Low Cost solution for Pose Estimation of Quadrotor

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Outline

Introduction

- Our goal is to make robust systems capable of Navigating in GPS denied environments.
- Exploring the enormous scope of Indoor Navigation (Surveillance, Disaster Management or systems for first response).
- System which can be used Ubiquitously overcoming nonuniform environmental conditions.

Introduction

Why No to GPS!!

- GPS signal are highly dependent on the operating conditions.

Localization

- The major milestone for autonomous navigation is localization.
- Recently, SLAM based techniques are showing promising results.
- Our major focus is on localization working on range based sensors like UWB, Wi-Fi and augment with IMU (accelerometer, gyroscope and magnetometer) and optical flow camera.

Previous approaches

Attitude estimation

- Estimation of IMU and MARG orientation using a gradient descent algorithm (Madgwik, 2011).
- Experimental comparison of sensor fusion algorithms for attitude estimation (Cavallo, 2014).

SLAM approaches

- ORB-SLAM: a versatile and accurate monocular SLAM system (Mur-Artal, 2015).
- Towards a navigation system for autonomous indoor flying (Grzonka, 2009). A laser based SLAM approach.

Previous approaches

Challenges

- Vision and Lidar SLAM approaches require sensor with heavy payload and are computationally inefficient.
- The attitude estimation approaches are computationally efficient citing the usage of micro-controllers, but loses accuracy.

Our approach

- We make use of on-board computers along with bringing down the computation involved in SLAM processes and assigning more computation to attitude estimation.

Our Approach

Why range based solutions (UWB sensors)

- Payload efficient: requires just 25-30gm of additional payload.
- Processing efficient: SLAM based solutions require higher computational cost which in process requires powerful and heavy processors.
- Cost efficient: These solutions are cheaper. Wifi systems are becoming common to lots of Places.

Pose Estimation using UWB sensor

- An EKF based solution to estimate the position and attitude of the system.
- Uses gyroscope, accelerometer and magnetometer data for quaternion estimation.
- Fusion of Sonar with accelerometer for height estimation.
- Fusion of velocity from optical flow camera with the accelerometer data for position estimation.
- A SLAM based approach for the UWB sensor position estimation and simultaneously correcting for system's position.

Quaternion Estimates

- Gyroscopic data is main input in the prediction step of the Kalman fusion process for acquiring quaternion.
- Gyroscopic data suffers from bias and an integrating solution can thus result in erroneous output in long run.
- Assuming that the accelerometer data in the body frame when operated by the predicted quaternion will result in gravity vector.
- Thus the accelerometer serve as measurement correction.

Quaternion Estimates

Prediction Step for Quaternion

$$S_\omega = [0 \quad \omega_x \quad \omega_y \quad \omega_z], \qquad \dot{q} = \frac{1}{2} q \otimes S_\omega$$

$$\dot{q}_{\omega,t} = \frac{1}{2} q_{\omega,t-1} \otimes S_\omega, \qquad q_{\omega,t} = q_{\omega,t-1} + \dot{q}_{\omega,t} \Delta t$$

Accelerometer Update

$$E_g = [0 \quad 0 \quad 0 \quad 1], \qquad B_a = [0 \quad a_x \quad a_y \quad a_z]$$

$$B_a = q^*_{\omega,t} \otimes E^b_g \otimes q_{\omega,t}$$

$$e_a = z - \hat{z}_a = \begin{bmatrix} ax - 2(q_1 q_3 - q_0 q_2) \\ ay - 2(q_0 q_1 + q_2 q_3) \\ az - 2(\frac{1}{2} - q_1^2 - q_2^2) \end{bmatrix}$$

Quaternion Estimates

Accelerometer transformation

$$a_b = \begin{bmatrix} cos\theta cos\psi & cos\theta sin\psi & -sin\theta \\ -cos\phi sin\psi + sin\phi sin\theta cos\psi & cos\theta cos\psi + sin\phi sin\theta sin\psi & sin\phi cos\theta \\ sin\phi sin\psi + cos\phi sin\theta cos\psi & -sin\phi cos\psi + cos\phi sin\theta sin\psi & cos\phi cos\theta \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

Magnetometer Update

- The accelerometer however cannot correct for the yaw motion as the rotation about yaw parallels the gravity direction.
- Based on the magnetic field of the earth we can find the north direction.
- Our approach uses a Magnetic distortion compensation model (Madgwick's AHRS) for the yaw estimation.

