Indoor SLAM for Micro Aerial Vehicles Using Visual and Laser Sensor Fusion

Elena López, Rafael Barea, Alejandro Gómez, Álvaro Saltos, Luis M. Bergasa, Eduardo J. Molinos and Abdelkrim Nemra

Abstract This paper represents research in progress in Simultaneous Localization and Mapping (SLAM) for Micro Aerial Vehicles (MAVs) in the context of rescue and/or recognition navigation tasks in indoor environments. In this kind of applications, the MAV must rely on its own onboard sensors to autonomously navigate in unknown, hostile and GPS denied environments, such as ruined or semi-demolished buildings. This article aims to investigate a new SLAM technique that fuses laser and visual information, besides measurements from the inertial unit, to robustly obtain the 6DOF pose estimation of a MAV within a local map of the environment. Laser is used to obtain a local 2D map and a footprint estimation of the MAV position, while a monocular visual SLAM algorithm enlarges the pose estimation through an Extended Kalman Filter (EKF). The system consists of a commercial drone and a remote control unit to computationally afford the SLAM algorithms using a distributed node system based on ROS (Robot Operating System). Some experimental results show how sensor fusion improves the position estimation and the obtained map under different test conditions.

Keywords Micro Aerial Vehicles · Indoor navigation · Sensor fusion · Simultaneous Localization and Mapping · Robot Operating System

1 Introduction

The growing research on MAVs and the consequent improvement of technologies like microcomputers and onboard sensor devices, have increased the performance

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requirements of such kind of systems. Enabled by GPS and MEMS inertial sensors, MAVs that can fly in outdoor environments without human intervention have been developed [1,2,3]. Unfortunately, most indoor environments remain without access to external positioning systems, and autonomous MAVs are very limited in their ability to operate in these areas.

Traditionally, unmanned ground vehicles operating in GPS-denied environments can rely on dead reckoning and onboard environmental sensors for localization and mapping using SLAM techniques. However, attempts to achieve the same results with MAVs have not been as successful due to several reasons: the inaccuracy and high drift of Inertial Navigation Systems (INS) compared to encoder-based dead reckoning, the limited payload for sensing and computation, and the fast and unstable dynamics of air vehicles, are the main challenges which must be tackled.

Especially, pose estimation is essential for many navigation tasks, including localization, mapping and control. The technique used depends mainly on the available on board sensors, which in aerial navigation must be carefully chosen due to payload limitations. Through their low weight and consumption, most commercial MAVs incorporate at least one monocular camera, so VSLAM (Visual SLAM) techniques have been widely used. However, most of these works have been limited to small workspaces which have definite image features and sufficient sun light. Furthermore, computational time is too high for the fast dynamics of aerial vehicles, making difficult to control them. On the other hand, despite their greater weight and consumption, range sensors such as RGB-D cameras or laser range sensors have also been used on MAVs due to their fast distance detection.

This paper focuses on fusion of laser, monocular vision and IMU (Inertial Measurement Unit) to robustly track the position of a MAV using SLAM. To face the computational requirements, the system is composed of a flight and a ground unit, so that code can be distributed in different nodes using ROS (Robot Operating System). In order to calculate pose which is relatively insensitive to errors, 2D map is generated based on laser. The estimated footprint position of the MAV is then filtered with IMU and VSLAM information using an EKF (Extended Kalman Filter) to obtain a full 6DOF pose estimation, that is demonstrated to be robust under different illumination and environmental test conditions.

The remaining part of this paper is organized as follows. Section 2 discusses related work. Section 3 describes the overall system. The SLAM approach is explained in section 4. The experimental results are presented in Section 5. Finally, it is followed by the conclusion and future work in Section 6.

2 Related Work

The most challenging part of SLAM for MAVs is to obtain the 6DOF pose of the vehicle without odometry information. To do this, different sensor sources have been suggested, such as laser range sensors [4], monocular cameras [5], stereo cameras [6] or RGB-D sensors [7,8].

