ESE 650 - Learning in Robotics
Unscented Kalman Filters And Image Panoramas

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Introduction

Problem Statement

The objective of the project is to use the noisy signals from an IMU containing a 3 axis gyroscope and a 3 axis accelerometer to obtain a robust estimate of the orientation of an object rotated in 3D space and using the orientation to stitch a panoramic image of the photos taken by a camera mounted on the object. We are also provided ground truth of the orientations from a Vicon system.

Description of approach

I smoothed out the raw signals from the accelerometer to reduce the high frequency noise and then removed the bias from all the input signals. I multiplied the appropriate sensitivities to the signals which I obtained by comparing the signals with the ground truth from the Vicon data. I implemented Unscented Kalman Filters(UKF), to obtain the orientation of the image which is in the form of a rotation matrix, from which one can extract the roll, pitch and yaw angles. Using these angles I pasted the images, in the appropriate position on a large canvas, initially without any transformation and then considering only about the image plane. Both the techniques work only near the center of the canvas. Throughout the report I refer to the equations and the terminologies on the "A Quaternion-based Unscented Kalman Filter for Orientation Tracking" paper by Edgar Kraft, University of Bonn.

Methodology

The methodology can be split into the UKF and the panorama part:

UKF

a) The IMU data was cleaned out by first smoothing out the accelerometer values by using Savitzky-Golay filtering with a third degree polynomial and with a frame size of 31. Then the bias was estimated by looking at the data when the IMU was stationary and removed from the signals.
b) To estimate the sensitivity of the accelerometer, I tried to tweak the cleaned accelerometer signals until the rotation of those vectors with the rotation matrices from Vicon produced the global true g of [0 0 -1].
c) To estimate the sensitivity of the gyroscope, I tuned the signals with a scaling factor until the quaternions generated from the gyroscope data matches the quaternions obtained from the rotation matrices of the Vicon data. To compute the quaternions from the gyroscope, I do a small time update to get the rotation quaternion to the next state, q_{Δ} and then used the equations (10), (11), (12) on the paper. To obtain the quaternions from the rotation matrices of the Vicon data, first the matrices were converted to an axis angle representation and the quaternion was obtained from equation (14), (15), (16) on the paper.
d) I initialized my state vector to [1;0;0;0;0;0;0], where the first four terms correspond to a quaternion giving the orientation and the next 3 terms give the angular velocity.

e) I obtain the sigma points using the equations (34), (35) and (35). To go from the six dimensional noise space (W) to the seven dimensional state space we convert the rotation vector of the disturbance to quaternion we use equations (14), (15) and (16). We use the same equations to move back and forth from rotation vector to quaternion space and vice versa.

f) The P and Q covariance matrices are made to be diagonal matrices and Q is made as a function of the time step.

g) The normal state updates are done according to the paper.

h) The mean of the updated state is obtained by gradient descent for the quaternions (52), (53) and (54) and for the angular velocities as just the mean. And then corresponding covariance is obtained P_k^-.

i) The space is converted to the measurement space by converting the quaternion of the updated sigma points in the Y space to the acceleration due to gravity in the local frame using equation (27) but we perform quaternion inverse the vector quaternion and quaternion as in our case the quaternion represents the rotation from the body frame to the world frame. The measurement covariance (P_{xx}) is obtained according to equation (68) and (Pvv) is obtained as

$$P_{vv} = P_{zz} + R$$

where R is the noise covariance of the IMU. We compute the cross correlation matrix (P_{xz}) which takes us from the measurement space to the six dimensional state space (70) and (71).

j) The Kalman gain is computed using equation 72. Then the innovation vk is obtained as the difference between the mean of the predicted measurements and the actual measurement. The final update is done according to equation (73). But the tricky part here is that the 7dimensional state space has to be converted to 6dimensional (14), (15) and (16) to do the update and then be transformed back to the seven dimensional.

k) The parameters set for the covariances are
P_1 = eye(6) * 0.002
Q = eye(6) * 0.001 * ($time_k$ - $time_{k-1}$)
R = eye(6)
R(1:3,:) = R(1:3,:)*0.001
R(4:5,:) = R(4:5,:)*0.0002
R(6,:) = R(6,:)*0.001

Panorama

a) The rotation matrices are converted to roll, pitch and yaw angles.

b) The camera is positioned facing x direction and the depth of the image is assumed to be at some depth and the plane to which the image is projected to be 25 times the distance. The x axis is assumed to pass through the center of the canvas.

c) By doing similar triangles we can get the elevation from the pitch angles and the lateral displacements from the yaw angles.

d) I produce two techniques to make the panorama.
    a. In the first case, I just use the pitch and the yaw angles for elevation and lateral shift from the center of the canvas.
    b. In the second case, I produce the elevation and lateral shifts, but I also produce rotations to the images by affine transformation using the roll angles. From the rotated images I take the convex

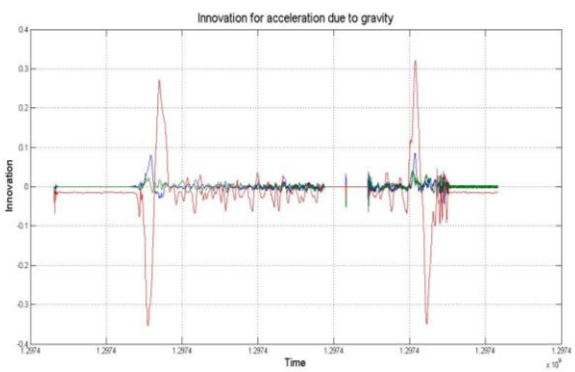
hull of the rotated image and copy it back to the canvas.

Results

The algorithm works very well for most of the given.

Problem & Solutions of Tracking

1) Whenever the roll, pitch or yaw angles go beyond 140 degrees, the accelerometer values, produces too much noise. So, the innovation from the acceleration due to gravity is neglected. This does not affect the accuracy of tracking too much as the drifts are corrected when the object comes out of this angle space.
2) The yaw drifts as there is no way to correct the drift in the yaw angles without a magnetometer.



As we see there are two big spikes in the graph of innovation for acceleration due to gravity which are avoided by not picking innovations which are too large. This is the graph plotted for the dataset 8.

A link to the video of tracking with rotplot.m is given below. This is for dataset 2.

https://www.youtube.com/watch?v=s7UQKXhYSgU&feature=youtu.be

Problem & Solutions of Panorama

1) The Panorama works very well when the angle shifts are small but when the angles get large as I am not performing a homography, we can see that the shifts causes the images the images to move away from each other producing discontinuities in the image.
2) There is also rotation of the camera which is taken care by the affine transformation with the roll angles but since I am pasting a convex hull of the transformed image.

This is with method 1.