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Autonomous Mapping and Exploration of UAV Using Low Cost Sensors

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Abstract: Mapping and exploration are important tasks of mobile robots for various applications such as search and rescue, inspection, and surveillance. Unmanned Aerial Vehicles (UAVs) are more suited for such tasks because they have a large field of view compared to ground robots. An autonomous operation of UAV is desirable for exploration in unknown environments. In such environments, the UAV must make a map of the environment and simultaneously localize itself in it which is commonly known as the SLAM (Simultaneous Localization and Mapping) problem. This is also required to safely navigate between open spaces, and make informed decisions about the exploration targets. UAVs have physical constraints of limited payload, and are generally equipped with low-spec embedded computational devices and sensors. Therefore, it is often challenging to achieve robust SLAM on UAVs which also affects exploration. In this paper, we present an autonomous exploration of UAV in completely unknown environments using low cost sensors such as LIDAR and RGBD camera. A sensor fusion method is proposed to build a dense 3D map of the environment. Multiple images from the scene are geometrically aligned as the UAV explores the environment, and then a frontier exploration technique is used to search for the next target in the mapped area to explore maximum possible area. The results show that the proposed algorithm can build precise maps even with low-cost sensors, and explore the environment efficiently.

Keywords: Autonomous mapping and exploration; UAVs; sensor fusion

1. Introduction

Exploration and mapping in unknown environments is a crucial task for intelligent robots to achieve complete autonomous behaviour. Recent advances in unmanned aerial vehicles (UAV) have allowed mapping and exploration in difficult to access areas that were previously not possible using unmanned ground vehicles. UAVs have been deployed in areas that are deemed dangerous for human operation, and provide important information about the environment in applications such as search and rescue, site inspection, victim search in disaster situations and monitoring. UAV must be designed to operate autonomously with no prior information about the environment. To navigate in such environments, the UAV must be capable of doing SLAM or simultaneous localization and mapping as it explores the area. This is important, as the information perceived is utilized to safely navigate between free spaces and allows intelligent exploration of areas that were not previously mapped. Many variants of SLAM techniques have been successfully implemented in the past that uses different sensors and the data is fused to provide informed decisions about the environment[1–5]. Although,

31 this puts a lot of constraint on the design aspect of the UAV, due to the limited payload capacity, and
 32 onboard computation, affecting the total flight time. Another problem is when the UAV is exploring in
 33 GPS denied environments such as indoor environments, and has to completely rely on the onboard
 34 sensors for localization and navigation. Mobile robot exploration in indoor environment has been
 35 extensively researched in the past and there are many existing techniques available mostly for ground
 36 robots including multi-robot systems[6–8]. Exploration using UAV on the other hand is challenging
 37 due to 6 DOF motion control. Thus, there is a need of compact unmanned aerial system (UAS).

38 In this paper, we introduce an UAS with low cost RGBD sensor for the purpose of mapping and
 39 exploration of unknown indoor environments. RGBD sensors are used as primary sensor for mapping,
 40 since it can provide fairly accurate 3D information about the scene. Also, images from the camera can
 41 be utilized to navigate the UAV from ground station control in cases when the autonomous operation
 42 is not possible. The images from the camera are used for matching previously visited scenes and
 43 enhance the consistency of the map been built. A frontier based exploration strategy is used to cover
 44 maximum region of the map. We present the proposed system by simulating an actual UAV and
 45 exploring in complex indoor environment using ROS and Gazebo.

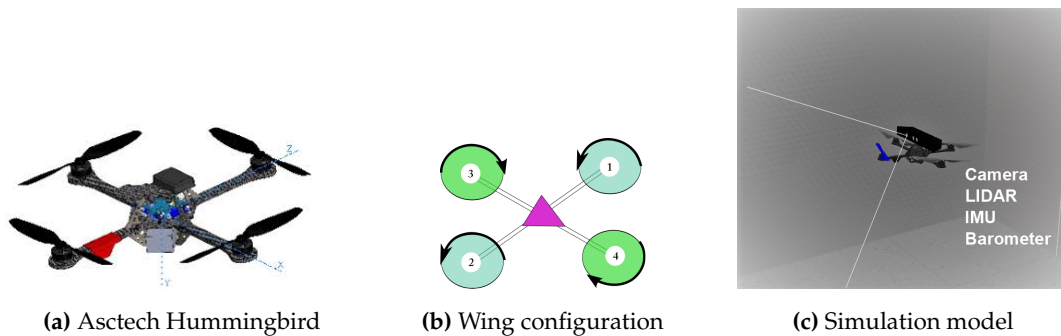


Figure 1. Developed UAV simulation model

46 2. Simulation Design

47 The simulation model is based on the Asctec Hummingbird multirotor (Fig. 1a) and is equipped
 48 with an IMU for 9DOF position estimate, barometer for altitude control, a Microsoft Kinect that doubles
 49 as an RGBD camera and a 2D LIDAR. The wing configuration is as presented in Fig. 1b, and shows
 50 the forward motion by the arrow. From tests we found that this configuration provides better agility
 51 with the kinect sensor mounted on the top. The kinematics and dynamics of the UAV were adopted as
 52 described in [9].

