UAV Map Construction and Path Planning System based on SLAM Technology

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Abstract. In recent years, people's technological advancement has led to the rapid development of drone technology, but there is still a long way to go before the realisation of drone technology that does not require a human to operate it. Currently, people's drone technology is at the stage where it does not require humans to enter the cockpit to operate it, but only needs to be remotely controlled from a remote location.However, with the current level of science and technology, it is not yet possible for people to realise the autonomous path planning function of UAVs in unfamiliar environments and completely out of people's control, relying only on their own fitted sensors to realise according to the coordinates and characteristics of the destination.Therefore, to address the problem that UAVs cannot realise autonomous obstacle avoidance, this paper proposes a new design idea to explore the feasibility of combining SLAM technology and UAV technology, so that UAVs can acquire the surrounding environmental data through visual and laser sensors and feedback the data to the SLAM system after being instructed. The SLAM system constructs a map model of the surrounding environment from the data returned, and uses the cell decomposition method and the artificial potential field method to carry out autonomous path planning on this map to achieve the effect of autonomous obstacle avoidance for UAVs.

Keywords: UAV, SLAM Algorithm, Path Planning.

1 Introduction

Initially, UAV was mainly used in the military field. It has repeatedly accomplished various military tasks with outstanding achievements in wars, such as signal information collection, and target localization. Therefore, it has great potential and value in military operations. Nowadays, the technology of military UAV is increasingly mature, playing many roles such as reconnaissance, decoy, and interference. Meanwhile, UAV is also widely used in civilian field, such as aerial photography, meteorological research and disaster rescue. At present, UAV technology is capable of remote control at the remote end. However, there is still

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defects for the autonomous path planning and obstacle avoidance function after the UAV is removed from remote control manipulation. With the development of UAV technology, the intelligence and autonomy of UAV is an inevitable trend of development. Among them, map construction and path planning of UAV are the major problems. There are already some practical solutions for autonomous UAV localization and path planning in known environments. However, it is still the focus of research to create a map and use it for path planning in extreme or completely unknown environments so that it can complete tasks autonomously and efficiently. Simultaneous Localization and Mapping (SLAM) has become one of the mainstream research directions to solve this problem.

SLAM technology enables a mobile robot to construct a map consistent with its surroundings and determine its current position. Therefore, solving SLAM technology is the focus of achieving UAV autonomy. In 1986, SLAM technique was proposed by two researchers, Smith and Cheeseman [1]. With the introduction of probability into the SLAM technique, the robot's position and the noise of its operation can be displayed by using a method based on probability distributions. Thus, SLAM technology was first widely used in the field of robotics. Nowadays, SLAM techniques allow UAV to use sensors to collect data in unfamiliar environments and combine their data for map construction and simultaneous localization. The current mainstream SLAM technologies are broadly classified into three categories, namely laser SLAM, visual SLAM, and multi sensor assisted laser/vision multi-sensor fusion SLAM technology. In unpredictable and complex environments with various obstacles such as indoors, mountains and forests, GPS is unable to fulfil its tasks due to problems such as insufficient observation satellites and interference with signals. Based on the above problems, a map construction and path planning system can be performed using SLAM algorithms with laser and vision sensor fusion.

In recent years, the research on visual SLAM technology has made great progress. In this paper, visual SLAM technology is applied to UAV. It describes how the UAV can construct map information of its surroundings in an unknown environment by using visual SLAM technology assisted by laser sensors. Simultaneously, it locates the UAV and applies it to the path planning to finally achieve the obstacle avoidance function. Firstly, this paper will provide an overview of how to achieve map construction using vision SLAM technology from five aspects: information acquisition from visual sensors, visual odometry, loop closing, back-end optimization and mapping. The common methods that currently exist in each step are summarized and compared. After that, how it can be implemented in combination with laser sensors is described. Then in terms of path planning, two path planning methods, approximate cell decomposition method and artificial potential field method, are introduced in detail. Finally, the existing problems of UAV SLAM technology path planning are discussed and relevant suggestions are made.

2 Map Construction with Visual SLAM Algorithms

Visual SLAM can be roughly divided into five steps: information acquisition from visual sensors, visual odometry (VO), loop closing, back-end optimization and mapping [2]. Its general flow is shown in Figure 1. Firstly, data is collected through visual sensors and then it is inputted into the front-end. Then, based on its collected data, the motion relationship of the images at adjacent moments can be analyzed by the front-end visual odometry to estimate the motion trajectory of the UAV and its position. However, it inevitably generates a drift problem. Therefore, in order to reduce the cumulative drift problem caused by computational and motion aberrations, the vision SLAM algorithm performs loop closing. It uses the bag-of-words model of vision to determine whether the UAV returns to the once-passed position by calculating the similarity between images. Meanwhile, noise is generated due to the process of mapping. Therefore, the back-end optimization is used to deal with the noise problem in the visual SLAM algorithm to correct the shape of the UAV trajectory. Finally, a 3D point cloud of the scene can be acquired in real time based on the optimized data from the back-end, and a grid map can be built using the point cloud projection.

