ESE 650 Project 2: Orientation Tracking

You

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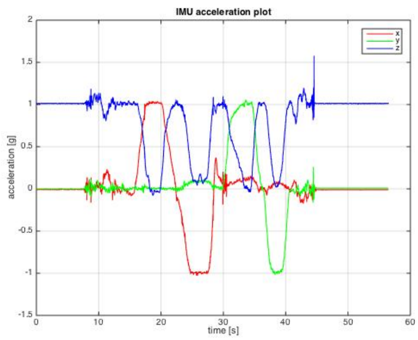
1 Introduction

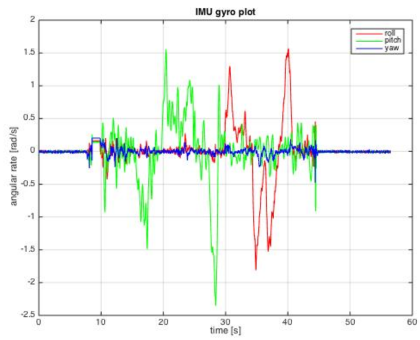
In this project, we were tasked with tracking the orientation of a sensor rig equipped with a 6-DOF IMU and a camera. Using the orientation data, we were to stitch a panoramic image using the video feed from the camera. To achieve this, I implemented an Extended Kalman Filter (EKF) to fuse gyroscope and accelerometer data to track orientation. I also implemented an Unscented Kalman Filter (UKF), as outlined in [1], as an alternative to the EKF and compared the results, concluding that the UKF was far superior. Ground truth orientation data from a Vicon motion tracking system was provided as reference.

2 Sensor Calibration and Synchronization

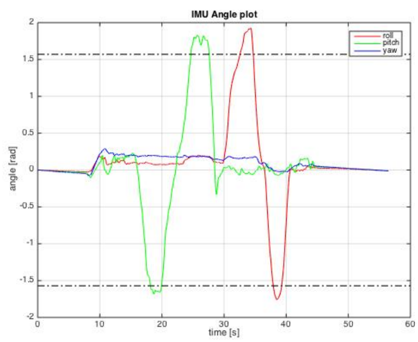
The first step in this project was to calibrate the IMU data and synchronize the associated Vicon and camera data as they all were recorded at different rates. This was achieved by finding the closest Unix time stamp of each data component to each other. The second step was to find the proper bias and scale factor for the accelerometer and gyro data. Figure 1 below shows the result of the calibration.



(a) Accelerometer calibrated to g's.



(b) Gyro data calibrated to rad/s.



(c) Integrated gyro data calibrated for bias.

Figure 1: Pictures of animals

The following equations were used for calibration:

$$\vec{a}_c = \alpha_s(\vec{a}_r - \vec{a}_b)$$

$$\vec{\omega}_c = w_s(\vec{\omega}_r - \vec{\omega}_b)$$

where $\vec{a}$ is acceleration, $\vec{\omega}$ is angular velocity, and the subscripts r, b, and s indicate the raw value, bias, and scale factor respectively.

3 Extended Kalman Filter

Due to the non-linearity in the dynamics of orientation tracking, an EKF was implemented. The EKF kept track of a state vector $\vec{x}_k$ which consists of an orientation and instantaneous angular rate, where orientation is represented with a quaternion and angular rate with an angular velocity vector in the body frame of the sensor rig. Angular velocity was set in the dynamics of the model, and the acceleration from the accelerometer was used in the measurement model. The dynamics model is given by a first order approximation of the time derivative of the quaternion:

$$\vec{x}_{k+1} = \frac{d}{dt}(\vec{x}_k)\Delta t + \vec{x}_k$$

$$\begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \\ \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix}_{k+1} = \frac{1}{2}\Delta t \begin{bmatrix} 0 & -\omega_1 & -\omega_2 & -\omega_3 & 0 & 0 & 0 \\ \omega_1 & 0 & \omega_3 & -\omega_2 & 0 & 0 & 0 \\ \omega_2 & -\omega_3 & 0 & \omega_1 & 0 & 0 & 0 \\ \omega_3 & \omega_2 & -\omega_1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}_k \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \\ \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix}_k + \begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \\ \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix}_k$$

