A Real-time Fast Incremental SLAM Method Using Laser Range Sensor for Indoor Flying

Huang Dongze[1] , Cai Zhihao[1], WangYingxun[1]and He Xiang[1]

[1]*National Key Lab of Science and Technology on Aircraft Control*
Beihang University, Beijing, China.

ABSTRACT

Recently, numerous efficient approaches to simultaneously localization and mapping (SLAM) based on ground robots have been proposed. However, we may encounter difficulties when applying the algorithms to those systems with higher real-time requirements, such as micro aerial vehicles (MAVs). This paper presents a fast and effective solution to SLAM problems, enables a quadrotor to autonomously explore unknown indoor environments. We propose a probabilistic approach to estimate the position. The estimation error is reduced by the evaluation function with a penalty term. Furthermore, Bayesian method is used to update the occupancy probability grid map and provides an effective way to solve sensor uncertainty. Experimental results carried out by using a laser range sensor on a quadrotor platform in indoor environment show that the incremental SLAM strategy has a superior performance.

1 INTRODUCTION

Micro aerial vehicles (MAVs) have been used in many applications in the real world, such as searches, rescues, inspections, and a lot of military tasks which are dangerous or difficult for people. However, sometimes GPS is unavailable when MAVs explore unknown indoor areas. Considering that, recently there has been increasing researches in navigation and mapping problems, which are often referred as simultaneous localization and mapping (SLAM) problems, but almost all of them focus on ground robots. Because of the limited onboard processing capacity in most MAVs, the use of complex SLAM algorithms seems challenging. Furthermore, laser data acquired from the three-dimensional surrounding environments is more difficult to deal with than the two-dimensional.

According to the types of computation methods, SLAM algorithms can be classified into two categories, one is based on extended Kalman filters (EKF-SLAM)[1-3], the other is using Rao-Blackwellzed particle filters (RBPF-SLAM)[4, 5]. For the former, one of the most difficult problems is the feature extraction. Most papers[2] make use of laser intensity information to recognize landmarks, which may fail in the environments with walls and corridors. In literature [2, 3], maintaining the knowledge of the relative relationships between all landmarks makes EKF-SLAM computationally intractable. Rao-Blackwellzed particle filters were proposed as an effective mean to solve the SLAM problems[4,5]. Scan matching is applied to minimize errors of odometry during mapping, which is convenient for the distribution of particles. Since each particle maintains its own map, an important problem of this approach is how to keep the number of particles small. This problem can be solved by combining scan matching and RBPF which can obviously decrease the number of required particles[4]. However, most of these SLAM algorithms cannot run in real-time for indoor exploration because each practical carries an individual map of the environment, which is computationally expensive and requires a mass of memory.

We present a real-time fast incremental SLAM algorithm capable running on MAV platforms for autonomous indoor flying. A laser range finder is used to collect the environment information surrounding the MAV. An inertial measurement unit (IMU) is also needed to determine the vehicle attitudes which are used to transform the three-dimensional data of laser into a two-dimensional plane. A reference map based on probabilistic scan matching algorithm is proposed to estimate current location of MAV. Although our scan matching algorithm and Olson's method which is presented in literature [6] both use a probabilistic grid map, it differs in two significant ways: the forming of local map and the search strategy during estimating position. In fact, our scan matching algorithm is faster and with more accuracy. The final occupancy grid map is built incrementally with the Bayesian update based on the current position and the observation of MAV. Localization errors and sensor uncertainty will be reduced during mapping.

This paper is organized as follows. In the following section, we will discuss the algorithm for scan matching. In section 3, Bayesian mapping is explained in detail. At last, we conclude a set of experiments results which validate our real-time fast incremental SLAM algorithm running on a quadrotor platform in Section 4 and Section 5.

2 Relative Position Estimation of Scan Matching

Since MAVs don't have wheel odometry to measure relative position, they must rely on exteroceptive sensors, matching the incoming measurements one after the other to get the current relative motion. This process can be performed on both laser scans and camera images. Laser scan matching algorithms can be described as the following: considering the MAV sensing an environment from the two laser scans $\boldsymbol{z}_1$ and $\boldsymbol{z}_2$, the aim is to find the optimal rigid body transform $\boldsymbol{T}(\varphi, \Delta x, \Delta y)$ that aligns the current laser scan with the previous scan. Transform $\boldsymbol{T}$ is parameterized by three values: two translational components Δx, Δy and a rotational component φ. The process of scan matching can be explained by figure 1. Because the same points will not be measured due to the motion of the vehicle, each scan matching algorithm must find a way to deal with correspondences between laser points. It is usually solved in three ways: matching the individual point from current scan with one point in the previous scan, such as the Iterative Closest Point (ICP)[7]; extracting higher level features such as lines and corners and then matching them; creating a likelihood map from previous scans and then matching current scan to that map, such as Olson's method. Notice that laser scanner measures range in a 2D plane, while the MAV moves in full 3D environment. Therefore, we need to transform laser data to 2D plane using attitude angle measured by IMU, as shown in figure 2.