53 2.1. Software

54 All simulations were performed on the Gazebo software. Gazebo comes with the physics engine
 55 that can imitate actual motions of different configuration of UAV and makes it possible to test out
 56 the UAS in different scenarios both indoor and outdoors[10]. It is also convenient for quickly testing
 57 algorithms, adding new sensors and fast prototyping design changes. For programming and control,
 58 we used ROS or robot operating system. ROS is a middleware for robotics providing software
 59 framework for robot software development[11,12]. It provides broad collection of libraries that provide
 60 functions to robot with focus on manipulation, perception and mobility. It also provides various set of
 61 tools for debugging, testing and visualizing sensor data and tools for networking for multi-robot and
 62 distributed systems. Another reason for using ROS is due to its excellent integration with the Gazebo
 63 simulator.

64 2.2. Control and Estimation

65 An Extended Kalman Filter was used to fuse all the sensor data coming from the UAV into a
 66 single navigation information to control the velocity, orientation and position of the UAV along with

67 sensor error bias. A set of PID controllers were implemented to control the attitude, yaw rate, and
68 velocity of the vehicle along with heading. The output values that contains the thrust and torques
69 are then translated into motor voltages that gives response that is similar to actual aerial vehicle. The
70 open source ArduPilot was used as a flight controller that translates these messages into necessary
71 motor voltages and is used to simulate and fly the vehicle [13]. The parameters for each element can
72 be fine tuned to get desirable response such as hovering at a place or complex maneuvers. Other
73 techniques for path planning can be implemented in the control loop to obtain smoother response
74 from the UAV[14]. Such software in the loop approach provides greater flexibility in testing algorithms
75 before actual implementation on real platform and avoids the risk of damage or injury.

76 3. Methods

77 This section describes the mapping and exploration methods used for the experiments.

78 3.1. SLAM

79 To operate in unknown environment with or without GPS signals, the UAV needs to implement
80 SLAM to ascertain its position in the environment and gather sensor data that is used to build the map
81 of the environment. For mapping we used the GMapping or grid mapping to create a 2D occupancy
82 grid map from the LIDAR data and pose data from the UAV. The 2D grid map was also utilized for the
83 frontier exploration which is explained later. The GMapping method uses a Rao-Blackwellized particle
84 filter that re-samples each particle in an iterative manner, dropping the bad particles while ensuring
85 that good particles remain. The mathematical details about the method can be found in [1]. A laser
86 scan matching algorithm is employed that estimate the pose of the vehicle from consecutive laser scans.
87 This ensures that sampling points are selected in an area around the current pose thereby reducing the
88 number of particles required by the particle filter algorithm and making it computationally effective.
89 As the UAV explores the environment, the grid map is updated continuously. The 3D pointcloud
90 generated from the kinect sensor is also stored to reconstruct a dense 3D map of the environment.

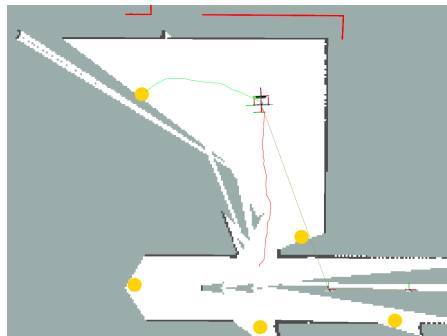


Figure 2. Frontier exploration on the UAV. The yellow circles are the frontiers detected on the grid map.