Quaternion Estimates

Magnetometer Measurement Update

$$B_m = [0 \quad m_x \quad m_y \quad m_z]$$

$$E_h = [0 \quad h_x \quad h_y \quad h_z] = q_E^B \otimes B_m \otimes q^{*}{}_E^B$$

$$E_b = \left[0 \quad \sqrt{h_x^2 + h_y^2} \quad 0 \quad h_z\right] = [0 \quad b_x \quad 0 \quad b_z]$$

$$e_m = z - \hat{z}_m = \begin{bmatrix} mx - 2b_x(\frac{1}{2} - q_2^2 - q_3^2) + 2b_z(q_1 q_3 - q_0 q_2) \\ my - 2b_x(q_1 q_2 - q_0 q_3) + 2b_z(q_0 q_1 + q_2 q_3) \\ mz - 2b_x(q_0 q_2 + q_1 q_3) + 2b_z(\frac{1}{2} - q_1^2 - q_2^2) \end{bmatrix}$$

Quaternion Estimates EKF

State Vector and Observation Vector

$$\nu_t = \begin{bmatrix} q_0 & q_1 & q_2 & q_3 & m_x & m_y & m_z & x & y & z & V_x & V_y & V_z & x_d & y_d & z_d \end{bmatrix}_t^T$$

$$z_t = \begin{bmatrix} a_x & a_y & a_z & m_x & m_y & m_z & V_{x,\mathcal{B}} & V_{y,\mathcal{B}} & h_{\mathcal{B}} & R \end{bmatrix}_t^T$$

Measurement Update

$$\begin{aligned} \hat{z}_{MARG} &= \begin{bmatrix} \hat{z}_a \\ \hat{z}_m \end{bmatrix} \\ K_{MARG} &= H_{MARG}\hat{\Sigma}(H_{MARG}\hat{\Sigma}H_{MARG}^T + Q) \\ \nu_t &= \hat{\nu}_t + K(z - \hat{z}) \\ \Sigma_t &= (I - K_{MARG}H_{MARG})\hat{\Sigma}_t \end{aligned}$$

Attitude estimates (roll)

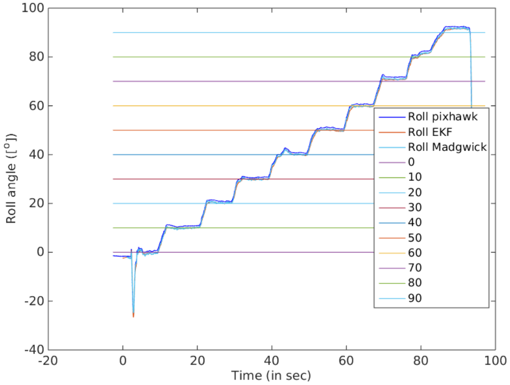

Figure: Estimated roll

Attitude estimates (roll)

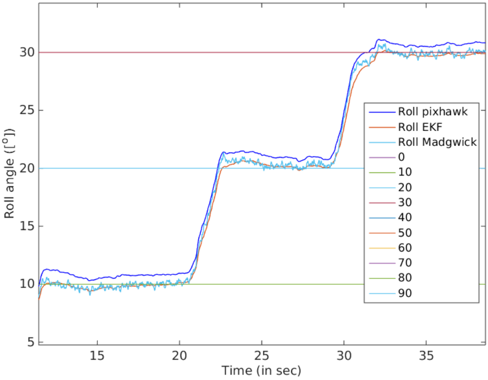

Figure: Estimated roll

Attitude estimates (pitch)

