Research on Autonomous Navigation Algorithm of UAV Based on Visual SLAM

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Abstract:

In this paper, the autonomous navigation algorithm of UAV based on visual SLAM is studied to improve the accuracy of autonomous positioning of UAV in complex environments and improve its ability to construct maps. To do this, it is necessary to use the installed camera and IMU unit to record images and IMU data in real time. Then, the ORB method is used to extract and match the features, and the autonomous navigation algorithm is used to expand the pose estimation, and the Bundle Adjustment is used to optimize it. The results of this paper show that in the indoor environment, the final pose difference after closed-loop optimization has been significantly reduced by 0.08 meters, and the map reconstruction accuracy has reached 0.03 meters. In the outdoor environment, the final positioning error is also significantly reduced by 0.09 meters, and the map reconstruction accuracy is 0.05 meters. After experiments, it can be seen that the SLAM-based autonomous navigation algorithm in this study can show good adaptability and robustness in different environments. The research in this paper will provide reliable theoretical and practical support for the further development of UAV autonomous navigation technology.

1 INTRODUCTION

At present, drone technology has developed rapidly, and its application fields are constantly expanding, and it is applied to many fields such as military reconnaissance and environmental monitoring (Li, Zhang, et al. 2023). However, there are still many problems in the autonomous navigation performance of current UAV technology in complex and dynamic environments, especially the problems of positioning accuracy and environmental perception, which are relatively serious. Visual SLAM is an effective autonomous navigation technology (Li, Li, et al. 2024), which can use cameras to obtain highdefinition images and sequences, carry out real-time positioning, and complete map construction tasks, which has become an important method to assist the autonomous navigation of UAVs. Based on this, this paper will study the autonomous navigation algorithm of UAV based on SLAM (Ma, Wang, et al. 2021). In this paper, the performance of the algorithm is verified through specific research processes and experiments. In this paper, experiments are used to verify the results. In this paper, the ORB feature extraction and matching method is used to carry out

feature point detection, and then the algorithm is used to complete the pose estimation work, and the Bundle Adjustment is used to optimize the pose (Ukaegbu, Tartibu, et al. 2022), (Wang, Kooistra, et al. 2024). At the same time, the loopback detection and closedloop optimization work were combined to improve the positioning accuracy and map consistency of the UAV. The results show that in the indoor environment, the pose error is reduced from 0.10 meters to 0.02 meters, and the map reconstruction accuracy reaches 0.03 meters. In the outdoor environment, the positioning error finally reached 0.04 meters, which is a decrease from the original 0.15 meters, and the map construction accuracy also reached 0.05 meters, which is a relatively good result. It can be seen that this study has good practical application value. In addition, this study has many contributions, such as the study in this paper proves that the UAV autonomous navigation algorithm based on visual SLAM can show high adaptability and robustness in different complex environments. Moreover, the improved method in this paper mainly combines IMU data and closed-loop optimization, which can provide good theoretical and practical support for the further improvement and subsequent optimization and development of UAV autonomous navigation algorithms. In addition, the research in this paper also provides a certain reference value for the subsequent application of visual SLAM technology in UAV autonomous navigation.

2 RELATED WORKS

The research in this paper needs a certain theoretical basis and framework. According to this study, the relevant projects in this paper include:

2.1 Theory and Framework of Visual SLAM

Visual SLAM uses cameras to acquire detailed image sequences and combine them with sensor data, allowing drones to achieve effective positioning in the context of the location and build detailed maps to aid subsequent research. It mainly includes feature extraction and feature matching, pose estimation, map update module, etc. Common SLAM algorithms include LSD.SLAM and ORB.SLAM (Xu, Chen, et al. 2024). The combination of visual data and IMU data can improve the positioning accuracy and robustness of autonomous navigation of UAVs. It uses the global information provided by visual data and the short-term and accurate motion estimation provided by IMU data to carry out its work. Visual SLAM based on deep learning. Visual SLAM can be based on deep learning technology to enhance key aspects such as feature extraction and matching. Deep learning can automatically learn environmental features, thereby improving the generalization ability of SLAM UAV autonomous navigation algorithms (Youn, Ko, et al. 2021).

