

Development of a drone obstacle avoidance system based on depth estimation

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Abstract

This study developed an obstacle avoidance system for drones using depth estimation from RGB cameras, aiming to reduce reliance on expensive sensors like RGB-D cameras or LiDAR. The system employs the deep learning model ZoeDepth for depth estimation and integrates it with ROS and Gazebo for simulation. Two autonomous systems were evaluated: one using RGB-D cameras and the other using depth estimation with RGB cameras. Experimental results show that while the RGB-D camera system outperformed in accuracy, the depth estimation-based system provided cost-effective and reasonable performance, especially in complex environments. The research concludes with plans to improve the system for denser obstacle environments and conduct real-world experiments.

Keywords: Deep Learning, Autonomous vehicle, Presumption of Depth,

1. Introduction

In recent years, drone surveys have been conducted at disaster sites and on remote islands. In such locations, it is difficult for a person to operate a drone in close proximity due to safety, labor, and financial costs. Although there are advanced technologies that allow drones to follow predetermined routes remotely, there is the problem of collisions with drones when there are unexpected obstacles along the route. In addition, there are few drones equipped with sensors that can measure a wide range of distances, such as RGB-D cameras and LiDAR, which are necessary for obstacle detection. In this study, I developed and evaluated an autonomous system that can avoid obstacles using an RGB camera installed on a common drone.

2. System Overview

In this study, I develop two autonomous moving systems with different sensor inputs: the first is an autonomous moving system with RGB-D camera sensor input, and the second is an autonomous moving system with RGB camera sensor input. The first is to evaluate the system proposed in this study. The distance information necessary for obstacle detection is obtained from the RGB cameras by depth estimation.

2.1. Depth Estimation Model

The depth information was estimated using ZoeDepth, a depth-learning model that estimates depth from a single image [1]. The model is a metric depth estimation model,

which is built by fine-tuning a model trained on a relative depth dataset with a metric depth dataset. Fig1 shows the RGB image and (b) shows the depth image estimated from the image in (a).

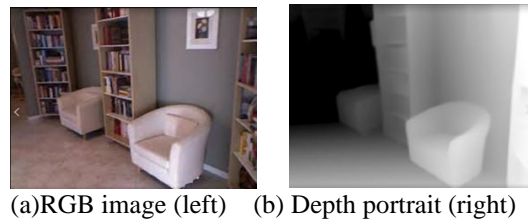


Fig 1 Example of depth presumption

2.2. Building a Simulation Environment

The simulation environment was built on the assumption that DJI's DJI Air 2S is handled as actual equipment. The simulation environment was built on the assumption that DJI's DJI Air 2S would be used as the actual device. Gazebo, ROS (Robot Operating System), and ArduPilot were used to construct the simulation environment. Gazebo provides a 3D robot simulation environment that uses a physics engine to simulate the environment and the robot's movements in real time, while ROS handles communication and data processing between devices and provides system flexibility and scalability. Fig2 shows the drone and environment projected on Gazebo.

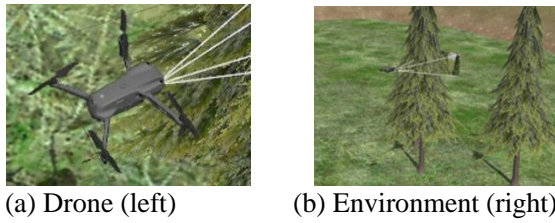


Fig 2 Simulation Environment

2.3. Autonomous Mobility Systems

For autonomous movement and obstacle avoidance, I used the ROS Navigation Stack, a collection of frameworks and tools that provide a set of functions necessary for autonomous robot navigation through the environment. The Navigation Stack is a collection of tools and frameworks that allow the robot to move autonomously through its environment. RGB-D images are used as input to RTAB-Map [2]. The user then sets the destination in the autonomous system, and the drone moves toward the destination. The generated map of the surrounding environment is updated as needed, and obstacles are detected in real time and appropriate route corrections are made.

3. Experiment

Experiments were conducted in a simulation environment to see if the two developed obstacle avoidance autonomous systems could avoid obstacles and reach the set destination. As shown in Fig3, the robot's initial position $(x,y,z)[m],(0,0,3)$ was set as the origin, and the destination $(12,0,3)$ was set. In each of the three obstacle situations, the robot made three autonomous movements to the destination in two patterns, and evaluated whether it could avoid the obstacles in the two patterns, and the error between the destination and the actual location.