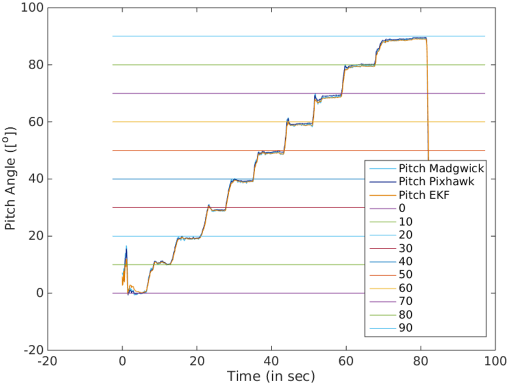

Figure: Estimated pitch

Attitude estimates (pitch)

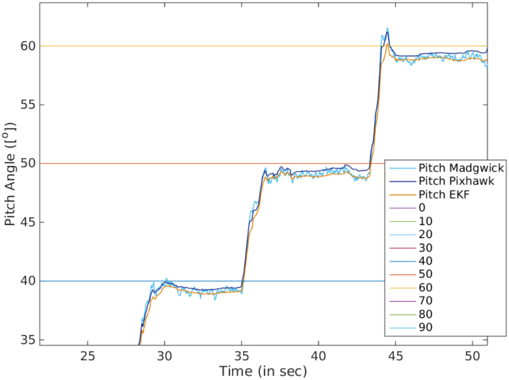

Figure: Estimated pitch

Attitude estimates (yaw)

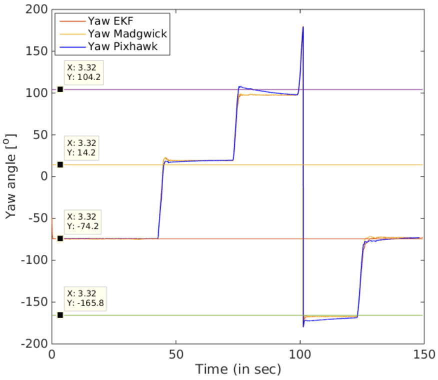

Figure: Estimated yaw

Attitude estimates (yaw)

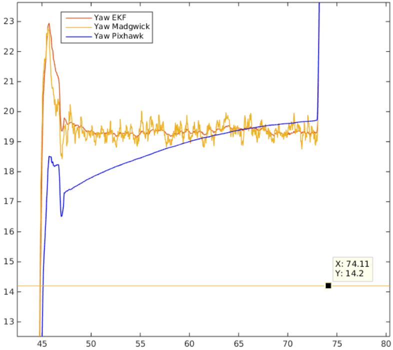

Figure: Estimated yaw

Attitude estimates (yaw)

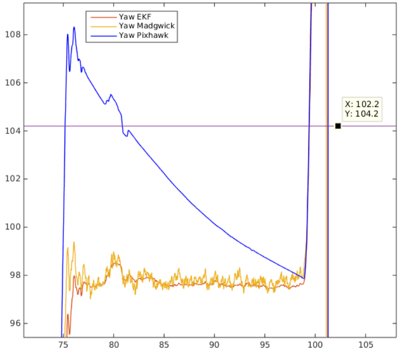

Figure: Estimated yaw

Attitude estimates (yaw)

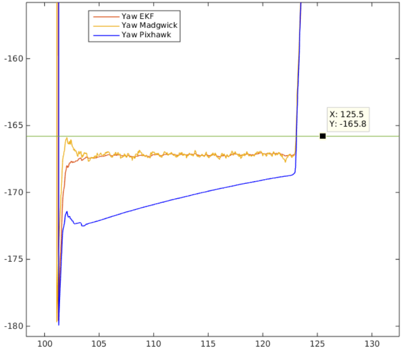

Figure: Estimated yaw

Attitude estimates (yaw)