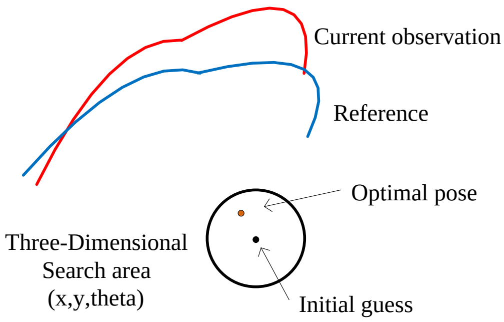

Figure 1.Illustration of scan-matching

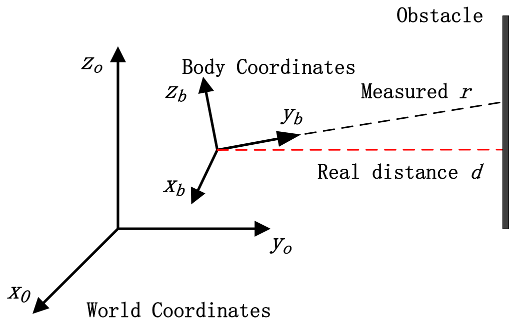

Figure 2.Correction of measured laser data

a) Laser data preprocessing

Suppose that the laser coordinates coincides with the body coordinates of MAV. Sensor of IMU measures the attitude between body coordinates and world coordinates. The laser range finder measures a set of distances r_i and direction angles α_i along the $x_b - y_b$ plane. Each of these distances and angles can be represented by a two-dimensional vector $\boldsymbol{r}_i = \left(r_i \cos\alpha_i \quad r_i \sin\alpha_i\right)^T$. $\boldsymbol{T}_b^o(\theta,\phi,\psi)$ is the transformation matrix from the body frame to the world frame and it is determined by three-axis attitude angle from IMU. θ, ϕ and ψ represent pitch, roll and yaw respectively. Since more accurate calculations of yaw angle will be acquired from scan matching algorithm, the transformation matrix can be simplified as $\boldsymbol{T}'$ by following equation:

$$\boldsymbol{T}' = \begin{bmatrix} \cos\theta & 0 \\ \sin\theta\sin\phi & \cos\phi \end{bmatrix} \tag{1}$$

Thus, we can compute the real position of laser endpoint $\boldsymbol{z}_i$ from the following equation:

$$\boldsymbol{z}_i = \boldsymbol{T}'\boldsymbol{r}_i \tag{2}$$

b) Map based probabilistic scan matching

ICP scan matching algorithm needs to compute the correspondences explicitly, which is a process of challenging and error prone. Large amount of calculation can be omitted if we use one approach with no-correspondences. As mentioned above, we can create a map $\boldsymbol{m}$ of environment from previous scans, and then match the new scan against that map. Suppose that MAV moves from $\boldsymbol{x}_{i-1}$ to $\boldsymbol{x}_i$, where $\boldsymbol{x} = (x \quad y \quad \varphi)^T$. The observation $\boldsymbol{z}_i$ depends on the environment map $\boldsymbol{m}$ and the current robot's position. Our goal is to find maximize posterior distribution over the MAV's position as follows:

$$\hat{\boldsymbol{x}}_i = \underset{\boldsymbol{x}:=(x\ \varphi\ y)}{\arg\max}\ p(\boldsymbol{x}_i \mid \boldsymbol{x}_{i-1}, \boldsymbol{m}, \boldsymbol{z}_i) \tag{3}$$

There are two critical questions in order to calculate equation (3). One is where does the map $\boldsymbol{m}$ comes from， the other is how to find the maximum likelihood value through the search algorithm. We use Olson's method to perform a robust exhaustive search over candidate areas. However, exhaustive searching method may increase the amount of computation, so we have to reduce the search area, which will result in no maximum point in limited search areas.

Therefore, we make several changes to Olson's method. We discrete the map in different resolution levels, the low-resolution map is used to quickly identify areas that might contain the global maximum and the higher-resolutions are used to find the maxima in certain areas. This multi-level resolution is more robust and faster to find the best pose.

