study

Shreya Mane

Research Fellow, Department of Research and Development, Astroex Research Association, Deoria, 274001-India

ABSTRACT

The two primary navigation systems for airplanes nowadays are global navigation satellite systems (GNSS) and inertial navigation systems (INS). Small mistakes in the readings of vehicle accelerations and rotation rates can result in non-negligible integration drift because INS navigation is based on the dead-reckoning concept. Image-aided inertial navigation, a different navigation method that is increasingly being considered in navigation applications, offers fully autonomous navigation because it only relies on onboard sensors that provide information from the dynamics of the vehicle and the observation of the surroundings. When other navigation systems that need external equipment, like the Instrument Landing System (ILS) or Global Navigation Satellite System (GNSS), are lost, this one may be utilized as a backup. Aside from the specific context of civil aviation, it might be interesting to use a further autonomous means of navigation like video measurement that could replace the need for additional ground or space infrastructure during precision approaches (currently done with ILS or GPS augmented with GBAS or SBAS). This work extends the monocular SLAM approach for optical-aided navigation and visual Simultaneous Localization and Mapping (SLAM) for satellite-denied aircraft navigation. It does this by utilizing several sensors with various viewing orientations. Since downward optical sensors observe different movements from forward-looking cameras, it is simple to combine the advantages of both. Combining these two techniques makes it possible to more robustly estimate each of the six motion components, producing state estimation for optical-aided navigation solutions that is more stable and precise. The state-of-the-art in image-aided navigation systems is proposed in the current work. The essential components or traits of these techniques are described. On the basis of this, a proposal is made for an approach and landing operations video-based navigation system. This is the initial phase of a feasibility study for a video-based airplane landing system.

Keywords: Simultaneous Localization and Mapping (SLAM), global navigation satellite system, inertial navigation system

INTRODUCTION

Based on the observation of the skies, visual navigation is one of the oldest known forms of navigating (it was called celestial navigation). Using tools to calculate the angles between stars and the horizon or vertical, some of the navigators were able to approximate their location. The fundamental idea of visual navigation is summarized by a straightforward fact: the best way to determine our position in relation to our environment is to observe the world and the objects around us. Currently, the Global Navigation Satellite System (GNSS) and Inertial Navigation System (INS) are the primary navigational aids used by high-end transport aircraft. To give a degree of performance that may meet needs ranging from en route activities down to Non-Precision Approaches (NPA) and Required Navigation Performances (RNP) procedures, they are even frequently combined in a hybridized architecture.

The addition of additional sources of information—whether or not they are already on board—and the use of their measurements in a more global, hybridized architecture are solutions for enhancing the performance of navigation systems and achieving the most demanding missions. The key benefit of combining data from several sources is that it can make up for the shortcomings of each source while also enhancing the reliability and accuracy of the projected navigational parameters. The development of lightweight, low-cost video sensors with high resolution has sparked interest in the extraction of precise navigational data from optical measurements, such as position, velocity, or attitude. Currently, certain airplanes are equipped with cameras, which are primarily intended to aid the pilot in ground navigation or to amuse passengers during flights. However, observing the landscape in the immediate area might serve as a useful source of navigational data. For instance, an image flow measurement may be a good indicator of the aircraft's position, speed, and orientation. But accurate transcription of the landscape's intricacies must take into account the physical constraints and features of a video sensor, such its resolution, range of view, size, and placement.

A simple photograph can reveal a lot of information through visual measures. A basic digital optical sensor uses a complementary metal-oxide semiconductor (CMOS) or a charge-coupled device (CCD) to measure the amount of light entering an aperture (CMOS). This measurement, which acts as a snapshot of the surrounding area, gives details on the amount of light falling on each sensor pixel. In order to determine a pixel's location in the image frame, the data related to each pixel must be linked to its coordinates. In order to identify specific pixels in the image that correspond to points of interest in the landscape, an optical sensor is frequently linked to an image processing system. Last but not least, the positions of those pixels, photographs of features (or points of interest), may contain geometric information useful for navigation.