91 3.2. Exploration

92 For autonomous exploration, we used the frontier exploration method. A frontier on the map is
93 the boundary between explored and unexplored regions. The algorithm works on a simple principle
94 where upon visiting such frontiers constantly increases new information about the area and pushes
95 the boundary as more areas are explored[15]. The exploration algorithm aims at detecting, labeling
96 and listing all the edges (cells) that are explored and unexplored as frontier regions. By calculating the
97 minimum size threshold, it generates a list of suitable frontiers for the vehicle to navigate to from its
98 current pose while ignoring smaller frontiers. The selection for the next best frontier to visit is based
99 on different criteria, such as, distance to the frontier from the current pose, and the size of the frontier.
100 As the UAV continuously explores the region the grip map is updated using the SLAM method and is
101 utilized for autonomous navigation. Figure 2 shows the UAV exploration using frontier algorithm. The

102 yellow circles are the detected frontiers. The red trajectory is UAVs current trajectory, and the green
 103 trajectory shows the plan to selected next frontier. Figure 5 shows the gazebo model of the indoor
 104 scene. It has several rooms with similar looking features along with corridors and doors. The UAV
 105 was able to explore all the areas successfully using the frontier exploration. Figure. 3b, shows the final
 106 grid map obtained by the exploration method.

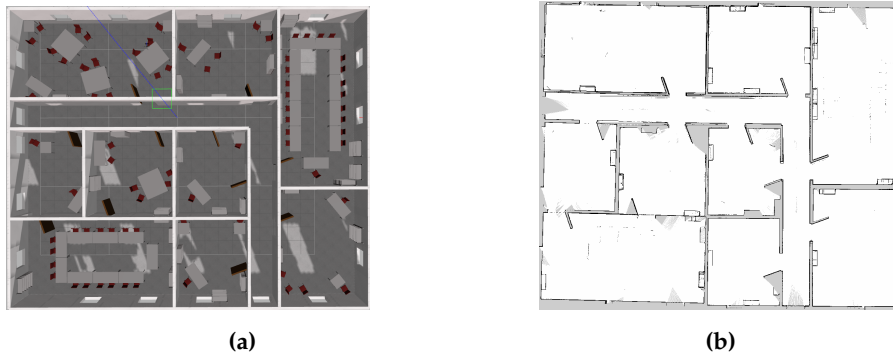


Figure 3. (a) Gazebo environment and, (b) result of 2D grid mapping using UAV exploration

107 3.3. Navigation

108 Once all the areas are explored, autonomous navigation can be done using the obtained grid map.
 109 The navigation planner uses the global and local planner to autonomously navigate from one pose to
 110 another in the grid map. The global planner plans the path from the current pose to the goal pose using
 111 A-star algorithm, while the local planner generates the linear and angular velocities along the global
 112 path while avoiding static or dynamic obstacles based on the cost map parameters. The local planner
 113 uses the dynamic window approach (DWA planner) to sample the velocities[16]. The exploration node
 114 only provides the goal pose (x, y, z, θ) , and these are converted into NED(North-East-Down) frame.
 115 The poses are then translated into motor velocity commands to send to the flight controller which uses
 PID to navigate to the goal pose.

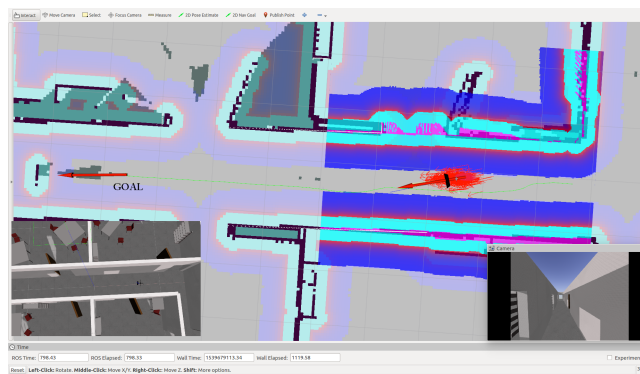


Figure 4. Autonomous navigation using Adaptive Monte Carlo Localization.

116 Prior to setting the goal and autonomous navigation, it is important to set the initial position of
 117 the UAV in the map. This is achieved by setting the initial pose of the UAV in the grid map. A scan
 118 matcher node then corresponds the laser scans with respect to the map, and corrects the position of
 119 the UAV[17]. Once the UAV has localized itself in the map, goal pose can be given for autonomous
 120 tasks. The localization is done using the Adaptive Monte Carlo Localization (AMCL) stack available
 121 on ROS. AMCL is a probabilistic technique to localize a moving robot system in the given map. It uses
 122 the Monte Carlo localization approach wherein particle filters are used to track the pose of the robot
 123 against a known map [1,18]. The localization is done by matching the laser scan data at a given pose
 124 of the robot with the map. If at any given time, the autonomous navigation fails, a fail-safe system is
 125 implemented that commands the UAV to land. An emergency signal is send to the control station and
 126

127 manual flight operation of the drone can be implemented using the live camera feed from the RGBD
128 camera to retrieve the vehicle.

