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Observability analysis and filter design for a vision inertial absolute navigation system for UAV using landmarks

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ABSTRACT

This paper focuses mainly on the research of the vision inertial absolute navigation system (VIANS) for Unmanned Aerial Vehicle (UAV) using landmarks. Firstly, the model of the VIANS is established. Secondly, Extend Kalman Filter (EKF) and Unscented Kalman Filter (UKF) are designed, respectively, to get the estimations of absolute position, absolute velocity and attitude of the UAV. And the nonlinear degree of the VIANS is analyzed to design a more suitable navigation filter for the VIANS. Thirdly, the observability matrix of the VIANS is derived based on the Differential Geometric theory, and the influence of the landmark distribution on the degree of observability of the VIANS is analyzed based on the condition number of the observability matrixes. Finally, simulations are carried out to validate the correctness of observability analysis and the effectiveness of the designed navigation filter.

1. Introduction

Recent years have seen an exponentially increasing use of Unmanned Aerial Vehicle (UAV) for both military and civilian applications [1]. Currently, most UAVs (Unmanned Aerial Vehicles) rely on GPS/Inertial Navigation System (INS) to get absolute position, absolute velocity and attitude of the UAV in the navigation coordinate frame. However, GPS signals can be disturbed and jammed easily, and cannot work when UAVs flying at low-altitude in obstacle-strewn terrain such as urban, canyons/mountain or forests [2,3]. Moreover, INS alone will produce accumulated error, and it is too sensitive to the initial value.

Vision sensors have good performance in anti-disturbance, military concealment and catching object movement information [4–7]. Furthermore, they are low-cost and lightweight. So much research work has been done on the vision-based navigation for UAV [8–14]. In Ref. [8–10], optical flow is utilized in the vision-based navigation. However, the absolute position and attitude estimates of the UAV cannot be obtained since optical flow can only measure the relative velocity of features. Moreover, the optical-flow-based navigation could only been applied in basic maneuvers, such as takeoff, landing, and hovering. In Ref. [11] and [12], a vision-aided navigation system is proposed while GPS signal intermittent available. And an Extended Kalman filter (EKF) for performing the tasks of vision-based mapping and navigation is utilized. When GPS is available, multiple observations of a landmark point from the vision sensor allow the point's location in the inertial space to be estimated. When GPS is not available, points that have been sufficiently mapped out can be used for estimating the absolute position, absolute velocity and attitude of the UAV. However, the system is effective only when GPS signal is

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intermittent available, so it is not an autonomous absolute navigation system in essence. In Ref. [13], a vision-based navigation system, which combines inertial sensors, visual odometer and geo-referenced aerial image, is proposed. And the position information from geo-referenced aerial image can be used to compensate the drift of the UAV state estimation, which occurs when only inertial sensors and visual odometer are used. However, a lot of environmental information should be known and stored in the on-board computer in advance, which leads to the decrease of battlefield flexibility and the increase of storage space and calculation time. The authors of Ref. [14] present a vision-based navigation system to enable a small UAV flight through a forest when the absolute positions of trees are known roughly, by using a monocular camera and Inertial Measurement Unit (IMU). An Unscented Kalman Filter (UKF) is applied to estimate the state of the UAV as well as the positions of trees in the forest based on the bearings to the trees and IMU measurements. Simulation results for a UAV navigating through a 2D environment were presented. However, the initial UAV position and velocity are assumed to be known accurately.

On the basis of the predecessors' research work, a vision inertial absolute navigation system (VIANS) for UAV based on known landmarks is proposed in a GPS-denied environment by using IMU and a monocular camera. The image positions of the landmarks and the measurement of the IMU are fused by a navigation filter to get the absolute position, absolute velocity and attitude of the UAV. The landmarks are generally easy to be identified and need smaller storage compared with the geo-referenced aerial image of the environment around the flight path.

