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Research on Multi-Sensor Data Collection and Mapping Methods

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ABSTRACT

In today's information society, the importance of collecting data through multiple channels continues to increase. This article focuses on the use of drones for large-area forest information collection and tree analysis. In complex environments, there are a series of problems in obtaining tree mapping information with a single sensor, such as single use scenarios, low accuracy, limited viewing angles, and high requirements for computing power. To address these challenges, this paper proposes a Bayesian-based multi-sensor fusion strategy to overcome the limitations of a single sensor by integrating depth camera and lidar data. Experimental results show that the proposed method significantly improves the accuracy of mapping surrounding trees and the ability to collect information. The multi-sensor fusion strategy effectively reduces the problem of repeated data processing and improves the comprehensiveness of collected data. It meets the requirements of real-time performance and accurate collection of surrounding scenes.

KEYWORDS

3D lidar; Depth camera; Point cloud fusion; Bayesian estimation

1. INTRODUCTION

In recent years, UAVs have received widespread attention due to their high maneuverability and adaptability to terrain [1], and have been widely used in search, rescue, cargo transportation and other fields [2]. However, most UAVs are mainly used for fixed outdoor environments or indoor high-speed flight. This article aims to solve the mapping and obstacle avoidance problems encountered when collecting information in large forests in the wild.

Traditional UAV obstacle avoidance solutions are mainly based on a single sensor, such as radar or camera, but these methods have limitations in dense forest environments. To this end, this paper proposes a Bayesian-based multi-sensor fusion strategy that combines depth camera and lidar data. Currently, research on multi-sensor fusion [3] mainly focuses on two directions: probability-based and deep learning-based. This article focuses on methods based on probability, such as the multi-sensor information fusion strategy based on Kalman filtering in the literature [4]. However, this method has high computational complexity when dealing with nonlinear systems. In order to solve this problem, literature [5] proposed a multi-sensor fusion method (NNMDF) based on neural networks. However, due to the high requirements of neural networks on computing power and the limited applicability in forest environments. Among the existing methods, literature [6] proposed a camera and millimeter wave radar fusion scheme, but its effect is not good and does not meet the usage scenario of this article. On the other hand, literature [7] proposed a fusion strategy based on Bayesian filtering based on two-dimensional and three-dimensional sensors for indoor environments. However, in understory environments with dim light and numerous small obstacles, a more applicable Bayesian fusion strategy is needed.

Therefore, this paper proposes an improved Bayesian fusion algorithm to adapt to the data fusion of three-dimensional lidar and depth cameras, which meets the requirements of identifying small obstacles and real-time mapping in the understory environment. Experiments prove the superiority and feasibility of the proposed method.

2. MULTI-SENSOR FUSION DRONE DATA COLLECTION STRATEGIES AND METHODS

In view of the limitations of a single sensor, this paper proposes a mapping method based on multi-sensor fusion. The improved strategy is used to fuse the information of multi-line lidar and depth cameras, and is verified and simulated under the robot operating system ROS. The backend of the algorithm uses fused information to establish a navigation decision model to implement UAV path planning. The main process of UAV information collection is shown in Figure 1:

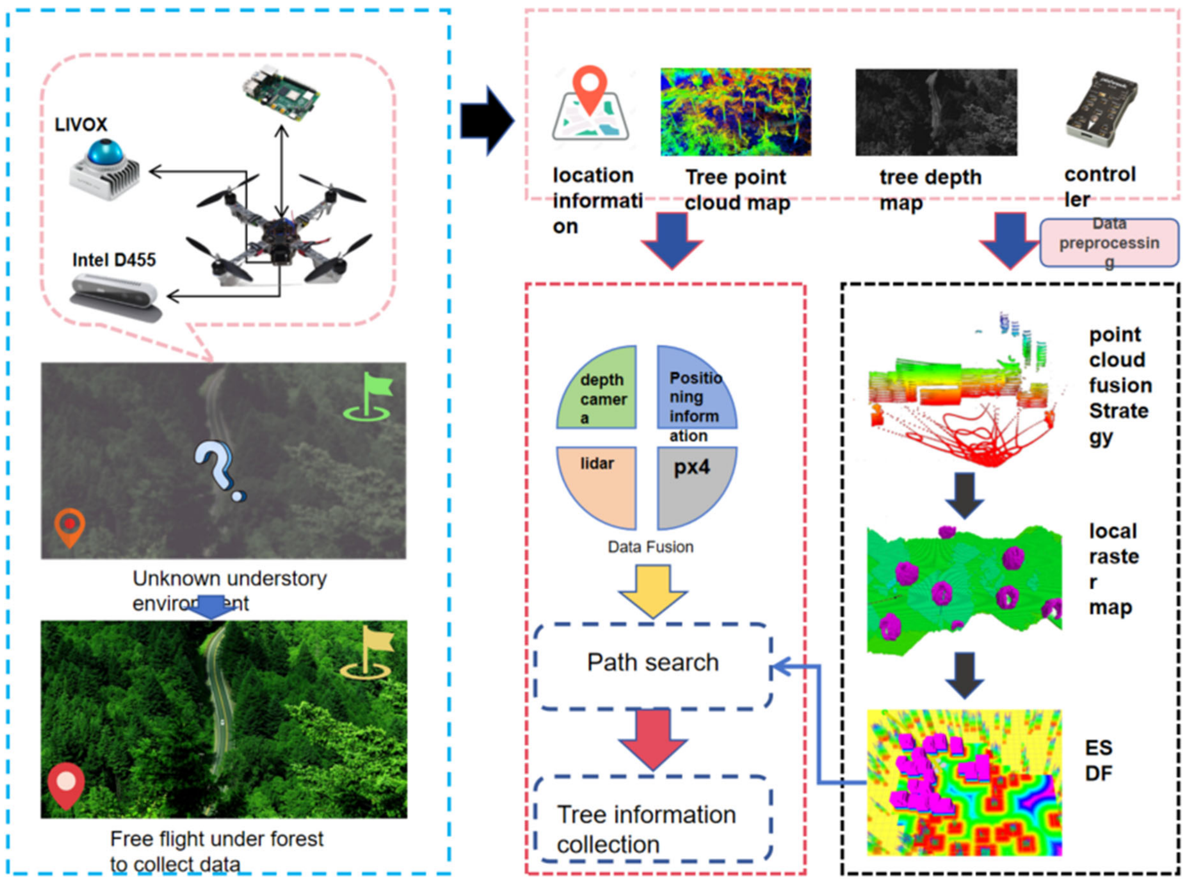

Figure 1: Data collection main process

2.1. Multi-sensor temporal and spatial synchronization

In the autonomous flight data collection mission of UAVs under the woods, the high consistency requirement for multi-sensor data is particularly critical. Considering the different installation positions of lidar and depth cameras on UAVs, in order to ensure their consistency in the same coordinate system before merging point clouds, it is necessary to ensure that the data obtained from the camera and lidar sensors are consistent with the spatiotemporal coordinate system. match. Time matching involves ensuring precise synchronization between different sensors, while common coordinate system matching requires geometric correction of external parameters between the three-dimensional coordinate systems of the sensors [8].

Rigid transformation can transform point clouds in two different coordinate systems into the same reference coordinate system. Assume that there are two point clouds that need to be registered, namely point cloud P and point cloud Q. The overlapping part is displayed by minimizing the distance between corresponding points. Point cloud registration is essentially a rigid transformation. Convert the point cloud P to the coordinate system where the target point cloud[9] is located, and express it through formula (1).

$$P = R * Q + T \tag{1}$$

Due to differences in the data collection frequency of each sensor, for example, the frequency of an IMU sensor can be as high as 100Hz, lidar is usually 10Hz, and the frequency of a depth camera is roughly 30Hz. Therefore, before data preprocessing, each coordinate system needs to be converted and synchronized in time.The time synchronization diagram is shown in Figure 2 below:

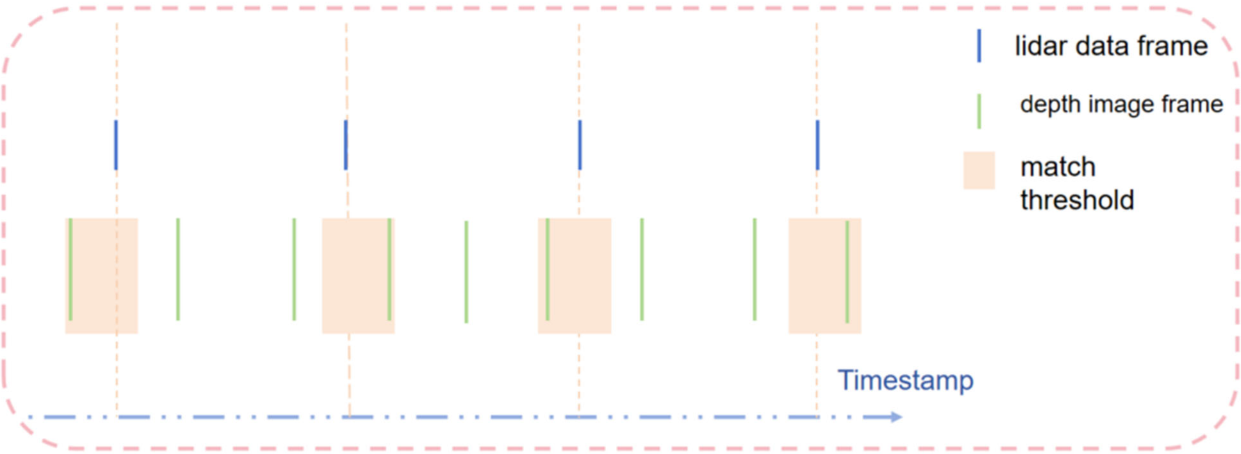

Figure 2: Timestamp alignment diagram

2.2. Improved Bayesian point cloud fusion algorithm

When a single sensor collects information[10], it will be limited by the collection angle. For example, the angle collected by the lidar used in this article is a semicircle, and the depth camera is a rectangular box. Simply superimposing multi-sensor point clouds will result in a large amount of duplicate data, which will increase the amount of calculation and memory usage. The sensor field of view is shown in Figure 3 below, in which the semicircle is the effective field of view of the lidar, and the orange rectangular frame is the field of view of the speed camera:

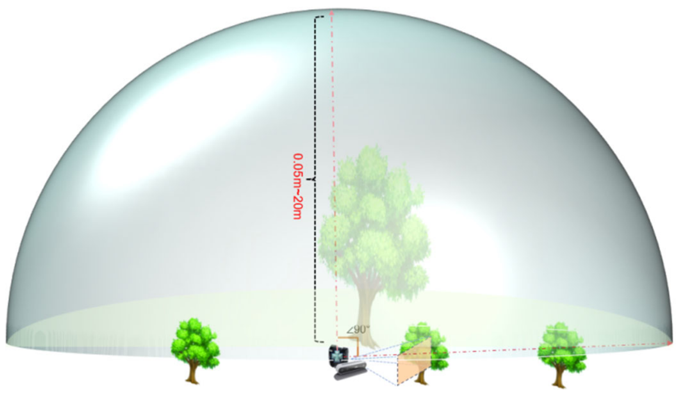

Figure 3: Sensor perspective diagram

For the three-dimensional point cloud information obtained by multi-line lidar and the depth information obtained by the depth camera, it is applied to the probability-based Bayesian[11] inference model method [10] for fusion. This method can predict n based on the existing vector Z. dimensional vector X, assuming the probability of observation and this time, the prior distribution is as follows:

$$p(x_k| Z^k) = \frac{p(z_k| x_k)p(x_k| Z^{k-1})}{p(Z^k| Z^{k-1})} \quad (2)$$

In the formula, $p\left(z_k| x_k\right)$ is the likelihood function based on the given sensor observation model; $p\left(x_k| Z^{k-1}\right)$ is the prior distribution of the conversion system model; $p\left(Z^k \middle| Z^{k-1}\right)$ is the normalized probability density function.

The point cloud map update strategy is based on the Bayesian model fusion strategy. O It means that the observed point cloud exists, O it means that the observed point cloud does not exist, A it means that the point cloud actually exists, and $\bar{A}$ it means that the point cloud actually does not exist. The above posterior probability is as follows:

$$P(A|O) = \frac{p(O|A)p(A)}{p(O|A)p(A) + p(O|\overline{A})p(\overline{A})} \quad (3)$$

$$P(A \mid \overline{O}) = \frac{p(\overline{O} \mid A)p(A)}{p(\overline{O} \mid A)p(A) + p(\overline{O} \mid \overline{A})p(\overline{A})} \quad (4)$$

According to the above strategy, the probability formula for updating the fused point cloud is as follows:

$$P = \frac{P_s P_m}{P_s P_m + (1 - P_s)(1 - P_m)} \quad (5)$$

Among them, P represents the probability value of fused point cloud update， $1-P_m$ and P_m respectively represents the prior probability of the existence of point clouds in the indoor environment, and the size is 0.5, P_s represents the likelihood probability that the depth camera detects the existence of point cloud.

3. EXPERIMENTS AND ANALYSIS

3.1. Build an experimental platform

The lidar used is Yushu four-dimensional lidar L1. This three-dimensional lidar has a ranging range of 0.05~15m, which can easily achieve medium and short range detection. Its scanning angle is 360°*90°, the scanning frequency is 10~15Hz, and the generated point cloud reaches 21,600 points/second. L1 uses omnidirectional ultra-wide-angle non-repetitive scanning, which can obtain high-precision and high-density point cloud data to achieve image-level scanning effects. In addition, this lidar has good anti-interference ability against indoor ambient light and outdoor strong light. Its low cost makes this technology widely feasible in practical applications. In addition, this paper also introduces a depth camera as a fusion sensor, which can output depth maps and RGB images. Specifically, OBI Zhongguang's Dabai series depth camera is used. Its detection distance range is

0.2~2.5m, the depth image resolution can reach up to 640*320, the depth accuracy at 1m can reach 12mm, and the average power consumption is less than 2w. It is suitable for for mobile robots.