129 3.4. 3D construction

130 The data gathered from the RGBD camera was used to generate dense 3D map of the indoor
131 environment. This is achieved by spatial alignment, where a series of images from same scene at
132 different times are geometrically aligned with different sensors or different view-frames[19]. A loop
133 closure detection method was employed that uses fast image matching technique by extracting robust
134 features from the image (eg. SIFT or SURF features). By matching previous local features to current
135 images that belong to a similar scene we can ascertain if the robot has returned to a previously mapped
136 region and close the loop. Figure 5a shows an example of feature matching using SIFT (Scale Invariant
137 Feature Transform) features in subsequent images recorded by RGBD camera[20]. For 3D construction,
138 ICP or iterative Closest Point method (3D variant) is used to match and stitch the 3D data obtained from
139 the RGBD camera. The generated pointcloud are transferred to OctoMap package in ROS that converts
140 the pointcloud into 3D occupancy grid map. OctoMap uses octree data structure to recursively divide
141 the pointcloud into octree cell that are further classified into occupied or unoccupied cells[21]. An
142 example of generated 3D occupancy grid of the indoor map is shown in Fig. 5b.

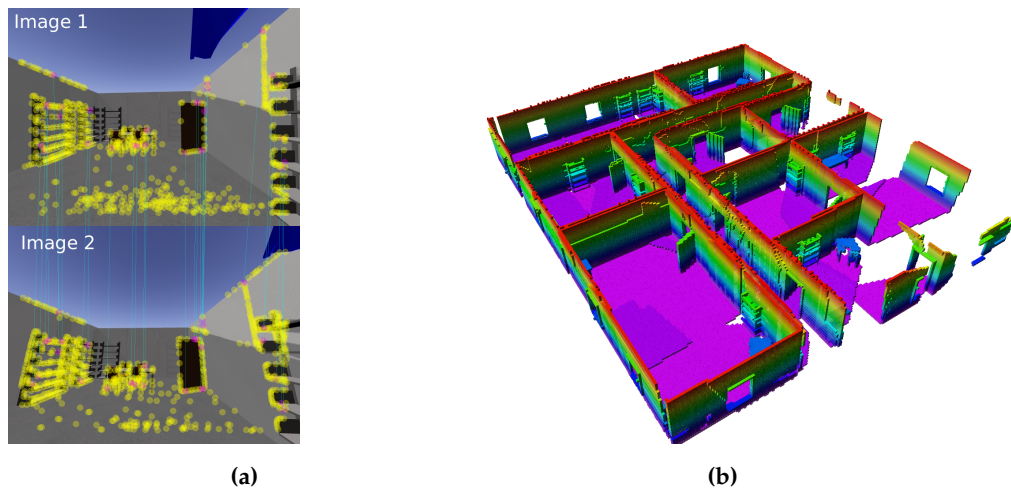


Figure 5. (a) Loop closure detection using SIFT features and (b) 3D reconstruction using OctoMap.

143 4. Conclusions

144 In this paper, we tested algorithms for autonomous mapping and exploration of a UAV in
145 unknown indoor environments. A simulation model of the drone was developed in gazebo simulator
146 and an indoor scene was constructed to test the proposed algorithms. Our aim of the research was to
147 test whether mapping and exploration can be performed only using low-cost RGBD sensors as the only
148 visual inertial sensor. A frontier exploration strategy was implemented to explore the indoor scene
149 using LIDAR data generated from the RGBD sensor. By generating navigation goals using the frontiers,
150 the UAV was able to explore the complete map. Furthermore, we implemented SLAM on the UAV to
151 get accurate 2D grid map of the scene that was used for autonomous navigation. A 3D reconstruction
152 method using OctoMap is presented that allows to create highly dense 3D maps of the environment
153 that can be further used for 3D navigation. From the results we confirm that autonomous operation
154 using only RGBD camera is possible for the UAV system. For future work we plan to implement
155 multi-drone system in simulation to reduce the time taken for mapping using the frontier exploration.
156 Also, we plan to test the proposed framework on real platform (UAS) for autonomous mapping and
157 exploration.

158 **Author Contributions:** A.A.R. and A.R. conceived the idea, designed, performed experiments, and summarized
159 the research; Y. K. made valuable suggestions to analyze the data and improve the manuscript. T. E. provided
160 important feedback to improve the manuscript. The manuscript was written by A.A.R.

161 **Conflicts of Interest:** “The authors declare no conflict of interest.”

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