Dead Reckoning and Terrain Image Processing as basis for UAV home-oriented navigation under foreign GPS-denied Environments

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Abstract

UAV navigation within GPS-denied environments has become increasingly critical in recent years due to modern heavy reliance on GPS and the rise of UAV use within GPS-denied and GPS-unstable zones. GPS reliance marks on the of the largest weaknesses of most autonomous UAV systems, and the loss of GPS signal often renders many autonomous UAVs as completely coordinately-impaired. To confront this issue, we present the implementation of a navigational system based on terrain imaging and dead reckoning for home-oriented navigation, which is viable even in foreign environments. We explore the possibility of various forms of image processing, such as feature matching and optical flow via template matching, in order to replicate similar data (ground speed, initial and ending orientation comparison) that would have otherwise been produced by GPS outputs. We use traditional dead reckoning methods as a path basis for the initial UAV navigation, and we utilize both physical implementation and formal methods to study the general applicability of this solution.

1 Introduction

Unmanned aerial vehicles (UAVs), such as quadrotors and fixed-wing drones, are used more frequently in recent years due to the combination of low cost and high user friendliness. The lightweight design and setup allows even novices to start drone implementation for personal purposes, expanding both the user base and general purpose for drone employment. These growing applications in daily life include emergency medicine transport to remote locations, environmental monitoring, surveillance photography, terrain imaging, and countless other growing fields. Regardless of application, all autonomous UAVs must contain a system for either returning to a source position or pathfinding to an ultimate destination.

Current and previous autonomous navigation systems for most UAV applications center primarily upon the utilization of Global Positioning Systems (GPS); this presents a significant challenge for current and future autonomous UAV flight, as this system of navigation is restricted by GPS-jamming devices, indoor environments, signal-denied zones, and increases in governmental legislation. Such signal-denied zones include dense tree regions, underground stores, and extraterrestrial landscape where the GPS signal is unable to penetrate solid walls and/or structures. Additionally, although the United States Department of Defense currently upkeeps the satellites used for GPS and provides their services free of cost, the Department reserves the right to deny services at any time, creating an external dependency that is often undesirable for third-party companies, organizations, and individuals.

To explore other avenues of autonomous navigation outside of GPS implementations, we propose combining traditional dead reckoning methods with various forms of terrain image processing, specifically for the return of the UAV to a source position within GPS-unstable zones. Aerial images, taken from the underbelly of the UAV aircraft with fitted cameras, present an opportunity for computer vision techniques to yield similar flight data that would have otherwise been produced by GPS outputs, regardless of environment interference that could impair coordinate systems. The UAV takes a photo of its source location upon liftoff at the beginning of its flight. Upon the loss of GPS-signal, the UAV estimates its trajectory home via simple dead reckoning, and checks the current terrain images with the previously taken photo of its source location; if the images do not match and the dead reckoning estimation is off due to drift or miscalculation, then the UAV will fly in a spiral pattern until the source location is found. Although this presents a possibility for total loss, we expect to minimize this error associated with the dead reckoning methods through use of accumulated terrain imaging for real ground speed and drift estimations. It is notable that this method for autonomous navigation requires very little computational power and minor memory access during the original flight of the UAV (merely taking a photo of its initial environment for future reference), and the system only becomes truly active when GPS-signal is lost. This method also is suitable for completely foreign environments, as there is no pre-flight training, offline map access, or annotation of the environment required beforehand.

2 Related Work

2.1 Traditional Dead Reckoning

Dead reckoning has been used for centuries as the default estimation for the return to a home destination after keeping a log of the previous relative distances and angles traveled. By updating a record of the relative angles shifted and the distances traveled for each angle position, a simple required angle rotation and distance can be calculated, as shown in Figure 1. We propose using this method as the starting point for our UAV home-oriented navigation upon the loss of GPS signal.

In addition, we supplement these dead reckoning calculations with other estimations (wind speed, real ground speed, etc.) in order to oppose the effects wind and drift upon the UAV trajectory. Previous work demonstrated by Wang *et al.* (2018) explores methods of estimating UAV wind velocity with minimal sensor use through calculating an airspeed vector, based upon derivations of the wind disturbances between rotor speed and UAV acceleration [11]. Implementable methods for estimating UAV thrust, drag coefficient, and wind drag are also explored.

2.2 Visual Navigation Approaches

Computer vision techniques have shown considerable promise for the task of autonomous UAV navigation. Previous approaches have utilized Simultaneous Localization and Mapping (SLAM), convolutional neural networks (CNNs), and Visual Odometry, amongst others. We will highlight the fundamental methods for each of these previous approaches, as well as the associated strengths and weaknesses for each.

Simultaneous Localization and Mapping (SLAM) methods focus upon building and updating a map of an unknown environment while simultaneously updating the UAVs position within the map itself. Smith *et al.* (1986) defined the foundation of SLAM for general robotic implementations several decades ago, and it has since been applied to fields outside of the scope of the original paper [10]. Lopez *et al.* (2017) demonstrates a system of SLAM to record UAV localization in GPS-denied zones through integrated use of vision, laser, and inertial measurements [6]. This implementation yields experimental results that improves the estimated trajectory of the UAV compared to traditional baseline techniques.

