**Pose Estimation**

The six degree of freedom pose of the center of mass of the UAV in the world frame is (x, y, z, Φ, θ, ψ), where Φ is roll angle, θ is pitch angle, and ψ is yaw angle.

Body frame is the center of mass of the UAV. xb is the preferred forward direction and zb is perpendicular to the plane of the rotors pointing vertically up during perfect hover.

Use ZXY Euler angles to model rotation in the world frame. To translate from body frame to world frame:

1. rotate about the zw axis by the yaw angle, ψ
2. rotate about the intermediate y axis by the pitch angle, θ
3. rotate about the xb axis by the roll angle, Φ

Rotation matrix to transform from body frame to world frame is

R = R(zw, ψ)R (y, θ) R(xb, Φ), where the Rs are elementary rotation matrices with respect to the x, y, and z (see [3] pages 4-9 for additional details).

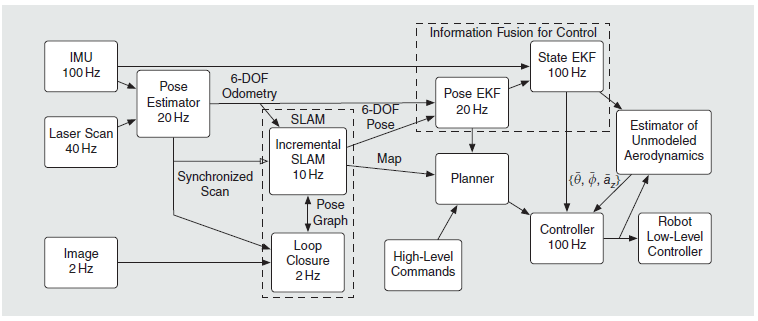


Figure 1. The architecture diagram with update rates from [1].

The Iterative Closest Point (ICP) Algorithm (see [2] for an overview of the concept) finds the transformation between two sets of data points and provides an estimate of (x, y, ψ). This algorithm resides in the *Pose Estimator* process in Fig. 1. It will be necessary to improve on the speed of the basic algorithm.

The basic *ICP algorithm*:

*Input: A reference point cloud and the new data point cloud.*

*Output: An estimate of (x, y, ψ)*

*Step 1. Preprocessing cleans the data.*

*Step 2. Matches the associated points from the reference to the data using the neighbor search. It can use features to identify associated points.*

*Step 3. Weighting changes the importance of some pairs.*

*Step 4. Reject some of the pairs*

*Step 5. Compute the error for each pair and where they should be located.*

*Step 6. Find the best transformation (minimization)*

*Step 7. Loop back to step 2, unless there is convergence.*

Step 2 is very computationally intensive. Penn uses a grid-based search [4] to reduce the computation requirements of the closest point search. Another resource reduces the computational complexity [5], but I have not studied it enough to determine if it will reduce the computation enough (but it does go through the steps in more detail).

Chetverikov‘s paper [4] effectively breaks the point clouds down into regions (boxes). The paper uses squares, but the regions can be rectangles or arbitrary shapes. We can probably use squares or rectangles. This decomposition occurs prior to the neighborhood search.

SLAM TEAM ADD Chetverikov’s algorithms here… You need both the Boxing and search algorithms.

The output of the *Pose Estimator* and the *Incremental SLAM* processor are the inputs to the *Pose EKF* process. This process combines (fuses) the IMU data with the corrected laser range finder scans and provides altitude estimates. Penn uses a variant of work done at the University of Freiburg [6]. Note that Freiburg also uses mirrors with their LRF.

The input to the variant of the Kalman Filter (KF) [6], which actually uses two KFs. Frieburg’s paper does an excellent job of describing the algorithm in Fig 2, and the team needs to read this paper. Note also that [6] has a better picture of the mirrors they use for the LRF.

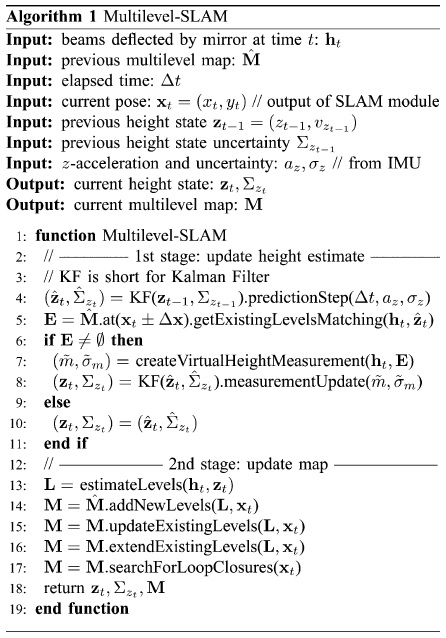


Figure 2. The Multilevel-SLAM algorithm from Univ. of Frieburg [6] that Penn uses a variant of the Kalman Filter, lines 3-11.

Penn estimates (Φ, θ) based solely on the IMU data.

The *Incremental SLAM* process completes portions of Freiburg’s algorithm, specifically, the matching (lines 5-10) and step 5 of the ICP algorithm. The results of the ICP steps prior to step 5 are combined with the IMU data in order to correct the error in the ICP algorithm Step 5. The correction is done by aligning the incoming scans with the map. This comparison uses Chetverikov‘s boxing and searching algorithms.

This process uses an occupancy grid (as an example of occupancy grids pp. 281-290 of [7]) to track where items are located in the area. In my quick review of the papers, it is not clear from any of the papers which type of occupancy grid they are using. I suspect one that has a square grid with grid squares that are not too small, but also not too large. We can discuss what we think the grid sizes should be, but I suspect not smaller that the UAV, plus or minus the error in the LRF, and not so large that a window or a door would be missed.

A new layer of the multi-layered occupancy grid is created when a stable floor transition is detected by the pose estimator.

The output of the *Incremental SLAM* process is a Pose Graph. The Pose Graph includes a representation of the robot poses and the transitions between poses. The graph nodes are the individual robot pose positions and the links between nodes are the relationships between the poses. The pose note at time t0 is connected to the pose note at time t1, and may be connected to a pose node at some later time tx if the UAV has completed a loop and returns to the same position as represented by the node for t0. Figure 3 (in [1]) provides two examples of Pose Graphs that show a single loop (Figure 3.a) or multiple loops (Figure 3.b) through the environment.

The next step is Loop Closure and the SURF paper. Suspect that they are singling out features from the database for comparison given that they are working in man made environments.

**References**

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