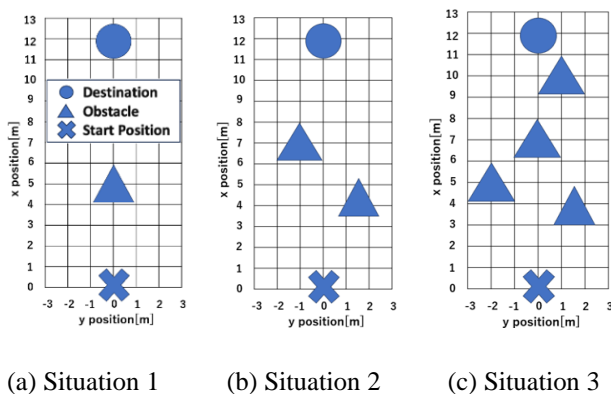


Fig 3 Obstacle situation

4. Experimental Results

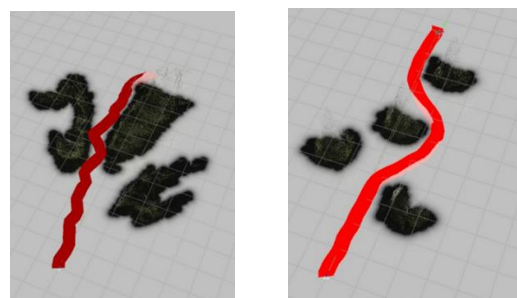
table1 and table2 summarize the experimental results of the autonomous moving system using depth estimation and the autonomous moving system using the RGB-D camera, respectively. table1 and table2 show that the system was able to avoid obstacles in all obstacle situations. In all obstacle situations, the autonomous system with the RGB-D camera had a smaller error with the destination. The autonomous system using depth estimation showed smaller errors in relation to the destination as the number of obstacles increased. Fig4 shows the path taken by the drone and the results of the drone's recognition of obstacles in obstacle situation 3 for each of the autonomous systems tested. Fig4 shows that the autonomous moving system using depth estimation has a larger area recognized as the same obstacle than the autonomous moving system using the RGB-D camera.

table 1 Autonomous mobility system using depth estimation

Situation	Avoiding Obstacle	Destination Error(Average)[m]
Obstacle Status1	○	6.2334[m]
Obstacle Status2	○	3.9669[m]
Obstacle Status3	○	2.2863[m]

table 2 Autonomous moving system using RGB-D camera

Situation	Avoiding Obstacle	Destination Error(Average)[m]
Obstacle Status1	○	0.4951[m]
Obstacle Status2	○	0.5881[m]
Obstacle Status3	○	0.3669[m]



(a) Depth estimation of Drone trajectory (left)

(b) Drone trajectory by RGB-D camera (right)

Fig 4 Drone trajectory and obstacle recognition results

5. Consideration

The accuracy of the estimated depth was lower than the depth obtained from the RGB-D camera. It is thought that fluctuations occurred in the distance from obstacles based on depth estimation, resulting in a wider area recognized as an obstacle, as shown in Fig4 (a). In addition, the autonomous moving system used visual information from the camera and depth information to estimate the drone's self-position. The autonomous movement system uses visual information from the camera and depth information to estimate the drone's self-position. In this case, I believe that errors in depth information accumulated as the drone moved, resulting in errors between the destination and the location where the drone arrived. table1 shows that the more obstacles there are, the smaller the error between the destination and the autonomous system using depth estimation. This is because the number of feature points such as edges and corners in the image increases as the number of obstacles increases, and the accuracy of self-position estimation increases as a result. To improve the accuracy of self-position estimation, I believe that the drone's self-position estimation can be achieved by using sensors such as GPS and IMU and integrating these sensors, instead of using only visual and depth information.

6. Conclusion

In this study, a simulation environment was constructed. I also developed and evaluated an obstacle avoidance system for drones based on depth estimation. As a result, the system was able to recognize and avoid obstacles, although the accuracy of self-position estimation was less than that of the RGB-D camera system. In the future, I will develop an obstacle avoidance system for environments with more obstacles and conduct experiments in real environments.

References

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