

Vision-based Drone Navigation for Orbital Inspection of Pole-like Objects

Jyi-Shane Liu^{1,2}

¹Department of Computer Science
National Chengchi University
Taipei, Tawian

²Pervasive Artificial Intelligence Research Labs, Taiwan
liujs@nccu.edu.tw

Wei-Chao Chang

Department of Computer Science
National Chengchi University
Taipei, Tawian
107753035@nccu.edu.tw

Abstract—We present a research work on autonomous visual navigation for aerial inspection on man-made construction. In particular, we focus on developing orbital inspection of pole-like objects. Our technical contribution is in two folds. First, we address the problem from a system perspective and design a complete technical solution. Second, we implement the technical design, integrate all functional components, and employ the developed system on a quadrotor for field test.

Keywords—vision-based navigation; orbit inspection

I. INTRODUCTION

In recent years, there has been increasing research interest in taking advantage of aerial inspection with drone platform for real-world applications. While manually operated or semi-automated navigation approaches [1][2] have partially demonstrated the potential value of aerial inspection on man-made construction, some obstacles still exist for widespread use. In this paper, we present a research work on autonomous visual navigation for orbital inspection of pole-like objects.

II. AUTONOMOUS ORBITAL NAVIGATION SYSTEM ARCHITECTURE

Our technical agenda is to provide a fully automated drone control system without human pilot assistance or intervention in any step of the orbital inspection process. The functional division of the navigation process includes target object image matching, mapping and localization, trajectory derivation, navigation control, and failure (error) recovery. All functional components are integrated with behavior tree as the control architecture for real time execution.

A. Object Image Matching and Visual Simultaneous Localization And Mapping

An inspection task starts with a designated object and a specified task requirement of image coverage of the object. Given a distant image of the target object, the drone would visually identify the target object after taking-off and fly toward the object. For this functional component of object identification, we adopt the image feature matching technique. In particular, we use the Scale Invariant Feature Transform (SIFT) algorithm from OpenCV library.

In order to successfully and safely navigate itself around the target object, the drone would need to rely on a map of the

environment and a way to position itself in the map. The map would lay out perceivable landmarks as scene feature points. By knowing its continuously updated location on the map, the drone can dynamically calculate a suitable trajectory around the target in the environment so as to perform the assigned inspection task. We use ORB-SLAM [3] for its functional versatility and sensory simplicity. We also use drone's IMU data to transform ORB-SLAM map scale to real-world coordinate scale.

B. Orbit Derivation and Navigation Control

Orbit derivation is a technical step to calculate an orbital path around the target object. Given that we have positioned the drone in front of the target object by object image matching, we can further infer that a central region of feature points in ORB-SLAM map represents the collective location of the target object. The mean coordinate of this region of feature points is calculated and used as the virtual centroid of the target object. The distance between the edge of feature point region and the mean coordinate is also estimated as the radius of the pole-like target object. An orbital radius is then calculated by adding a pre-determined orbit-to-object-surface distance to the object radius.

In an ideal world, this circular orbital path can be followed perfectly by executing the corresponding translational and rotational movement. However, wind conditions and less precise motor driven movement cause constant deviation. Navigation control performs dynamic correction on drone position in order to rectify occurring deviation from the target orbital path. At each tick of navigation control cycle, the drone would estimate its current location with respect to the target object and compare to the planned orbital path.

C. Failure Recovery and Behavior Tree

In order for the drone to be resilient to unexpected conditions in real world environments and the imperfect algorithmic outcomes, an autonomous system must also be able to recover from potential failures. When tracking loss happens, ORB-SLAM needs to re-localize itself with previous key frames. During orbital flight, unchanged pose estimation by ORB-SLAM after a movement command signifies a tracking loss. A reversal movement command is then given to navigate the drone back to its previous location and help ORB-SLAM recover.

We use the behavior trees [4] control architecture as the sense-and-act mechanism. With a tree-like representation, a behavior tree embeds a logical structure to switch among behaviors under various conditions. As a design method, a subtree represents a modular designed behavior and can easily be reused and composed with a larger behavior tree. As a control architecture, the dynamic behavior of an artificial agent in a situated environment is directed and regulated by the procedural logic embedded in the tree-like structure.

III. EXPERIMENTAL RESULTS

The task environment is a riverside park. We select a bridge pier as the target object of orbital inspection task. The size of the bridge pier is about 1.0 meter in width and 6.2 meter in height. The experiments include three subsets of autonomous task flights with a different orbital radius. The orbital radius is set to be 2, 3, and 4 meters, from the structure surface of the bridge pier. Each subset of a fixed orbital radius involves a total repeat of 10 flights so as to establish an indicative level of performance. The overall performance index is to observe whether an orbital inspection task can be successfully completed. Two additional performance metrics, distance deviation and orientation deviation, are used to provide a quality measurement of the orbital flight, as shown in Figure 1.



Figure 1. Both lateral deviation and orientation deviation are measured in camera image

The overall performance index is to observe the task completion rate. For each subset of 10 flights on orbit radius of 2 meters, 3 meters, and 4 meters, the success rate is 80%, 90%, and 100%. Two flights, one each on 2-meter orbit and 3-meter orbit, were not completed due to ORB-SLAM lost track and the failure recovery actions could not rectify the errors. Another failed flight on the 2-meter orbit resulted from the operator's manual control interruption based on safety concern.

TABLE I. PERFORMANCE ON LATERAL/ORIENTATION DEVIATION

Orbit Radius	Lateral/Orientation Deviation		
	Overall average distance/deviation	Maximum average distance/deviation	Maximum point distance/deviation
2 m	0.33m/71.77px	0.44m/118.1px	0.75m/257px
3 m	0.31m/64.63px	0.54m/98.21px	0.89m/254px
4 m	0.38m/51.98px	0.59m/61.31px	1.1m/125px

The results in Table I shows the lateral and orientation deviation performance. In general, orbiting larger radius produces larger lateral deviation during path traversal. This orbit following performance is not satisfactory in accuracy but may be sufficient for practical use. The low image resolution

may adversely affect the ORB-SLAM localization, especially in further distance away. The overall trend that shorter orbit radius causes more orientation deviation is consistent with the geometry that an angular movement at closer range creates wider view shifting. In general, the average target view shifting around 10% of image width from image centroid provides evidence to capable orbit inspection. The developed system successfully show the ability to perceive the orientation deviation, adapt to the deviation, and dynamically adjust the drone's orientation so as to continue the orbit traversal.

We also provide a top-down view of representative actual orbital trajectories in Figure 2. The actual orbital trajectories in real-world coordinate scale were derived by a transformation from ORB-SLAM map coordinate with the drone's IMU data. Overall, the trajectory observation shows that, despite not being perfect, an autonomous orbital navigation is achieved.

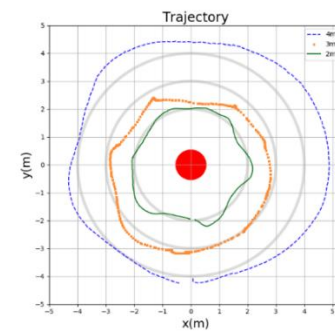


Figure 2. A top-down view on representative actual orbit trajectories

IV. CONCLUSION

This work presents a technical approach to develop a vision-based autonomous navigation system for orbital inspection tasks on pole-like objects. We use behavior tree to integrate various functional modules, from object image matching, ORB-SLAM, orbit derivation, to failure recovery. The developed system has been implemented on a quadrotor and field tested on a real bridge pier in an outdoor environment. Extensive experiments show successful system autonomy and task performance.

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