Due to weight limitations, most of the works only use the onboard camera and IMU to apply VSLAM (Visual SLAM) techniques [9,10,11,12,13,14]. These systems demonstrate autonomous flight in limited indoor environments, but their approaches have been constrained to environments with specific features and lighting conditions, and thus may not work as well for general navigation in GPS-denied environments. On the other hand, the high working rate of actual laser scanners, along with their direct and accurate range detection, make them a very advantageous sensor for indoor navigation. Several works, such as [4,15,16], fuse laser and IMU measurements to obtain 2D maps and to estimate the 6DOF pose of the MAV.

However, there are very few works in which both laser and vision are used to solve the SLAM problem in MAVs. The main challenge is the computational charge, that can't be afford by the onboard processors. For example, in [17] laser and IMU are fused to estimate the 6DOF position of the robot, whilst vision is only used to loop closure in the obtained map. In [18] laser and vision are used, but to solve separately the outdoors and indoors odometry problem.

In this work, laser, vision and IMU measurements are fused to solve the SLAM problem in complex indoor environments and robustly estimate the 6DOF pose of the MAV, using a distributed system with a flight unit and a ground station.

3 System Overview

We address the problem of autonomous indoor MAV localization as a software challenge, focusing on high level algorithms integration rather than specific hardware. For this reason, we use a commercial platform with minor modifications, and an open-source development platform (ROS), so that drivers of sensors and some algorithms can be used without development.

3.1 Hardware Architecture

Our quadrotor MAV, shown in figure 1, is based on the ARDrone from Parrot [19]. This MAV can carry up to 120g of payload for about 5min. It's equipped with two cameras (one directed forward and one directed downward), an ultrasonic altimeter, a 3-axis accelerometer and 2 gyroscopes. It incorporates an onboard controller based on ARM 468 MHz processor with 128 Mb DDR Ram, with a Linux distribution. It also provides a USB port and is controlled via Wireless LAN.

To the commercial platform, we have added a Hokuyo URG-04LX laser for direct range measuring, an additional upward facing sonar and a Raspberry-PI board for reading and transmitting these sensor measurements. The Raspberry and the remote computer are both connected to the ARDrone network to control the robot.

Fig. 1 The experimental platform with onboard computation and sensing.

Although the ARDrone comes with some software for basic functionality [20], it's not open-source nor easy to modify, and so we treat the drone as a black box, using only the available W-LAN communication channels to access and control it. Specifically, these are the inputs/outputs we use in our SLAM system:

- Video channel, to receive the video stream of the forwards facing camera, with maximal supported resolution of 320x240 and frame rate of 18fps.
- Navigation channel, to read onboard sensor measurements every 5ms. The data used by our system are:
  - Drone orientation as roll, pitch and yaw angles $\left(\overline{\Phi}, \overline{\Theta}, \overline{\Psi}\right)$.
  - Horizontal velocity in drone's coordinate system $\left(\overline{vdx}, \overline{vdy}\right)$, calculated onboard by an optical-flow based motion estimation algorithm [20].
  - Drone height $\overline{h}$, obtained from the ultrasound altimeter measurements.
- Command channel, to send the drone control packages, with the desired roll and pitch angles, yaw rotational velocity and vertical speed:

$$\mathbf{u} = \left(\hat{\Phi}, \hat{\Theta}, \hat{\Omega}, \hat{v}z\right) \tag{1}$$

Besides this, a ROS node in the Raspberry-PI reads the Hokuyo laser scan and broadcast it through the drone's network.

3.2 Software Architecture

As it's shown in figure 2, the onboard controller and processor perform sensor readings and basic control of the MAV. The ground station executes our SLAM system and also the planning and control strategies, the last ones being out of the scope of this paper.