Since measurements were accelerometer readings, I was only able to extrapolate the the tilt of the acceleration vector with respect to the body frame. Two Euler angles, roll ϕ and pitch θ, were obtained from the acceleration vector, and subsequently converted to a quaternion. The measurement model for the observation $\vec{o}_k$ is given by the following:

$$\vec{a}_k = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}$$

$$\phi = \tan^{-1}(\frac{a_2}{a_3})$$

$$\theta = \tan -1(\frac{-a_1}{a_3})$$

$$\psi = \int_0^k \omega_3(t)dt$$

$$q_a = \begin{bmatrix} \cos(\phi/2)\cos(\theta/2)\cos(\psi/2) + \sin(\phi/2)\sin(\theta/2)\sin(\psi/2) \\ \sin(\phi/2)\cos(\theta/2)\cos(\psi/2) - \cos(\phi/2)\sin(\theta/2)\sin(\psi/2) \\ \cos(\phi/2)\sin(\theta/2)\cos(\psi/2) - \cos(\phi/2)\sin(\theta/2)\sin(\psi/2) \\ \cos(\phi/2)\cos(\theta/2)\sin(\psi/2) - \sin(\phi/2)\sin(\theta/2)\cos(\psi/2) \end{bmatrix}$$

$$\vec{o}_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}_k \begin{bmatrix} q_a \\ \tilde{\mathbf{0}} \end{bmatrix}_k$$

The covariances and Kalman gain were calculated in the usual way.

Updates only occurred when $a_2 < 0.9g$ and $a_3 < 0.9g$ because at full pitch or roll, the resulting quaternion became degenerate and updates became unusable. Updates were also limited to when $|\vec{a}_k| < 1.1g$ for obvious reasons.

4 Unscented Kalman Filter

The UKF was implemented as outlined in [1]. Noise was carefully tuned to properly match the stitching.

5 Sample Results and visualization

A sample visualization is provided in Figure 2 below.

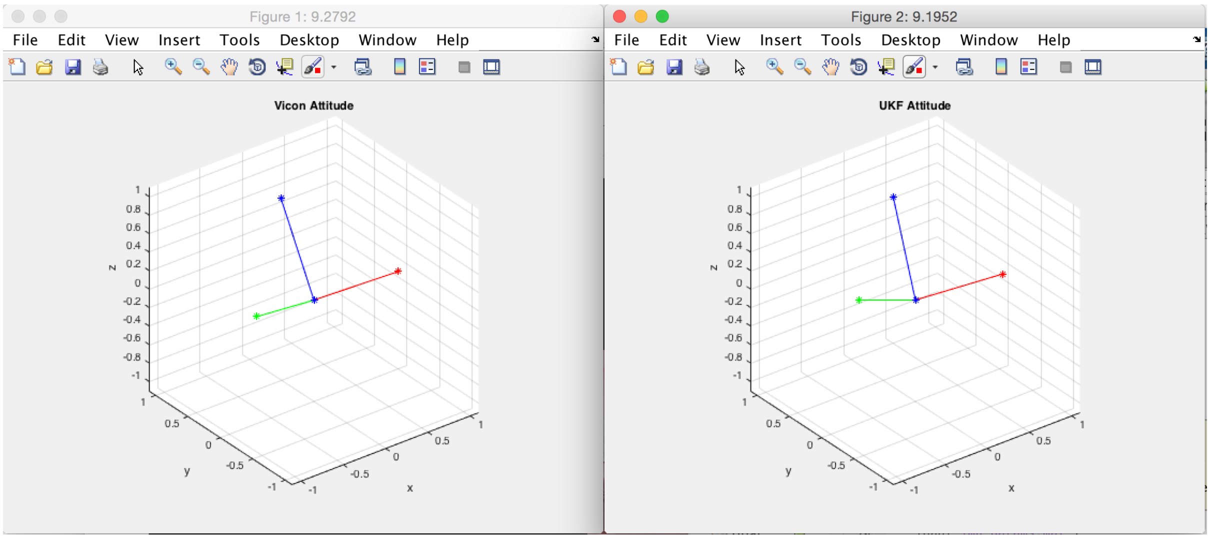


Figure 2: Sample visualization of orientation.

The resultant image stitchings for the EKF and UKF are compared in Figures 3 and 4 on the next page. We can see that the UKF was able to maintain vertical orientation slightly better than the EKF.