SIMULTANEOUS LOCALIZATION AND MAPPING (SLAM)

Optical approaches for pose (i.e., global position and angular orientation) estimation are well-known alternatives to GNSS [1]. Major approaches use a filter algorithm (particularly Kalman Filter and derivatives), which builds on the fundamentals of linked navigation and combines higher-frequent inertial strapdown with lower-frequent adjustments from other sensors. Corrections based on camera pictures, lidar, or radar sensing are added to or substituted for corrections based on satellite location and velocity to compensate for a potential loss of satellite signal. Due to the fact that these sensors do not immediately offer information on the pose or motion of the vehicle, significant data pre-processing is necessary, such as the extraction of motion vectors from image sequences and the fusing of this data with the primary data filter. Simultaneous Localization and Mapping (SLAM), which may incorporate bearing data from cameras and distance data from lidar or radar, is a very promising option. The work in [2] offers a comprehensive a description of the usage of SLAM in aviation navigation.

The fundamentals of visual or vision-aided positioning and navigation are now well understood as a result of a wide range of research activity, starting with some early thoughts about how a camera may be employed as a sensor for the positioning and navigation of automated aircraft [3, [4,] [5]. There has already been a lot of progress made, and surveys of unmanned aircraft navigation [6] or general concepts of this type of robotic vision [7] can provide a thorough introduction to familiarize oneself with the fundamentals. There are two basic branches of visual navigation that apply to aerial vehicles: On the one hand, full visual or visual-inertial navigation is being developed to allow for flight in satellite-denied situations (mainly small-scale, such indoor). These techniques are frequently tried using small or micro UAS, like quadrotors.

However, in large-scale contexts, absolute location is required, and visual methods are used to make up for brief satellite signal interruptions. However, the fundamental ideas are frequently the same. In general, solutions tend to be monocular since larger helicopters or fixed-wing aircraft are typically flown at greater altitudes than MAVs, such as the velocity, turn-rate, and error estimation described in [8]. Absolute scale and position can also be achieved during an outdoor flight at elevations within the range of absolute distance measurement, and wider-baseline stereo cameras [9], laser range finders [10], or other altimeters constitute a significant problem in this situation. The remaining options include measuring air pressure and air speed.

Control and State Estimation

Quadrotors are mechanically simpler and easier to manage than other kinds of rotorcraft. Due to system nonlinearities, cross couplings of the gyroscopic moments, and under actuation, operating a quadrotor is still a difficult challenge [11], [12]. See [13] and [14] for more details on piloting a quadrotor. The system's actual state must be available to any control method. A quadrotor's state typically consists of its orientation, location, and velocities. One of the first researchers to perform real-time state estimate with a flying robot was S. Thrun et al. [15] in 2006. They used a helicopter to carry out state estimation outside. In 2009, separately achieved state estimate for a quadrotor by Grzonka et al. [16] and Bachrach et al. [17]. Since then, researchers have looked at various state estimation setups, but a common feature of the majority of the methods is the use of Kalman filtering.

Learning maps is necessary for the deployment of an autonomous robot in a practical setting. In order to learn maps, it is important to handle a number of important issues, such as a) mapping, b) localisation, and c) path planning. Simultaneous planning, localization, and mapping (SPLAM), integrated autonomy solutions, or autonomy packages are terms that are frequently used to describe the integration of mapping, localization, and path planning [18]. You may find detailed information on various techniques for map learning components in relation to mapping and localization in [19], as well as for path planning in [20].

Mission Planning

An autonomous flying robot's mission planning is a series of steps that should be taken at specific times. It directs the robot's actions like a high-level decision maker and is a component of the navigation stack. Creating a list of navigational behaviors is one way to address this navigational challenge. Every action serves to accomplish and/or sustain a goal [21], [22]. Every action is a process or a control law. As an illustration, obstacle avoidance behavior upholds the objective of avoiding crashes, and follow-me behavior accomplishes the goal of keeping track of a person's location. For additional behaviors to occur, certain behaviors must first occur. For instance, a robot needs to be aware of its current location in order to conduct the return-home behavior. As a result, following a person requires localization behavior.