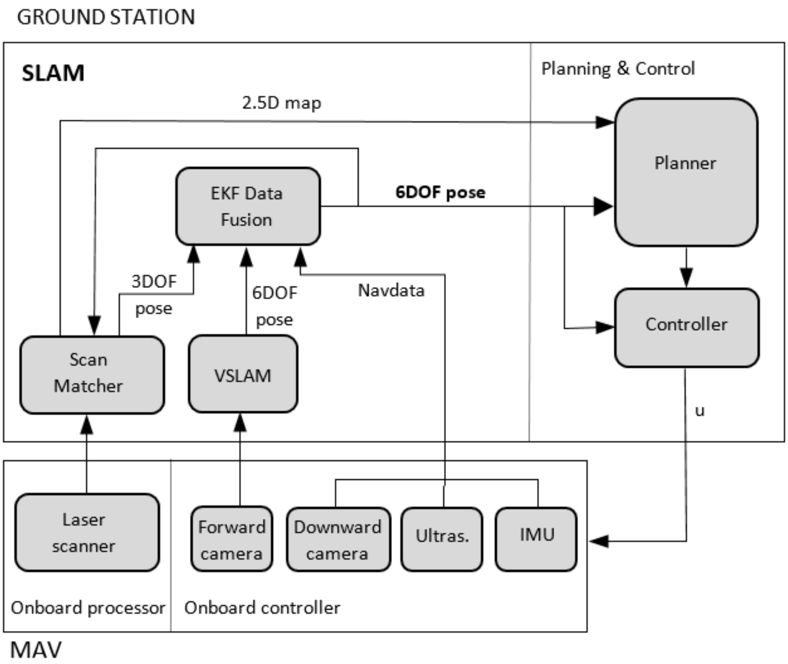

Fig. 2 The experimental platform with onboard computation and sensing.

The SLAM module consist of three major components: (1) a scan matching algorithm that uses laser readings to obtain a 2,5D map of the environment and a 3DOF pose estimation of the footprint of the MAV on the map; (2) a monocular visual SLAM system that obtains a 6DOF pose estimation and (3) an Extended Kalman Filter that fuses the last estimations with the navigation data provided by the onboard sensors of the MAV to obtain a robust 6DOF estimation of the position of the robot in the 2,5D map. This estimation is used, at the same time, as a priori assumption for the next scan matching step, closing the SLAM algorithm.

4 SLAM Approach

In the following subsections, we describe the modules of the SLAM system shown in figure 2.

4.1 Scan Matcher

This module aligns consecutive scans from the laser rangefinder to estimate the vehicle's motion. Although lots of scan matching techniques have been developed and applied to SLAM for ground robots moving on flat surfaces [21], most of them require odometric information that is not available in MAVs. However, the

HectorSLAM project [22], developed by the Team Hector of the Technische Universität Darmstadt, presents a system for fast online generation of 2D maps that uses only laser readings and a 3D attitude estimation system based on inertial sensing. This method requires low computational resources and it's widely used in different research groups because it is available as open source and based on ROS.

In this work, we adapt the HectorSLAM system to our scan matching module, in order to obtain a 2,5D map and a 2D estimation of the footprint pose of the MAV within the map, consisting in the (x,y) coordinates and yaw angle, that we call:

$$z_{LASER} = (x_L, y_L, \Psi_L) \tag{2}$$

The 2D pose estimation is based on optimization of the alignment of beam endpoints with the map obtained so far. The endpoints are projected into the actual map and the occupancy probabilities are estimated. The scan matching is solved using a Gaussian-Newton equation, which finds the rigid transformation that best fits the laser beams with the map. A multi-resolution map representation is used to avoid getting stuck in local minima. In addition, a 3D attitude estimation system based on the IMU measurements transforms the laser readings into a base-stabilized frame (horizontal to the ground) in order to compensate the roll and pitch movements when obtaining the 2.5D map.

Fig. 3 shows the map and footprint pose estimation obtained by the scan matcher in one of our experiments. Although HectorSLAM provides good results in confined environments, the lack of odometry information to detect horizontal movements (only attitude is obtained from the IMU and used to stabilize laser measurements) results in undesirable effects, such as shortening of corridors and not loops detection.

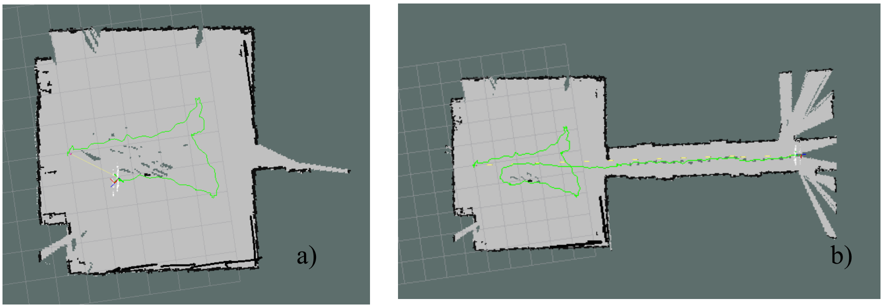

Fig. 3 Partial results of the scan matcher while moving around a room and along a corridor. The real length of the corridor is 17.6m, while it is shortened to 13.8m by the algorithm.