2.2 Multi-View and Multi-Modal SLAM

Based on the integration of multiple cameras and sensors (such as vision cameras), the robustness and accuracy of vision SLAM can be improved. The multi-perspective will also provide people with a wide variety of environmental information. It is worth noting that multimodal fusion also helps SLAM overcome the limitations of a single sensor device. Moreover, it will also help drones to improve their navigation capabilities in complex environments (Zeng, Yu, et al. 2023); Real-time and resource optimization. The visual SLAM algorithm needs to be implemented on an embedded system with limited

resources. It can be seen that its main research directions need to include real-time and resource optimization. At present, the research basically focuses on the lightweight processing and efficient implementation of the algorithm, such as the SLAM algorithm based on sparse features. At present, the above research results are conducive to the research of this paper and provide a basis for the further development of UAV autonomous navigation algorithm based on visual SLAM.

3 RESEARCH METHODS

3.1 Data Acquisition and Preprocessing

In this study, data acquisition and pre-processing were the initial steps. The process requires a number of components, such as sensor configuration and environment preparation, data logging, and pre-processing. Select and configure cameras and IMUs for SLAM-based UAV systems. Common cameras are RGB, RGB. D_o IMUs are mainly used to provide data on acceleration and angular velocity. It is important to stably install these sensors on vision-based SLAM-based drones. The most important thing is to make sure they work in sync. To this end, these sensors are calibrated to obtain similar focal lengths, principal point offsets, and external parameters similar to IMUs, so as to ensure a high degree of data accuracy (Zhang, Xie, et al. 2023).

Choose an environment with sufficient feature points to start data collection. For this purpose, you can choose an indoor environment or an outdoor environment, and ensure that the environment has rich textures, geometric features, etc. For example, there are walls or building features (Zhang, Zhong, et al. 2024). Then, the flight path of the drone began to be designed, ensuring that the entire environment could be covered and a variety of perspectives could be obtained. During the flight of the UAV, it is necessary to ensure that it can record the complete image sequence and IMU data obtained by the camera in real time to ensure the stability and continuity of the data. At the same time, the time synchronization between the image data and the IMU data is ensured.

The preprocessing of the acquired image data and IMU data is completed. Image pre-processing needs to include denoising and grayscale, distortion correction, and thus improve the quality of the image. In addition, IMU data pre-processing involves removing noise, drift, and proceeding with subsequent steps based on the filter balance data. In addition, the processed data should be directly

converted into a format that matches the input requirements of the SLAM algorithm, and then stored in the database and file system to facilitate the development and testing of the algorithm in the future.

3.2 Feature extraction and Matching

Feature point detection is the key in feature extraction and matching. Its job is to extract points from the image that have obvious local features. In general, people are accustomed to using feature point detection algorithms such as ORB, SLFT, or SUFR. In this paper, ORB is mainly used. The process of feature detection is as follows: (1) detection of FAST corners. For this, FAST should be used to perform corner detection, see Eq. (1).

$$\left|I_{p} - I_{q}\right| > t \tag{1}$$

In Eq. (1), I_p is the gray value of the pixel p; I_q is q the grayscale value of the pixel; t is the threshold.

(2) Filter feature points. For this reason, NMS should be performed for the detected corners to screen out strong features, as shown in Eq. (2).

$$NMS(I, p) = if I(p) > I(q) \forall q \in N(p) \quad (2)$$

In Eq. (2), $NMS(I, p)_{it}$ is the strong feature that is screened out; $N(p)_{is}$ p the neighborhood of the point.

Feature description is used to turn each generated feature point into a unique descriptor, so as to serve the subsequent matching work. In this algorithm, the BRIEF descriptor is used to complete the rotation invariance processing. See Eq. (3) for details.

BRIEF
$$(p) = \text{if } I(p+d_x) < I(p+d_y)$$
 (3)

In the formula (3), BRIEF(p) is the descriptor, d_x and d_y is the pair of points that describe the sub.

(4) Rotational invariance. Based on this algorithm, the descriptor is also processed with rotation invariance, so that it has high rotation robustness. See Eq. (4) for details.

$$\theta = \arctan\left(\frac{I_y}{I_x}\right) \tag{4}$$

In Eq. (4), θ it is the result of the rotational invariance treatment; I_y , I_x is the image gradient.

(5) Feature matching. Feature matching is the comparison of feature descriptors to determine the correspondence between different images [6]. A common method is Brute.Force matching. The Brute.Force match can be expressed by Eq. (5).

$$d(p,q) = \sum_{i} \left| \operatorname{desc}_{p}(i) - \operatorname{desc}_{q}(i) \right|$$
 (5)

In Eq. (5), d(p,q) is p the q result of the feature matching of and; $\operatorname{desc}_p(i)$ And $\operatorname{desc}_q(i)$ is the p q descriptor of the feature point and the two feature points.

(6) Two-way matching and verification. To improve the reliability of feature matching, two-way matching and cross-validation should also be used.