Obtaining the reference map $\boldsymbol{m}$ is a complex issue and requires a full solution to the SLAM problem. Some papers[8] use previous laser scan or last several scans as the reference map $\boldsymbol{m}$, which may cause accumulated error. In order to reduce the error, an evaluation function f with penalty term is designed to determine whether the current scan is suitable for use as a reference scan. It is given by:

$$f = \left[\sum_{i=1}^{n} \lambda_i score(i)\right]^{-1} + \sigma\left[\frac{1}{n}\sum_{i=1}^{n} \lambda_i^2 x_i^2 - \frac{1}{n^2}\left(\sum_{i=1}^{n} \lambda_i x_i\right)^2\right] \tag{4}$$

Where x_i is the maximum likelihood estimation of different resolution map, and x_i is a component of vector $\boldsymbol{x}_i$. λ_i is the positive weight of the each estimated result. The higher the resolution-levels, the greater the weights, and the sum of λ_i is 1, shown in Equation (5)

$$\sum_{i=1}^{n} \lambda_i = 1 \tag{5}$$

σ is a positive penalty parameter and $score(i)$ represents the number of grids successfully matched of i^{th} evaluation. We can separate Equation (4) in two parts. The first part shows the consistency of laser data, and the second part is a confident covariance estimation of x_i with penalty parameter. A successful scan matching reflects high consistency of measured data and small uncertainty of estimated results. In order to get a smaller function value, Equation (5) must have higher scores and lower covariance. If $f < \mathrm{V_T}$, where $\mathrm{V_T}$ is the threshold of the function, we have sufficient evidence to believe that the current scan can be integrated into the reference map $\boldsymbol{m}$. Therefore, comparing a new scan to the reference map gives much more accurate position estimation than comparing each scan only to the scan from previous time step, as it reduces the integration of small errors over time.

3 Occupancy probability grid maps using Bayesian update

In this section we will discuss how to learn an occupancy grid map from the laser sensor data using Bayesian Updating. The key idea of learning a grid map is to estimate the joint posterior $P(m \mid \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t})$. Suppose that the occupancy probability of a grid cell m can be computed independently for all sensor measurements. This estimation is performed given the observations $\boldsymbol{z}_{1:t} = \boldsymbol{z}_1, \cdots, \boldsymbol{z}_t$ and the trajectory $\boldsymbol{x}_{1:t} = \boldsymbol{x}_1, \cdots, \boldsymbol{x}_t$, which can be acquired from scan matching algorithm of previous section. One form of Bayesian theorem gives[9]:

$$P(m \mid \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t}) = \frac{P(\boldsymbol{z}_t \mid m, \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t-1}) P(m \mid \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t-1})}{P(\boldsymbol{z}_t \mid \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t-1})} \tag{6}$$

And the analogous way:

$$P(\neg m \mid \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t}) = \frac{P(\boldsymbol{z}_t \mid \neg m, \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t-1}) P(\neg m \mid \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t-1})}{P(\boldsymbol{z}_t \mid \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t-1})} \tag{7}$$

The odds formulation of equation (5) and (6) is convenient for computation:

$$\frac{P(m \mid \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t})}{P(\neg m \mid \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t})} = \frac{P(\boldsymbol{z}_t \mid m, \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t-1}) P(m \mid \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t-1})}{P(\boldsymbol{z}_t \mid \neg m, \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t-1}) P(\neg m \mid \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t-1})} \tag{8}$$

Assume that $\boldsymbol{z}_t$ is independent from $\boldsymbol{x}_{1:t-1}$ and $\boldsymbol{z}_{1:t-1}$ given known m, and applying Bayes rule we determine:

$$P(\boldsymbol{z}_t \mid m, \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t-1}) = P(\boldsymbol{z}_t \mid m, \boldsymbol{x}_t) = \frac{P(m \mid \boldsymbol{x}_t, \boldsymbol{z}_1) P(\boldsymbol{z}_t \mid \boldsymbol{x}_t)}{P(m)} \tag{9}$$

Finally, combining equation (8), (9) and applying the fact $P(\neg \mathrm{A}) = 1 - P(\mathrm{A})$ lead to:

$$P(m \mid \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t}) = \left[1 + \frac{1 - P(m \mid \boldsymbol{x}_t, \boldsymbol{z}_t)}{P(m \mid \boldsymbol{x}_t, \boldsymbol{z}_t)} \frac{P(m)}{1 - P(m)} \frac{1 - P(m \mid \boldsymbol{x}_{1:t-1}, \boldsymbol{z}_{1:t-1})}{P(m \mid \boldsymbol{x}_{1:t-1}, \boldsymbol{z}_{1:t-1})} \right]^{-1} \tag{10}$$

Equation (10) explains how to update belief about the occupancy probability of a grid map given a new measurement $\boldsymbol{z}_t$ at location $\boldsymbol{x}_t$. We usually assume that the initial belief $P(m)$ is 0.5 so that the prior can be removed from the equation. Actually, we just need to compute $P(m \mid \boldsymbol{x}_t, \boldsymbol{z}_t)$ at each time t.