4.2 Monocular SLAM

For monocular SLAM, our solution is based on LSD-SLAM (Large-Scale Direct Monocular SLAM) [23], available as a ROS package. This is a direct (featureless) monocular SLAM algorithm which, along with highly accurate pose estimation based on direct image alignment, reconstructs the 3D environment in real-time as pose-graph of keyframes with associated semi-dense depth maps. By the moment, and due to the high computational charge of 3D mapping, we are only using the 6DOF pose estimation of this algorithm as an input to the data fusion filter, and we use the 2,5D laser map for navigation.

Fig. 4 shows the 3D map and pose estimation obtained by the V-SLAM system in the same room of the experiment shown in fig.3. While results are good in this case, the system needs a high amount of visual characteristics that are not available in corridor areas or in dark zones, where it needs to be fused with other sensors.

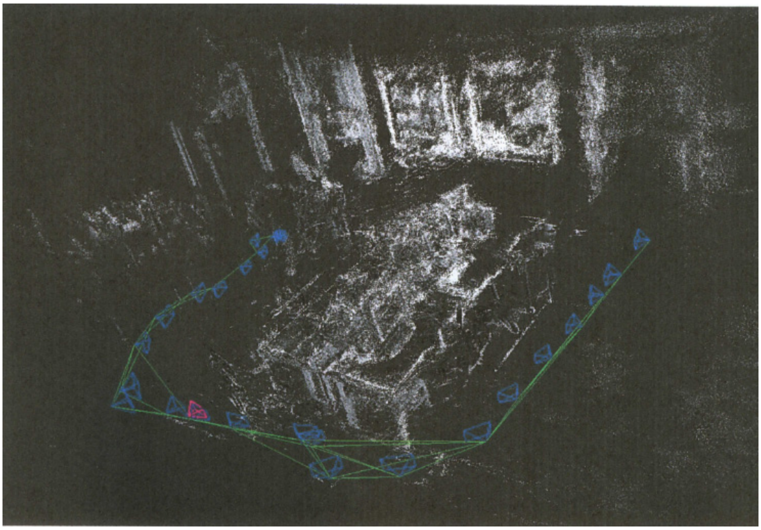

Fig. 4 Partial results of the VSLAM system while moving around the room of fig. 3.a).

4.3 Data Fusion with EKF

In order to fuse all available data, we employ an Extended Kalman Filter (EKF). This EKF is also used to compensate for the different time delays in the system, as detailed described in [24], arising from wireless LAN communication and computationally complex visual tracking.

The EKF uses the following state vector:

$$\chi_t := (x_t, y_t, z_t, vx_t, vy_t, vz_t, \Phi_t, \Theta_t, \Psi_t, \Omega_t)^T \quad \in \quad \Re^{10} \tag{3}$$

Where (x_t, y_t, z_t) is the position of the MAV in m, (vx_t, vy_t, vz_t) the velocity in m/s, $(\Phi_t, \Theta_t, \Psi_t)$ the roll, pitch and yaw angles in deg, and Ω_t the yaw-rotational speed in deg/s, all of them in world coordinates. In the following, we define the prediction and observation models.

a) Prediction Model

The prediction model is based on the full motion model of the quadcopter's flight dynamics and reaction to control commands derived in [24]. A new calibration of the model parameters has been done because the Hokuyo laser sensor weight considerably modifies the dynamics of the system.