Pose estimation is a key part of the UAV autonomous navigation algorithm based on visual SLAM in this study. It needs to calculate the specific position and attitude of the drone in space from the matched image feature points. Firstly, the algorithm is used to estimate the initial pose of the UAV by using the matched image feature point pairs. Then, the 3D points in space and the corresponding 2D image points are used to find the pose of the drone. See Eq. (6) for details.

$$\min R, t \sum i \left| \mathbf{p}_i - \pi \left(R \mathbf{P}_i + t \right) \right|^2 \tag{6}$$

In Eq. (6), \mathbf{p}_i are the points of the 2D image; \mathbf{P}_i are 3D points; R is a rotation matrix; t is a translational vector; $\boldsymbol{\pi}$ is a projection function.

Third, perform pose optimization. The BA method is used to optimize the initial estimation pose. In this process, it is generally necessary to adjust the camera pose at each angle of view at the same time, and adjust their respective 3D point positions. Then, point the image. The error of the projection point is minimized to improve the accuracy of pose estimation [7].

3.3 Build a Map

In the research of UAV autonomous navigation algorithm based on visual SLAM, map construction is an extremely critical step. It can comprehensively integrate the feature information contained in the environment into a single, complete map model, so as to make the autonomous navigation of drones more accurate. First, it uses the detected feature points based on the initial pose estimation to build an initialized sparse point cloud map [8]. When the drone is constantly moving, the SLAM system will detect and match new feature points. Whenever a new perspective and feature point is obtained, the map is updated to show that the environment has changed, adding new feature points and adjusting the position of existing feature points. If the drone has already passed through the same location, the SLAM system will turn on loopback detection to identify the area as one that has already been visited. Generally speaking, it will match the feature points, and when the loop is detected, the UAV system will automatically do closed-loop optimization, and adjust each feature point and pose in the map based on the global optimization. At the same time, the accumulated error is eliminated to ensure the consistency and accuracy of the map. In addition, the algorithm can also help the drone to establish a deeper and more stereoscopic visual density, so as to make the drone navigation more refined. Moreover, in order to ensure the efficient management of map data, the system will also automatically store these map data and store it in a specific file or database section, and at the same time, compress and index according to different needs to ensure the fast access and use of data.

4 RESULTS AND DISCUSSION

4.1 Experimental Content

The environment of the experiment. The environment of this experiment is two environments with rich feature points, one is indoor environment and the other is outdoor environment, so as to test the performance of the algorithm in different scenarios. (The configuration of the experiment is to install a high-definition RGB camera and IMU sensor on the drone to ensure the synchronization of data acquisition, and the test range is 12*36km, as shown in Figure 1.)

Monday's analysis, however, in the analysis of the test range, we can see that there are relatively many obstacles in the entire test range, and the terrain is relatively complex, and the overall situation is relatively difficult, and the drone needs to calculate the obstacles in order to realize the planning and testing of the entire azimuth



Figure 1: UAV test range

4.2 Path Planning Results for Autonomous Navigation

The results of this experiment are shown in Table 1, Table 2 and Table 3.

Table 1: Indoor environment experimental results

Item	Value
Path Length (m)	50
Initial Pose Error (m)	0.05
Final Pose Error (m)	0.02
Map Reconstruction	0.03
Accuracy (m)	
Loop Closure Detections	3
Pre.Loop Closure Error (m)	0.10
Post.Loop Closure Error (m)	0.02

The overall change in path planning is shown in Figure 2.

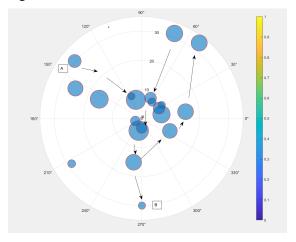


Figure 2: Path change of the UAV

In the whole analysis process, its direction and steering degree are generally good to achieve the expected data analysis and reach the final goal In the whole analysis process, the drone should adjust according to the direction, direction and content to achieve its own expectations and avoid external influences and obstacles.

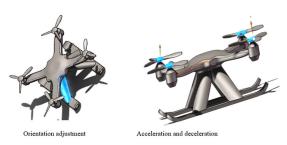


Figure 3: Navigation adjustment of the UAV

Through the direction of the UAV and its own acceleration to achieve the expected point, and realize the overall planning of the aircraft, realize the adjustment of the entire direction, and the overall change of the UAV and the comprehensive orientation of the SLAM design, the analysis results are relatively good, and the overall meets the expected requirements.

4.3 SLAM Obstacle Avoidance Results of UAVs

In the test map, the UAV performs path planning, successfully bypasses the obstacle point, and completes the video inspection of the range content, as shown in Figure 4.