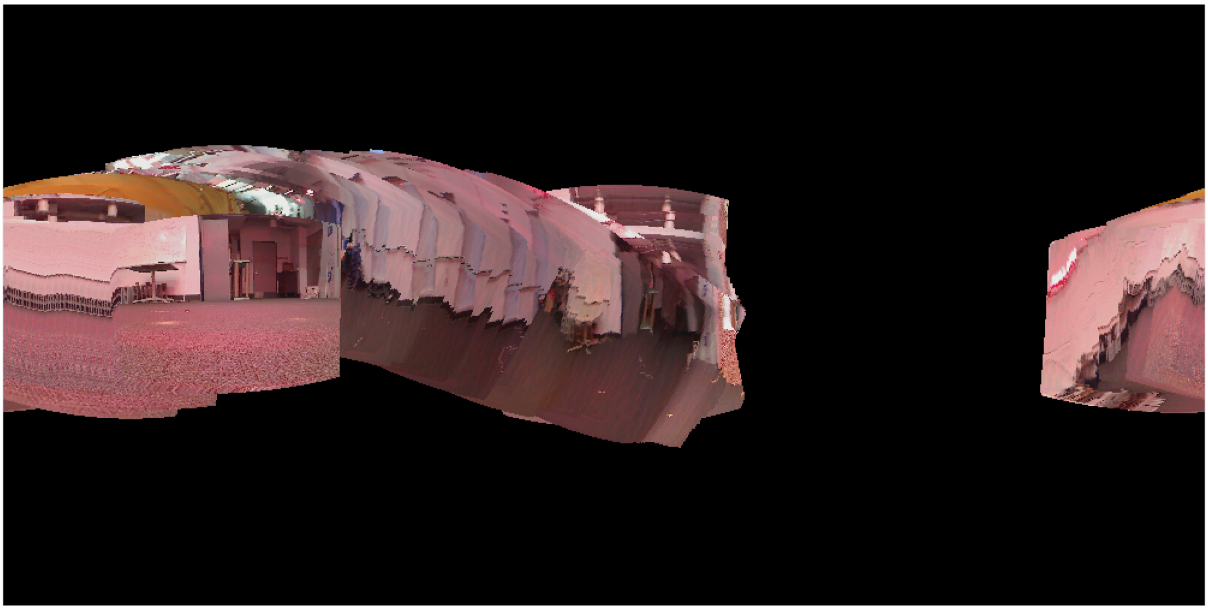


Figure 3: Sample EKF stitch.

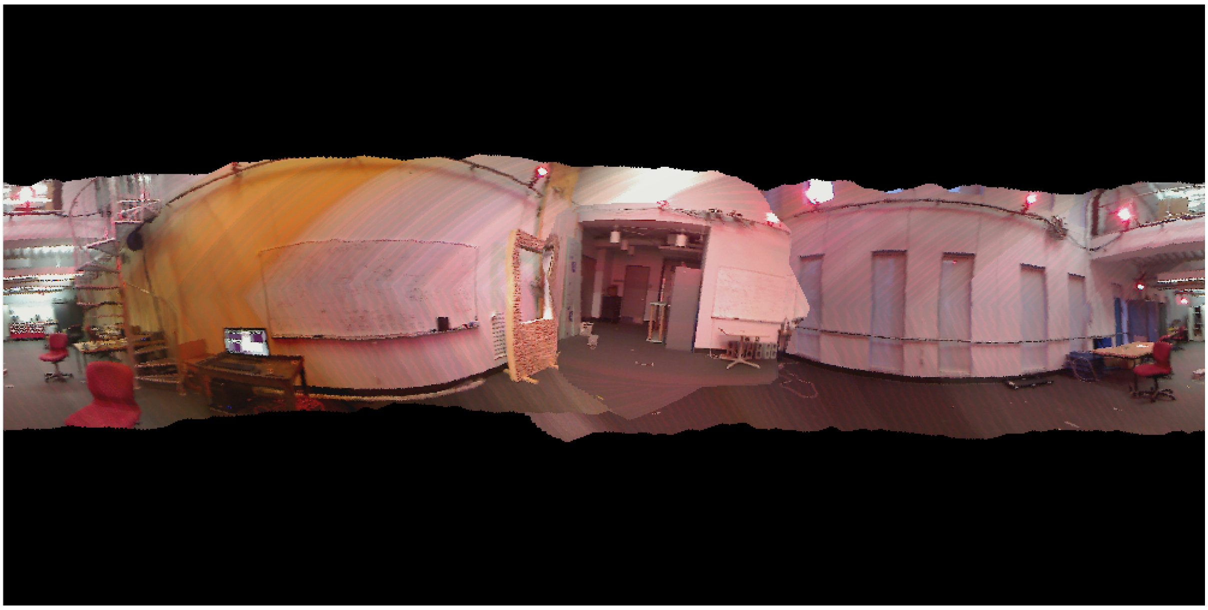


Figure 4: Sample UKF stitch.

References

[1] Kraft, Edgar. *A Quaternion-based Unscented Kalman Filter for Orientation Tracking*. Physikalisches Institut, University of Bonn, Germany.