The model stablishes that the horizontal acceleration of the MAV is proportional to the horizontal force acting upon the quadcopter, that is, the accelerating force minus the drag force. The drag is proportional to the horizontal velocity of the quadcopter, while the accelerating force is proportional to a projection of the z-axis onto the horizontal plane, which leads to:

$$\dot{vx}_t = K_1\left(K_2\left(\cos\Psi_t \sin\Phi_t \cos\Theta_t - \sin\Psi_t \sin\Theta_t\right) - vx_t\right) \tag{4}$$

$$\dot{vy}_t = K_1\left(K_2\left(-\sin\Psi_t \sin\Phi_t \cos\Theta_t - \cos\Psi_t \sin\Theta_t\right) - vy_t\right) \tag{5}$$

Furthermore, the influence of the sent control command $\mathbf{u} = \left(\hat{\Phi}, \hat{\Theta}, \hat{\Omega}, \hat{vz}\right)$ is described by the following linear model:

$$\dot{\Phi}_t = K_3\left(K_4\hat{\Phi}_t - \Phi_t\right) \tag{6}$$

$$\dot{\Theta}_t = K_3\left(K_4\hat{\Theta}_t - \Theta_t\right) \tag{7}$$

$$\dot{\Omega}_t = K_5\left(K_6\hat{\Omega}_t - \Omega_t\right) \tag{8}$$

$$\dot{vz}_t = K_7\left(K_8\hat{vz}_t - vz_t\right) \tag{9}$$

We estimated the proportional coefficients K_1 to K_8 from data collected in a series of test flights. From eqs (4) to (9) we obtain the overall state transition function:

$$\begin{pmatrix} x_{t+1} \\ y_{t+1} \\ z_{t+1} \\ vx_{t+1} \\ vy_{t+1} \\ vz_{t+1} \\ \Phi_{t+1} \\ \Theta_{t+1} \\ \Psi_{t+1} \\ \Omega_{t+1} \end{pmatrix} \leftarrow \begin{pmatrix} x_t \\ y_t \\ z_t \\ vx_t \\ vy_t \\ vz_t \\ \Phi_t \\ \Theta_t \\ \Psi_t \\ \Omega_t \end{pmatrix} + \Delta_t \begin{pmatrix} vx_t \\ vy_t \\ vz_t \\ K_1\left(K_2\left(\cos\Psi_t \sin\Phi_t \cos\Theta_t - \sin\Psi_t \sin\Theta_t\right) - vx_t\right) \\ K_1\left(K_2\left(-\sin\Psi_t \sin\Phi_t \cos\Theta_t - \cos\Psi_t \sin\Theta_t\right) - vy_t\right) \\ K_7\left(K_8\hat{vz}_t - vz_t\right) \\ K_3\left(K_4\hat{\Phi}_t - \Phi_t\right) \\ K_3\left(K_4\hat{\Theta}_t - \Theta_t\right) \\ \Omega_t \\ K_5\left(K_6\hat{\Omega}_t - \Omega_t\right) \end{pmatrix} \tag{10}$$

b) Inertial Navigation Observation Model

This model relates the onboard measurements obtained through the navigation channel of the quadcopter described in section 3.1 (that we called "navdata" in figure 2) and the state vector. The quadcopter measures its horizontal speed $(\overline{vdx}, \overline{vdy})$ in its local coordinate system, which we transform into the world frame (vx_t, vy_t). The roll and pitch angles measured by the accelerometer are direct observations of the corresponding state variables. On the other hand, we differentiate the height measurement and the yaw measurement as observations of the respective velocities. The resulting measurement vector $\mathbf{z}_{NAVDATA}$ and observation function $h_{NAVDATA}(\mathbf{x}_t)$ are:

$$\mathbf{z}_{NAVDATA,t} = \left(\overline{vdx}, \overline{vdy}, (\overline{h}_t - \overline{h}_{t-1}), \overline{\Phi}, \overline{\Theta}, (\overline{\Psi}_t - \overline{\Psi}_{t-1})\right)^T \tag{11}$$

$$h_{NAVDATA}(\chi_t) := \begin{pmatrix} vx_t \cos\Psi_t - vy_t \sin\Psi_t \\ vx_t \sin\Psi_t + vy_t \cos\Psi_t \\ vz_t \\ \Phi_t \\ \Theta_t \\ \Omega_t \end{pmatrix} \tag{12}$$