A laser range finder can be modeled by varying hit and missed areas over the sensed area. Considering a beam of certain distance in a direction, the grid line can be divided into three parts, as figure 3 shown. The grid cells of missed areas considered as free cells, the cell hit by beam called occupied cell and undetected region by beam regarded as unknown cells. We can describe the function of probability $P(m \mid \boldsymbol{x}_t, \boldsymbol{z}_t)$ using following preconditions: the prior of certain grid cell is 0.5, P_{free} is the probability for free cells and P_{occ} for endpoint cell. Typically, we define $P_{free} + P_{occ} = 1$. Figure 4 shows that the probability of function $P(m \mid \boldsymbol{x}_{1:t}, \boldsymbol{z}_{1:t})$ changes when a cell is seen several times as free or occupied.

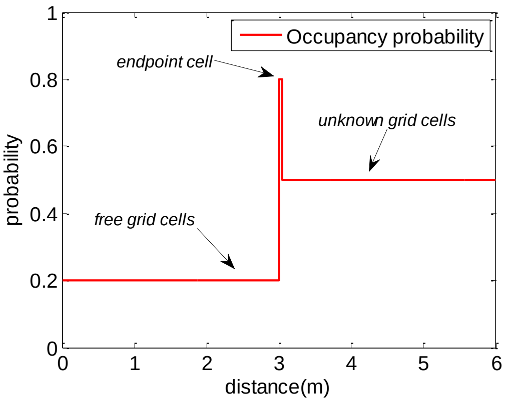

Figure 3

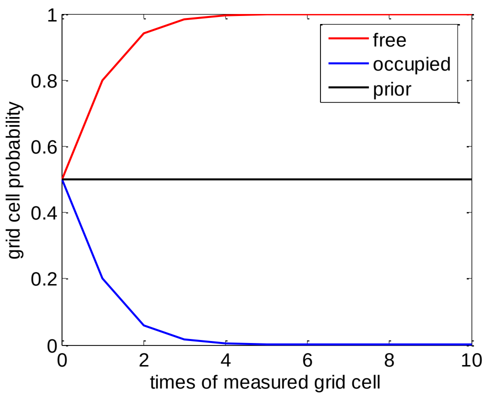

Figure 4

Figure 3 shows the probability of grid cells in a beam direction. Distance of the beam is 3 meters. $P_{free} = 0.2$ *and* $P_{occ} = 0.8$. *Figure4 shows the change of probability when a grid cell is measured several times as free or occupied.*

4 Experiments

The approach described above has been implemented and run online on our quadrotor platform. As figure 5 shown, our quadrotor equipped with an UTM-30LX laser range finder and an XSens IMU for estimating the attitude.

Figure 5. Our quadrotor platform (left), UTM-30LX laser range finder (middle) and XSens IMU (right).

The experiments were carried out in a variety of environments. The first example experiment was in Tsinghua experimental site. The size of this environment is 8m×8m. The quadrotor traveled 25m in an average speed of 0.5m/s. Figure 6 shows the map generated based on our algorithm and the trajectory after closing a loop. As we can see from the figure, our approach is effective. Moreover, the time required to execute one cycle is less than 10ms on our 1.6GHz processor, and it can be used to the closed-loop control in real-time.

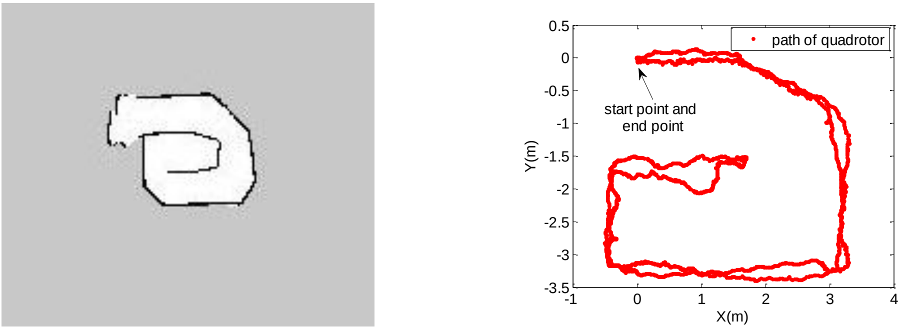

Figure 6. Map of Tsinghua experimental site (left) obtained in real time using our algorithm, and the trajectory of our quadrotor (right) after closing the major loop.