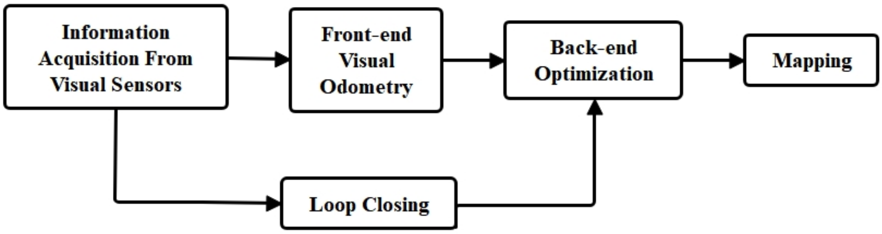

Fig. 1. Visual SLAM algorithm framework

2.1 Information Acquisition from Visual Sensors

The commonly used visual sensors for visual SLAM algorithms are usually categorized as monocular cameras, binocular cameras and RGB-D cameras. They are used to collect images of the surrounding environment and pre-process the information. Afterwards, the data is inputted into the front end. The main difference between the three is the availability of depth information. Among them, monocular camera means that only one camera is used to complete the data collection. It relies on triangulation in motion to calculate camera motion and estimate the spatial position of pixels. It does not have direct access to depth information and needs to move the camera to generate depth. Binocular camera refers to a camera with two lenses that can acquire 3D information and 2D images simultaneously. The two lenses can acquire images from different viewpoints of the same scene, and then the distance between the images and the real 3D information can be obtained through calculation. It can acquire depth information through parallax, but the calculation is larger. RGB-D camera can directly measure the distance of each pixel from the camera through infrared structured light or TOF principle. Depth information can be obtained as with binocular cameras, but it does not need to be obtained computationally. Table 1 lists the advantages and disadvantages of each of the three cameras to provide a reference for camera selection.

Table 1. Comparison of the advantages and disadvantages of the three cameras

Camera type	Advantage	Disadvantage
Monocular Camera	Low cost Wide field of view Unlimited detection distance	Scale Uncertainty Initialization problems No direct access to depth information
Binocular Camera	Unlimited distance Calculated depth	Complicated configuration High computational effort Restricted viewing angle
RGB-D Camera	Active depth measurement Direct acquisition of depth information	High cost Large size Short detection distance Interference by sunlight and material

2.2 Visual Odometry

The visual odometry is the front-end of the visual SLAM system. It provides data to the back-end by roughly estimating the motion of the camera based on the relationship between neighbouring images after the images are input to the front-end. In visual SLAM, there are two methods, feature point method and direct method, depending on whether features are extracted or not.

The filtering and extraction of feature points from the image output by the visual sensors using a visual odometry is called the feature point method. It obtains the camera motion between neighbouring frames by matching the feature relationships on the image. This method reduces the number of points that need to be matched in the algorithm, thus reducing the complexity of the algorithm and increasing the running speed of the algorithm. It has relatively high initialization adaptability. However, this method causes the loss of a large amount of additional information, resulting in the construction of maps containing less information. It obtains the camera motion between neighbouring frames by matching the feature relationships on the image. This method reduces the number of points that need to be matched in the algorithm, thus reducing the complexity of the algorithm and increasing the running speed of the algorithm. It has relatively high initialization adaptability. However, this method causes the loss of a large amount of additional information, resulting in the construction of maps containing less information. In addition, the number of feature points is usually affected by the texture. Therefore it is difficult to extract its feature information on texture-less obstacles such as walls and glass. Examples of utilizing the feature point method are SLAM algorithms based on scale-invariant feature transform (SIFT) [3], algorithms based on Speeded Up Robust Features (SURF) [4],

algorithms based on Features from accelerated segment test (FAST) features and so on [5].
The direct method directly calculates the camera motion based on the difference in pixel grey levels. It can process all the pixels directly, and it maintains the complete image information after the computation. The information included in the construction of the map is much more than the feature point method. However, it is based on the assumption that the grey values of spatial points are constant. This assumption is difficult to be satisfied due to the influence of factors such as illumination and the camera itself in reality. Therefore, the stability of the system constructed by the direct method is relatively poor.For example, large-scale direct monocular SLAM (LSD-SLAM) randomly initialize the depth of pixels during the initialization process [6]. As the algorithm runs, according to the newly acquired positional information and pixel information, the depth values of the pixels gradually converge to achieve the construction of the map.