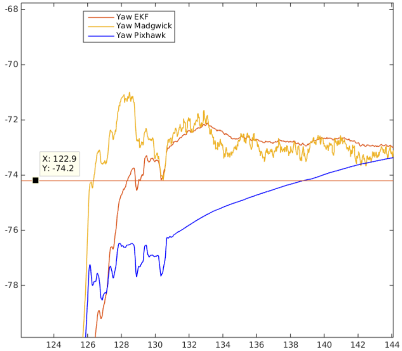

Figure: Estimated yaw

Attitude estimates

- The roll, pitch and yaw estimates approximates the ground truth results.
- The roll and pitch estimates show better results as compared to Madgwick's AHRS.
- The convergence of yaw estimates are fast as compared to pixhawk's EKF.
- The magnetic distortion compensation does not require user predefined direction.

Position Estimation

- Fusion of accelerometer data with the raw velocity measurement from optical flow camera.
- All vision based solution suffer from drift and in the long run diverges from ground truth results.
- However, for short duration flights result accuracy matches vision based ORB SLAM solution.

Position Estimation

- Fusing the Sonar data and the accelerometer data along with quaternion operations to account for non linearity.
- Sonar data is precise with an accuracy of $\pm$ 5cm but suffers from irregularities.
- High dependence on sonar can lead to noisy and inaccurate estimates of height.
- We pass the sonar raw estimates through a median filter, which sorts out the outlier values.

Position Estimation

Prediction Update

$$\hat{x}_t = x_{t-1} + V_{t-1}\Delta t$$

$$\hat{V}_t = V_{t-1} + (R_B^E a - [0, 0, g]^T)\Delta t$$

Measurement Update

$$\hat{z}_{PX4} = \begin{bmatrix} \hat{V}_{x,\mathcal{B}} \\ \hat{V}_{y,\mathcal{B}} \\ \frac{\hat{\nu}(10)_t}{(q_0^2+q_3^2-q_1^2-q_2^2)} \end{bmatrix}$$

$$\begin{aligned} K_{PX4} &= H_{PX4}\hat{\Sigma}(H_{PX4}\hat{\Sigma}H_{PX4}^T + Q) \\ \nu_t &= \hat{\nu}_t + K_{PX4}(z_{PX4} - \hat{z}_{PX4}) \\ \Sigma_t &= (I - K_{PX4}H_{PX4})\hat{\Sigma}_t \end{aligned}$$