Autonomous Behaviours

A group of actions known as autonomous behaviors are intended to help the robot navigate efficiently. These actions rely on path planning, exploration, and obstacle avoidance techniques. Behaviors like "follow-me," "go home," "advance to goal," and "return to me" are based on the behavior of "path planning between two specified points" and "follow-path." The highest priority behavior, avoiding obstacles, is carried out on two levels. The procedure is first carried out at the map level, where an ideal path is created and occupied cells are dilated. Second, it is carried out with the aid of a laser ranger while maintaining a safe distance from instantly detected obstructions that are closer than a set threshold.

Another behavior that detects particular targets and marks them on a 3D or 2D map of the environment is target localization. Targets are localized based on their colors using a target localization algorithm [23]. An arrow is used to indicate the localized targets on the produced map. This capability is shown in two movies of two experiments that are attached. As specified in the configuration file, the algorithm can recognize several targets of the same color or distinct hues. The targets are visible in the image frame, but since depth data is also accessible, it is simple to determine their 3D positions. The global coordinates of the targets are determined by converting the coordinates from the camera frame to the global frame given that the camera's pose is known.

Remote Mapping

Another practical characteristic for field applications is remote mapping. Monitoring the quadrotor's perception on small, mobile, and distant stations like tablets is frequently necessary. For instance, having access to the camera view of the quadrotor as well as 2D and 3D maps on various tablets can allow the mission planner or quadrotor users to handle the task effectively if the quadrotor is exploring a building where humans cannot enter.

The General SLAM Method

Optical Flow Input

Corresponding 2D points, which are separate image characteristics acquired using a feature tracking or matching technique, are used to characterize the movement of the input image. Although a quick Lucas-Kanade tracker [24] is used in the example given, other implementations may also be appropriate. Image feature uncertainties are modelled using covariance matrices that grow throughout the tracking time, as described in [25]. From triangulation, where the feature's distinctive IDs are copied to the 3D map objects, matches between 2D image features and 3D map objects are automatically available.

Localization

This is accomplished via point correspondences from 2D to 3D and their uncertainty. This is accomplished using a current image with 2D point IDs and the matching 3D objects, which are referred to as the map, and the monocular camera resectioning approach from [26]. For each new camera image, localization is carried out using feature reprojection error minimization, which yields a 3D position as well as an uncertainty covariance matrix. This can be used as an input for a state estimation filtering technique (like EKF).

Mapping

3D object point mapping is generally done by monocular triangulation using multiple camera poses known from the state estimator (i.e., which uses satellite navigation or vision-aided localization) and a set of 2D point correspondences from these images. Mapping can be done with lower frame rate, which means by using only salient key frames with significant changes of the camera view point. The mapping algorithm is generally based on known multi-view triangulation, which will be described later in sec. IV-C together with the new ideas of including altimeter measurements to reduce errors. The mapping procedure returns 3D object points including covariance matrix.

CONCLUSION

The concept is analogous to manual landmark navigation, where attitude is noted and maintained by gazing forward to distant locations while ground movement is more discernible when gazing downward. With a second mapping that is independent of the first camera map and a combined localization where a posture is fitted to all the camera observations, the visual SLAM method is improved internally. Theoretically, this will lessen the likelihood of visual qualities that are confusing and allow ego-motion estimation in situations when it might not be viable with just a downward camera. Accurate sensor co-calibration is necessary since, in practice, alignment problems can lower the quality as seen in the second flight. However, there is great promise in the possibility of minimizing the disadvantages of visual navigation with a single viewing orientation.

This essay discusses fixed-wing aircraft visual navigation techniques. The usage of cameras and image processing algorithms for motion and position estimates is widely known; therefore, this paper covers some challenges for the desired application. Since it is obvious, the desired vehicle movement must be discernible; otherwise, it cannot be inferred from visual sequences. The research calculates some preliminary limits for the camera system based on the assumption that rotation would have upper limits and that flight velocity will depend linearly on altitude. An overall applicability region is established along with a vehicle-dependent speed range and restrictions for metric motion estimate from altitude measuring. This does emphasize the difficulty of visual navigation for landing or low-altitude flights for fixed-wing aircraft.

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