3.2. Data collection accuracy experiment

This paper carries lidar and depth cameras on the UAV platform to conduct UAV mapping flight research. The experiment is conducted outdoors in a densely populated area with trees. The experimental site is shown in Figure 4 below:

Figure 4: Experimental woods

Using the Bayesian fusion strategy proposed in this article to perform Bayesian rule fusion on data obtained from two different sensors can effectively reduce the increase in calculations caused by multiple sensors while meeting the requirements of all-round information collection and autonomous navigation. , repetitive issues. The mapping results are shown in Figure 5 below, which can supplement the lidar's field of view.

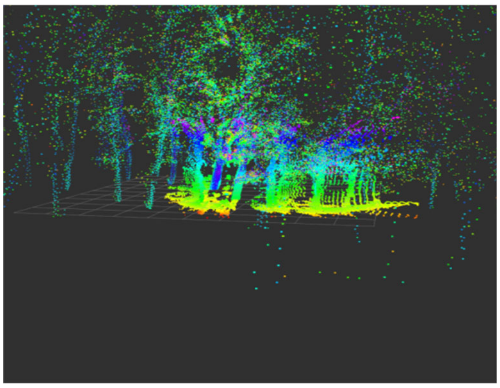

Figure 5: Point cloud fusion

In order to objectively verify the improvement in point cloud accuracy of multi-sensors, this article uses the trajectory prediction tool Evo for comparative evaluation. The data information of the trajectories obtained by running multi-sensors and single sensors in the odometer are comparatively evaluated. The specific analysis results are shown in the figure below, It can be seen that compared with the trajectory reference green line in the figure below, the average error of the red line before fusion is greater than the blue line。

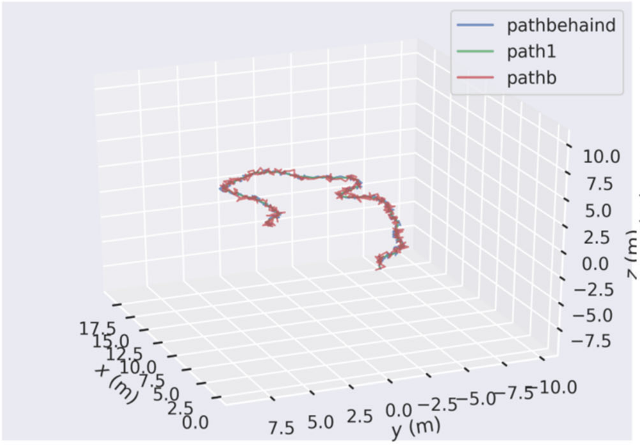

Figure 6: Trajectory diagram

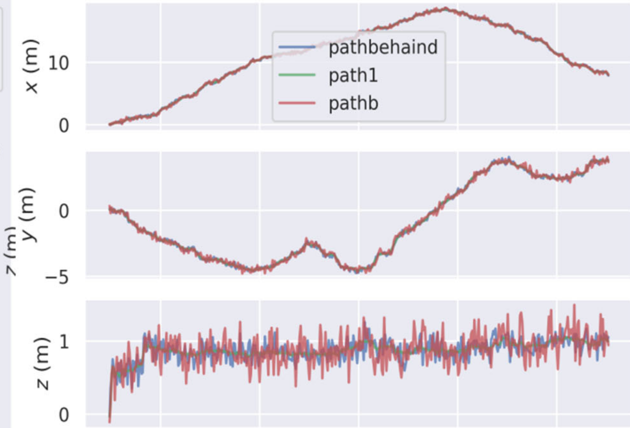

Figure 7: Error of each axis

3.3. Analysis of mapping results

Experimental results show that after merging point clouds, tree information collection is more complete and realistic. Not only can information be collected above the drone, but also where a single sensor is insufficient, another sensor can make up for it. The environment area of this experiment is about 400 square meters, and the trajectory of the robot is about 50 meters. The specific data of the map is as shown in the table below.

Table 1. Data sheet

Mapping method	Mapping speed/m.s	Field of view mapping range	Tree information collection density	Average error/m
Single sensor	0.0142	2	21500	0.0095
Multi-sensor fusion mapping	0.134	1~10	100000	0.0054

As can be seen from Table 1, although the point cloud fusion strategy proposed in this article has a slower fusion speed than a single sensor, it can effectively improve the accuracy and breadth of information collection.

4. CONCLUSION

This paper improves the multi-sensor fusion and global mapping strategies to enhance its information collection capabilities, reduce the amount of calculations, and increase the accuracy of environmental description. Running SLAM shows that the fused environmental point cloud information has better structure and accuracy, its predicted ontology trajectory is better, and its positioning is more accurate. After flight testing under actual woods, the accuracy of the range of collected tree information has been increased, effectively overcoming the disadvantages of data duplication from multiple sensors.

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