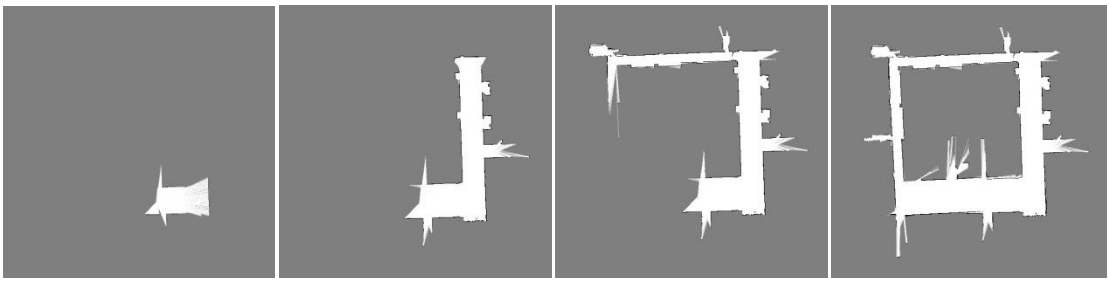

Figure 7. Incremental mapping of New Main Building of Beihang University. The left image shows the initial map and the right image shows the resulting map.

A second example of incremental maps obtained with our approach is depicted in figure 7. The maps show the sixth floor of 50m×50m large corridor environment of New Main Building at Beihang University. The grid resolution is 10cm. As can be seen from the figure, our quadrotor went around the circle in manual mode and still can successfully learn an occupancy probability grid map with high accuracy.

5 Conclusions

This paper has presented a real-time incremental SLAM method for MAV that combines a scan matching procedure with Bayesian mapping using laser scans. The scan matching routine is used to estimate the position with great accuracy and the mapping algorithm with Bayesian updating establish a higher precise global map of indoor environments. The practical experiment results using our quadrotor show that the approach is extremely fast and effective.

References:

[1] G. Dissanayake, H. Durrant-Whyte and T. Bailey, "A Computationally efficient Solution to the Simultaneous Localisation and Map Building (SLAM) Problem," in *IEEE International Conference on Robotics and Automation*, 2000, pp. 1009-1014.

[2] J. Guivant, E. Nebot and S. Bailker, "Autonomous Navigation and Map Building Using Laser Range Sensors in Outdoor Applications," in *Robotic Systems*. vol. 17, 2000, pp. 565-583.

[3] S. Clark and G. Dissanayake, "Simultaneous localisation and map building using millimetre wave radar to extract natural features," in *Robotics and Automation, 1999. Proceedings. 1999 IEEE International Conference on*, 1999, pp. 1316-1321 vol.2.

[4] D. Hahnel, W. Burgard, D. Fox, and S. Thrun, "An efficient fastSLAM algorithm for generating maps of large-scale cyclic environments from raw laser range measurements," in *Intelligent Robots and Systems, 2003. (IROS 2003). Proceedings. 2003 IEEE/RSJ International Conference on*, 2003, pp. 206-211 vol.1.

[5] G. Grisetti, C. Stachniss and W. Burgard, "Improved Techniques for Grid Mapping with Rao-Blackwellized Particle Filters," in *IEEE Transaction on Robotics*. vol. 23, 2007, pp. 34-46.

[6] E. B. Olson, "Real-time correlative scan matching," in *Robotics and Automation, 2009. ICRA '09. IEEE International Conference on*, Kobe,Japan, 2009, pp. 4387-4393.

[7] Z. Zhang, "Iterative Point Matching for Registration of Free-Form Curves and Surfaces," in *International Journal of Computer Vision*. vol. 13, 1994, pp. 119-152.

[8] S. Grzonka, G. Grisetti and W. Burgard, "Towards a Navigation System for Autonomous Indoor Flying," in *IEEE International Conference on Robotics and Automation*, 2009.

[9] H. Moravec, "Sensor Fusion in Certainty Grids for Mobile Robots," in *AI Magezine*. vol. 9, 1988, pp. 61-74.