Navigation filter design and influence factors analysis of the observability degree of the navigation system are the two key issues in the VIANS. The performance of several nonlinear filters including EKF and UKF is investigated only through Monte Carlo simulations in Ref. [15] and [16], and the nonlinear degree of the system which could influence the performance of navigation filter is not analyzed. In our paper, the performance of the EKF-based and UKF-based navigation filters is compared through analyzing the linearization error of the state and observation equations of the VIANS, which can provide a theoretical basis for the design and selection of navigation filters. The degree of observability reveals the sensitivity of the observation variable to the change of the system state, and it dramatically affects the convergence speed and estimation accuracy of the navigation filter [17]. Therefore, observability degree analysis is very important for the VIANS. Currently, there are two main methods to analyze the degree of observability of the system, which are based on the estimation error covariance matrix eigenvalues [18] and the condition number of the observability matrix [19–21], respectively. However, the behavior of error covariance is sensitive to the initial error covariance, and the relation between the observability and the error covariance can be misleading [22]. So we apply the condition number of the observability matrix to analyze the factors which could affect the observability degree of the VIANS. And we mainly focus on the influence of the different landmark distributions on the degree of the observability of the VIANS, which will provide a theoretical basis on how to select appropriate landmarks in actual flight.

The main contributions of this paper are as follows. Firstly, a VIANS for UAV based on the known landmarks is proposed, which is relatively simple and can be easily realized in actual engineering. Secondly, the nonlinear degree of the state and observation equations of the VIANS are analyzed to provide a theoretical basis for designing a better navigation filter. Thirdly, the influence of landmark distribution on the degree of observability, convergence speed and estimation accuracy of the VIANS is analyzed through theoretical analysis and simulations verification.

The rest part of this paper is organized as follows. In Section 2, relevant coordinates of the VIANS are defined. In Section 3, the state and observation equations of the VIANS are established. In Section 4, navigation filters for VIANS are designed based on EKF and UKF, respectively. The state and observation equations are linearized and their linearization errors are analyzed. And the performance of the two navigation filters is compared and verified by simulations. In Section 5, the observability analysis of the VIANS is presented based on the Differential Geometric theory and condition number of the observability matrix; the influence of landmark distributions on the degree of observability of the VIANS is analyzed and verified by simulations. Conclusions are given in Section 6.

2. Definitions and transformations of the coordinate frames

1) $Ax_\mathrm{i}y_\mathrm{i}z_\mathrm{i}$ is the ground coordinate frame. It is fixed on the Earth surface. Neglecting rotation and curvature of the Earth, a NEU (North-East-Up) frame can be considered as the ground coordinate frame. The range of the UAV is assumed not very long, so the ground coordinate frame can be regarded as the inertial coordinate frame.
2) $Ox_\mathrm{b}y_\mathrm{b}z_\mathrm{b}$ is the UAV body coordinate frame. The origin O locates at the centroid of the UAV. Ox_b coincides with the longitudinal axis of the UAV body, and its positive direction points to the head of the UAV. Oy_b locates in the longitudinal symmetric plane of the UAV body with its positive direction pointing upwards. Oz_b is perpendicular to the other two axes, and the three axes form a right-handed orthogonal coordinate frame.
3) $O_\mathrm{c}x_\mathrm{c}y_\mathrm{c}z_\mathrm{c}$ is the camera coordinate frame. The origin O_c coincides with O. $O_\mathrm{c}x_\mathrm{c}$ coincides with the longitudinal axis of the UAV body, and its positive direction points to the head of the UAV. $O_\mathrm{c}z_\mathrm{c}$ coincides with the optical axis of the camera with its positive direction pointing to the target. $O_\mathrm{c}y_\mathrm{c}$ axis is perpendicular to the $O_\mathrm{c}x_\mathrm{c}z_\mathrm{c}$ plane, and the three axes form a right-handed orthogonal coordinate frame.
4) $O_\mathrm{p}x_\mathrm{p}y_\mathrm{p}$ is the image plane coordinate frame. The origin O_p is the center of the image plane. $O_\mathrm{p}x_\mathrm{p}$ axis is parallel to the Ox_caxis, and its positive direction is consistent with $O_\mathrm{c}x_\mathrm{c}$ axis'. $O_\mathrm{p}y_\mathrm{p}$ axis is parallel to the $O_\mathrm{c}y_\mathrm{c}$ axis, and they are in the same direction.