c) VSLAM Observation Model

When LSD-SLAM successfully tracks a video frame, its 6DOF pose estimation is transformed from the coordinate system of the front camera to the coordinate system of the quadcopter, leading to a direct observation of the quadcopter's pose given by:

$$\mathbf{z}_{VSLAM,t} = f\left(\mathbf{E}_{DC}\mathbf{E}_{C,t}\right) \tag{13}$$

$$h_{VSLAM}(\chi_t) := \left(x_t, y_t, z_t, \Phi_t, \Theta_t, \Psi_t\right)^T \tag{14}$$

where $\mathbf{E}_{C,t} \in SE(3)$ is the estimated camera pose, $\mathbf{E}_{DC} \in SE(3)$ the constant transformation from the camera to the quadcopter coordinate system and $f : SE(3) \to \Re^6$ the transformation from an element of SE(3) to the roll-pitch-yaw representation.

d) Scan Matcher Observation Model

The scan matcher maintains a 3DOF estimation of the footprint pose of the MAV, that is considered as a direct observation of the corresponding state variables, as it's shown in the following linear observation model:

$$z_{LASER,t} = (x_{L,t}, y_{L,t}, \Psi_{L,t})^T \tag{15}$$

$$H_{LASER} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \tag{16}$$

4.4 SLAM Integration

For best performance, information between the scan matcher and the EKF estimate is exchanged in both directions. Thus, the 6DOF pose estimate of the EKF is projected on the xy-plane and is used as start estimate for the optimization process of the scan matcher, as it's shown in figure 2.

5 Results

In order to compare the performance of the SLAM system with the different sensors separately and fused in the proposed EKF, we teleoperated the MAV along one of the rooms and corridors of our work environment while registering data from laser, camera and ARDrone sensors. Figure 5 shows the footprint projections of the estimated 6D trajectories in three different executions of the SLAM system. In red it is shown the estimated trajectory when only the prediction model and the ARDrone navdata measurements are used; in this case, due to the inaccuracy of commands and the high drift of IMU measurements, the estimation is very poor. In green colour we show the estimation when using the prediction model and the laser scan matcher observation. Although the results are better than using only the scan matcher (see fig. 3), corridor is still shortened from 17.6m to 15.2m. In blue we show the results of the entire SLAM system, using commands for prediction and laser, visual and navdata observations for correction. The map shown in fig 5 corresponds to this execution of the EKF. In this case, we obtain the best map and trajectory estimation, in which loop closure is better in the room, and the estimated corridor length is 17.4m, very close to the real one.

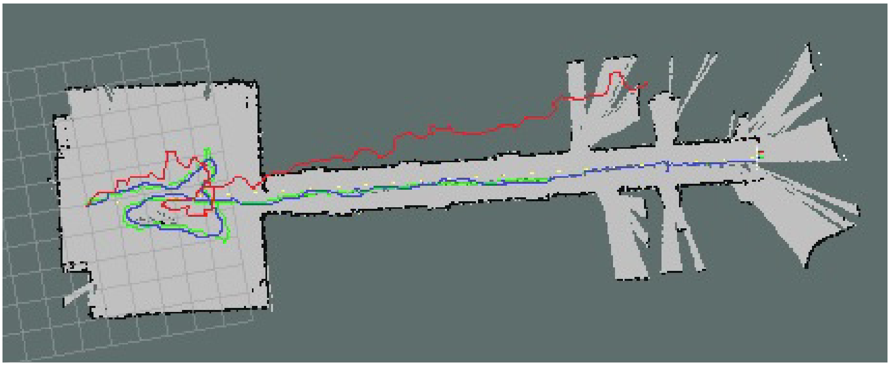

Fig. 5 Experimental results in three different executions of the SLAM system: (red) using prediction an navdata observation models; (green) using prediction and scan matcher observation model; (blue) using prediction and visual, scan matcher and navdata observation models.

6 Conclusions and Future Work

This paper shows work in progress and initial results of a indoor SLAM system for MAVs that fuses visual, laser and on board sensors to obtain a better estimation of the 6D pose of the MAV and a 2D map of the local environment. Fusing laser and vision is possible by using light algorithms running on a remote control station. In future work, we will add a large scale 3D mapping system with loop closure detection by using advanced VSLAM algorithms.

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