2.3 Loop Closing

Loop closing determines whether the UAV passes through the same place or not. It matches the current image features with the images that have been saved in the visual SLAM algorithm. If the similarity exceeds the set value, then it proves that the UAV has returned to the previously passed location. After that, constraint information is provided to the back-end optimization to correct the cumulative error. The problem of SLAM algorithm accuracy after long UAV flights is effectively improved. Since a large number of images are required to find features quickly and accurately for matching, it leads to excessive computation. Therefore, in order to improve the efficiency of the loop closing, vision-based Bag of Word (BoW) model is proposed. For example, FAB-MAP creates the bag of word using Chow-Liu tree theory [7]. It uses feature information extracted from large-scale image datasets as words through the SURF algorithm. However, the loop closing of bag of word is less effective for similar environments because it is highly influenced by the collected training set.

2.4 Back-end Optimization

Images usually suffer from various degradation such as low contrast, colour distortion and noise. The back-end optimization mainly deals with the noise problems present in the visual SLAM and improves the image quality. Therefore it is a critical part of map construction using visual SLAM. According to the different optimization methods, the back-end optimization is divided into two methods: filter and nonlinear optimization.
For the use of filters, the Mono-SLAM algorithm is a kind of optimization of the extracted feature points using an extended Kalman filter (EKF) [8]. It allows 3D trajectory reconstruction in unknown environments using a fast-moving monocular camera, ensuring real-time and drift-free performance from the structure to the motion model.

For nonlinear optimization, the parallel tracking and mapping (PTAM) algorithm proposes a front-back separation architecture [9]. It filters the key frames and extracts the feature point information in them. Its back-end uses a nonlinear method of bundle adjustment (BA). It significantly improves the efficiency of processing feature points in the back-end and thus improves the efficiency of back-end optimization. BA is a nonlinear optimization method based on graph optimization. The points in the graph represent the camera's position and the location of the feature points, and the lines represent the camera's observation of the feature points.

2.5 Mapping

Mapping is mainly based on back-end optimization data to construct maps corresponding to the surrounding environment. Based on RGB-D cameras, UAV can obtain real-time 3D point clouds of the scene. Meanwhile, point cloud projection can be used to establish local grid maps.

2.6 Laser and Visual Sensor Fusion

Visual SLAM algorithms can work stably in texture-rich dynamic environments, providing very accurate point cloud matching for laser SLAM. However, it relies on feature information in the environment. Therefore, when encountering a textureless environment, it is easy to lose tracking and reduce the accuracy of the map. In contrast, laser SLAM can localize in featureless environments. In addition, the camera is sensitive to light changes, resulting in possible problems in localization. Therefore, the accuracy of visual SLAM algorithms is low for low light environments. Laser sensors can operate stably in environments except for direct bright light, providing accurate distance information. Hence, fusion of laser and vision sensors can improve the accuracy of UAV localization and mapping by combining and complementing the advantages of both [10, 11]. Laser stability can be used to assist visual SLAM algorithms. When visual SLAM tracking is lost, the laser sensor can transmit the obtained position information to the visual SLAM system for secondary initialization until the visual SLAM system tracks successfully [11].

3 Path Planning

3.1 Methods of Path Planning

Unit Decomposition Method. When performing path planning, researchers use cellular decomposition to accomplish offline planning for full-coverage paths in statically known environments.The cell decomposition method is implemented by the following three steps, firstly, the free space in the bitmap space is divided into a number of small regions, each region as as a cell. Then a connectivity graph is formed with the cells as vertices and the neighbourhoods between the cells as edges.Second, cells containing an initial attitude and a target attitude are searched for in the connectivity graph, and paths linking the initial and target cells are searched. Finally, generate intra-cell paths based on the resulting sequence of path cells. The cell decomposition method is mainly divided into two categories: exact cell decomposition and approximate cell decomposition.

Artificial Potential Field Method. In robot path planning for obstacle avoidance, Kahatib proposed a local path planning algorithm called "artificial potential field method". The basic principle is to construct an artificial potential field. The obstacle is in high potential energy and the target point is in low potential energy.The potential energy difference between the obstacle and the UAV will form a combined force in different directions, and the low potential energy is attractive to the UAV man. After vector superposition of all the forces, a combined force will be generated, which is called the virtual force of the potential field [12]. The UAV is driven by the virtual force to approach the target point.