Height Estimation

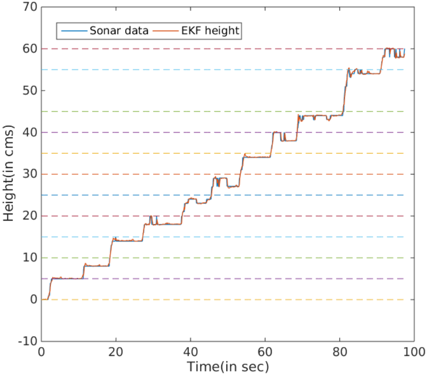

Figure: Estimated Height

Height Estimation

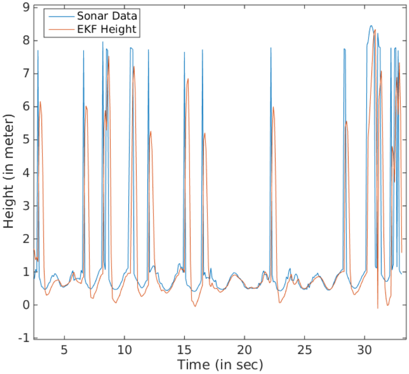

Figure: Estimated Height

Height Estimation

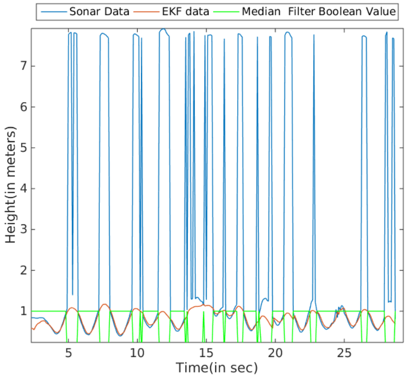

Figure: Estimated Height

Position Estimation

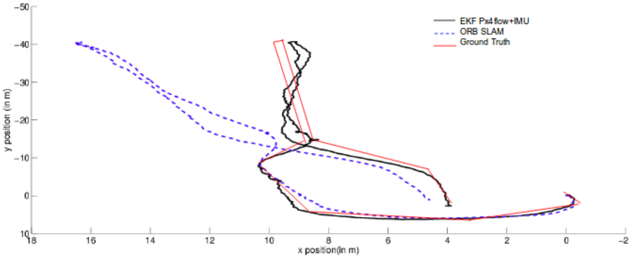

Figure: Estimated Position Only px4flow vs ORB SLAM

Range Only SLAM

- Range only data does not allow the other UWB sensor to be localized until we have accurate estimate of system position.
- Our approach make use of velocity-accelerometer fusion for initial measurements.
- Once the system is able to localize the UWB sensor the weight on the estimates from the UWB sensor is given more weight.

Range Only SLAM

$$\hat{z}_D = \sqrt{(\hat{v}_t(8) - \hat{v}_t(14))^2 + (\hat{v}_t(9) - \hat{v}_t(15))^2 + (\hat{v}_t(10) - \hat{v}_t(16))^2}$$

$$\begin{aligned} K_D &= H_D\hat{\Sigma}(H_D\hat{\Sigma}H_D^T + Q) \\ \nu_t &= \hat{\nu}_t + K_D(z_D - \hat{z}_D) \\ \Sigma_t &= (I - K_D H_D)\hat{\Sigma}_t \end{aligned}$$

Position Estimation

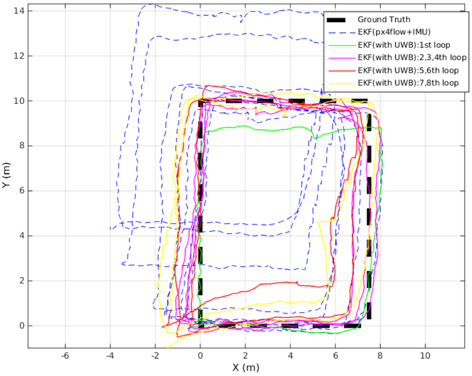

Figure: Position Estimate

Position Estimation

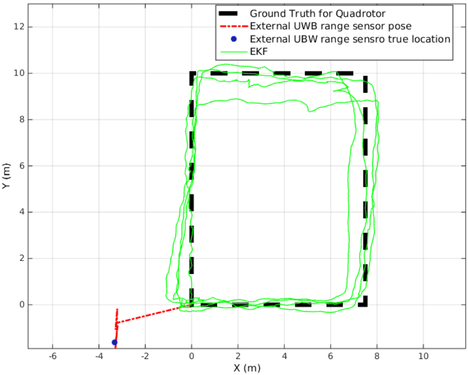

Figure: Position Estimate

Position Estimation

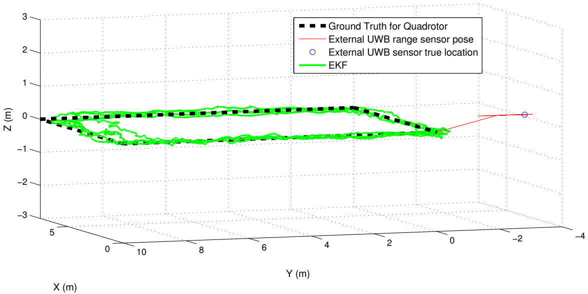

Figure: Position Estimate

Wifi Triangulation for Localization

- Better initialization of router position leads to better accuracy in position estimates.
- First interval involves data gathering and applying least squares to estimate router positions.
- The estimate router position serve as an initial guess to the EKF.