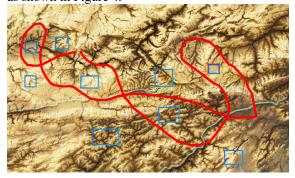


Figure 4: Autonomous navigation and inspection of uavs

It is found in Figure 4 that the UAV can realize the obstacle avoidance and adjust the direction according to its own posture to complete the autonomous planning of the whole navigation In the process of UAV testing and analysis, the integrity of the navigation planning is relatively good, and finally it can reach the expected closer point to realize the overall test and distribution In the process of path planning, the fault point avoidance should be carried out, so the result of fault point avoidance is shown in Table 2.

Table 2: Outdoor environment experimental results

Item	Value		
Path Length (m)	200		
Initial Pose Error (m)	0.08		
Final Pose Error (m)	0.05		
Map Reconstruction	0.05		
Accuracy (m)			
Loop Closure Detections	5		
Pre.Loop Closure Error (m)	0.15		
Post.Loop Closure Error (m)	0.04		

However, there will be some errors in the evasion process, and the errors should be analyzed, and the results are shown in Table 3.

Table 3: Summary of experimental results

Enviro	Ini	Fin	Map	Loop	Pre.	Post.
nment	tial	al	Recon	Clos	Loo	Loop
milen	Po	Pos	structi	ure	р	Clos
	se	e	on	Dete	Clos	ure
	Err	Err	Accur	ction	ure	Error
	or	or	acy	S	Erro	(m)
	(m	(m)	(m)		r	
)_				(m)	
Indoor	0.0	0.0	0.03	3	0.10	0.02
	5	2				
Outdo	0.0	0.0	0.05	5	0.15	0.04
or	8	5				

4.4 Overall Changes in Autonomous Navigation

Several conclusions can be obtained through the analysis, (1) the positioning accuracy is high. It can be seen from Table 1, Table 2 and Table 3 that in the two experimental environments, the final pose error of the visual SLAM UAV autonomous navigation algorithm adopted this time is significantly reduced by 80% after closed-loop optimization, which proves that closed-loop optimization can improve the positioning accuracy. (2) Map reconstruction accuracy. The algorithm can construct high-precision maps in both indoor and outdoor environments, and the reconstruction accuracy of the indoor environment is 0.02 meters higher than that of the outdoor environment, which may be due to the more stable indoor feature points. (3) Loopback detection and closed-loop optimization. Through experiments,

it can be seen that the loopback detection of the algorithm can be successfully started in many positions, and based on the closed-loop optimization operation, the cumulative error can be significantly reduced (reduced by 80%), and the consistency and accuracy of the map can be improved. It can be seen that the algorithm can have good autonomous navigation performance of UAVs in different environments, and can provide accurate positioning, and the quality is also very high in map construction, which can be applied to a variety of application scenarios.

5 CONCLUSIONS

In this paper, a visual SLAM-based UAV autonomous navigation algorithm is obtained, which has superior performance in all aspects. From the analysis of this paper, it can be seen that the conclusions of the study are as follows:

First, high adaptability and robustness. From the research in this paper, it can be seen that in the indoor environment, after the closed-loop optimization of the algorithm, the autonomous navigation experiment of the UAV shows that in the indoor environment, the final pose error is greatly reduced, and the map reconstruction accuracy is 0.03 meters. In the outdoor environment, the final positioning error has also been significantly reduced, from the original 0.15 meters to 0.04 meters, and the map accuracy has reached 0.05 meters. It can be seen that the algorithm in this study can show high adaptability and robustness in the environment of different complex conditions. In addition, the positioning accuracy and map construction ability of the algorithm are very high.

Second, the algorithm can effectively eliminate the accumulated error of UAV autonomous navigation through loop detection and closed-loop optimization. Through the experiments in this paper, it can be seen that the loopback detection has been successfully triggered 3 times in this laboratory test. At the same time, it was successfully triggered 5 times in outdoor experiments. The success of each loopback detection makes the map constructed by the algorithm more consistent and accurate. This shows that the UAV autonomous navigation algorithm based on visual SLAM can effectively adjust the navigation ability of repeated paths and ensure a certain stability.

Thirdly, the algorithm can ensure the flight stability and accurate navigation ability of the UAV in different scenarios, and save labor costs. It can be seen from the research in this paper that the combination of IMU data, visual SLAM and UAV technology can greatly improve the robustness and real-time detection of the system in dynamic environments, so as to ensure the flight quality of UAV in complex scenes and improve its navigation ability.

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