3.2 Path Planning System

In this paper, the rasterised map constructed by using SLAM technology on the surrounding environment and obstacle data returned from the UAV, and the location of its shape is marked in the rasterised map. After the UAV path planning system (hereinafter referred to as the system) then determines the start and end points, the system performs global flight path planning in the raster map using the Boustrophedon cell decomposition method. When an obstacle is encountered, the system adjusts the local flight path using a combination of simulated annealing and artificial potential field methods to avoid collision between the UAV and the obstacle.

Global Route Planning. After constructing the rasterised map, the UAV's surroundings can be broken down into multiple independent and bounded areas free of obstacles by using the Boustrophedon cell decomposition method and the added decomposition rules. The Boustrophedon cell decomposition method involves scanning the raster map from left to right with a vertical line. The connectivity of the scan line increases as it sweeps into the obstacle space and decreases as it sweeps out of the obstacle space [13]. When the connectivity of the scan line increases, one old unit ends and two new units are generated; when the connectivity decreases, two old units end and one new unit is generated [13]. After changing the spatial shape of the obstacle on the raster map, if there is an obstacle part inside the cell, the scan line connectivity remains unchanged. However, if the length of the scan line changes by more than half of the maximum width of the current cell, the old cell ends and a new cell is created.Other cases will only increase the size of the unit, rather than ending the old unit or creating a new one. Once the sweep is complete, it is determined that there are no obstacle sections within each cell. Subsequently, each cell is viewed as a node, and if similar nodes have connected regions, it can be assumed that these neighbouring nodes can be connected by edges to form a graph. The Manhattan is used in the raster graph to calculate the weight of each node connected to its edges through the edges, followed by the D* algorithm to complete the local path planning, thus achieving the function of global path planning.

Local Path Planning. During autonomous UAV flight, laser SLAM constructs a real-time rasterised map of the surrounding environment. The UAV marks the dynamic obstacles around it in the rasterised map and brings the data into an artificial potential field algorithm to obtain a locally optimal path. However, due to the following problems will be encountered when using the artificial potential field method for local path planning: when the gravitational force of the target point for the UAV and the repulsive force of the obstacle for the car are equal in size and opposite in direction, the UAV will form a state of equilibrium, which makes it unable to continue to fly; when there are multiple obstacles around the UAV, the repulsive field formed by a combination of multiple obstacles will make the UAV obtain the path planning to fall into a local optimal solution, and it will not be able to achieve successful obstacle avoidance [14]. In order to prevent this situation, some scholars have proposed that the simulated annealing method and the artificial potential field method can be combined, so that when the unmanned vehicle is caught in the local optimal solution it can be iterated and screened for solutions within a certain range of this solution. When there is another point that meets the conditions and is better than the previous optimal solution then repeat the above operation for the current optimal solution until the target point is reached.

4 Discussion

The path planning system proposed in this paper, which combines SLAM technique, cell decomposition method and artificial potential field method, is only applicable to UAVs flying in ideal environments and cannot be used in real environments yet. There are several reasons why the path planning system proposed in this paper cannot be used well in practice. 1) In this paper, the path planning method uses SLAM technology to construct a raster map of the environment and obstacles around the UAV in real time. However, due to the complexity and randomness of the real environment, constructing a raster map of the real-time environment requires more rasters, which increases the computational complexity and reduces the system robustness. 2) In local path planning, the path planning system will use SLAM technology to construct the global map, but only a small part of the map information is used, and most of the map area will not be used. This leads to a reduction in the real-time performance of the UAS. If only local map information is used, it leads to incomplete map information and increases the possibility of the UAV falling into a local optimal solution. 3) When unit decomposition is carried out in unknown environments with irregular distribution of obstacles, due to the poor real-time performance of the unit decomposition method and the easy existence of a large number of division units. This will make the planned path appear redundant steering, thus reducing the effectiveness of path planning.

5 Conclusion

Before realizing path planning for UAV in unknown complex environments, map construction of the surrounding environment is required. Based on the vision SLAM system, this paper summarizes and analyses the benefits and drawbacks of the common methods currently used to construct maps of unknown environments using UAV from five aspects: information acquisition from vision sensors, front-end vision odometry, loop closing, back-end optimization and mapping. Afterwards, the method of combining laser and vision sensors is illustrated. In addition, in terms of path planning, when in a static environment, the constructed map can be scanned and divided using the approximate unit decomposition method to achieve local path planning. Afterwards, the method of combining laser and vision sensors is illustrated. Meanwhile, in a dynamic environment, the artificial potential field method can be used for UAV path planning. With the continuous development of UAV technology, some aspects of the SLAM technique may be replaced by other methods. However, in order to meet the UAV can effectively complete the task, the improvement of algorithms and robustness of the SLAM system is still the focus of the current research in the field of UAV. It is believed that with the deepening research on visual SLAM system, it can play a vital role in the field of UAV map construction and path planning in the future.

6 Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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