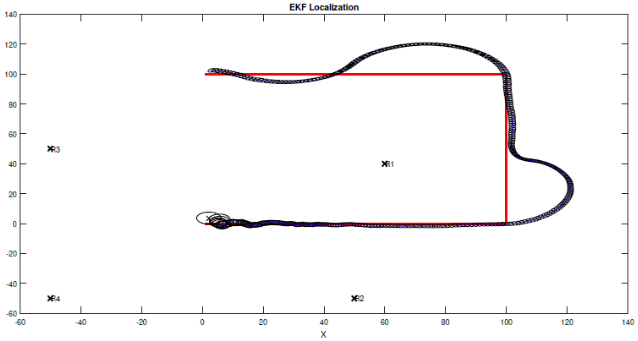

Figure: EKF Localization

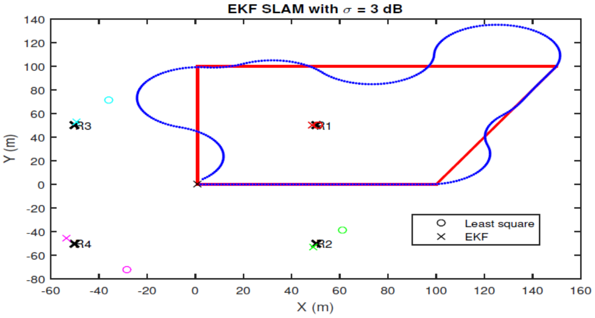

Figure: EKF SLAM

WiFi RSSI Fingerprinting

- A pre-calibration is done to extract a fingerprint of the RSSI signal.
- Based on the distribution we extract the position estimates.
- KNN and WKNN methods are used applying discrete or guassian distribution.

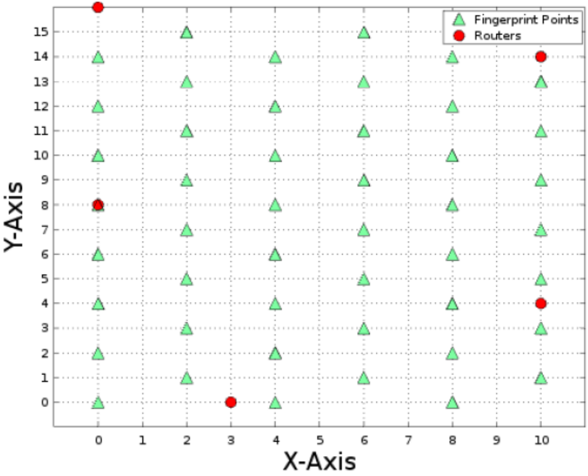

Figure: Data Gathering

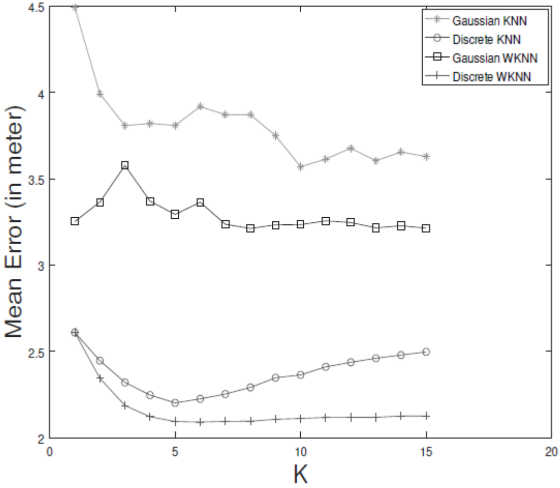

Figure: EKF Localization

Conclusion

- We presented solutions which do not require high computation cost.
- The presented sensor solutions are light weight allowing UAVs to have higher payload.
- The performance of the solution performs comparable to the state of the art techniques.