Convolutional Neural Network approaches have also demonstrated promising results. The work of Shamer *et al.* (2019) outlines an approach for UAV path-following in GPS-denied environments [8]. This method inserts waypoints for the UAV to follow in simulation of a flight trajectory, and it trains a convolutional neural network to output the yaw angle delta based on visual input for each respective path between waypoints. Although it was met with considerable success with a final cross distance track of 2.88 meters, it is notable that this system requires an offline map of the proposed foreign environment for extraction of distinct landmarks, and it also requires pre-flight training for each respective subpath between the multiple waypoints.

2.3 Feature Matching Approaches

Work in the field of computer vision outside of strict navigational implementations includes methods for matching keypoint features between images, as well as methods for finding subimages within a second image. The most widely accepted implementations of feature matching between two images are Scale-Invariant Feature Transform (SIFT), Speeded-Up Robust Features (SURF), Binary Robust Invariant Scalable Keypoints (BRISK), and Binary Robust Invariant Scalable Keypoints (BRISK), amongst others. As a considerable portion of this paper focuses upon feature extraction and matching algorithms for determining if the UAV has correctly located the source position, we give an overview of these various methods in determining which was most suitable for our purposes.

Lowe (2004) submitted ground-breaking work within the field of computer vision for his implementation of Scale-Invariant Feature Transform (SIFT), which is invariant to alterations in rotational orientation and scale [5]. This method uses gaussian blurring to reduce the noise of the image, a difference of gaussians approach to construct a scale space of the high contrast variations, and a threshold on minimum contrast to select the best keypoints. The corresponding keypoint descriptors are then created through the construction of a unique histogram of gradients for each keypoint. Lowe also proposes a method of selecting the best match between keypoints in two images by placing a maximum threshold on the ratio between the best- and second-best matches for each featured descriptor. As a high ratio indicates an ambiguous match, the paper suggests a threshold of 0.8 to reject approximately 90 percent of the incorrect matches while losing less than 5 percent of the correct machines.

Following this publication, several others submitted work on new forms of scale-invariant and rotationally-invariant feature extraction and matching methods. Bay *et al.* (2007) submitted the outline for Speeded-Up Robust Features (SURF), which is much faster than previous scale and rotation invariant feature matching approaches due to its reliance on integral images for image convolutions, rather than the previous difference of Gaussians approach of SIFT [1]. Calonder *et al.* (2010) proposed the implementation of Binary Robust Independent Elementary Features (BRIEF), which contains more efficient feature descriptors through the implementation of binary strings [2]. Leutenegger *et al.* (2010) submitted the framework for Binary Robust Invariant Scalable Keypoints (BRISK) for a feature extraction and matching approach that operates at a significantly lower computational cost [4].

Several studies have been conducted on the relative real-time merits and demerits of each of these various feature extraction and matching approaches. Darshana Misry *et al.* (2017) suggests that SURF implementations are computationally three times faster then SIFT implementations [7]. Maji *et al.* (2020) compares SURF and BRISK algorithms in the terrain imaging space, specifically for the feature recognition rate in video image processing after ten frames, and concludes that SURF features yield a 30 percent recognition rate while BRISK features maintain a rate of approximately 50 percent [9]. The authors note that possible design-inherent factors of their experimentation, such as the experiment's study on moon-comparable surfaces with similar repeated texture, may have affected the outputs of their results, and they also note that the BRISK features may have surpassed initial expectations due to the circular pattern for BRISK description generation (rather than the rectangle patterns for SURF). Furthermore, Karami *et al.* (2017) found that in performance testing for feature extraction and matching for distorted images, SIFT generally outperformed SURF and BRIEF, although at an expense of greater computational complexity (as compared with SURF) and memory requirement (as compared with BRIEF) [3].

Due to the wide success for keypoint extraction and matching despite changes in rotation and scale, which are inherent to UAV imaging with constant modifications in UAV orientation and altitude, as well as general better performance, SIFT will be implemented in our approach for feature matching between aerial images. The SIFT template within OpenCV also provides easier user implementation and greater supported documentation than other feature matching templates. Our implementation of SIFT will be used in the confirmation of whether the final estimated location corresponds with its initial beginning location.

3 Body

The body will **REPEAT** the same pattern, the same information, but with more detail. The body can consist of multiple sections. Typical sections would include a **Related Work** section in which you describe other research efforts related to your own and provide references to them. Also there would be an **Approach** section in which you describe the work you did, including experimental design, description of implementation, architecture, interfaces, and similar things. This section is the real core of the paper and tells your readers what you did. That would be followed typically by a **Results** section in which you describe the results of the experiments you did, or the testing of your system. You can save the conclusions you draw about the system for the **Conclusion** section.

Proposed Approach

Experimental Results

4 Conclusion

The body will **REPEAT** the same pattern, the same information, but with just enough de details to state the key results.

5 Acknowledgements

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