Uncented Kalman Filter Based Orientation Tracking

Qiong Wang
University of Pennsylvania
3401 Chestnut St., Philadelphia
qiong@seas.upenn.edu

Daniel Lee
University of Pennsylvania
3401 Chestnut St., Philadelphia
ddlee@seas.upenn.edu

Abstract

Data fusion is a significant part for robots integrated with various sensors. Kalman filter is one widely-used technique to merge data efficiently from different sensors. In this paper, one Uncented Kalman Filter (UKF) algorithm was developed to fuse the data from both the accelerometer and gyroscope to estimate and track the orientation of a platform in real time.

1. Introduction

This project was accomplished for coursework in ESE 650: Learning in Robotics at University of Pennsylvania. The objective is to implement a Kalman filter to track three dimensional orientation of a platform in real time. Data fusion is an essential method for real time system robot integrated with various sensors to obtain accurate and efficient data. Kalman filter is one of general techniques to fuse data and provide good result. As one way of Kalman Filter, in Uncented Kalman Filter (UKF), a nonlinear motion and sensor model was built through performing the sigma points on the model to estimate new results instead of linearizing the dynamics.

The tracking information data were provided from a Vicon system by motion capturing and the accelerometer and gyroscope in the Inertia Measurement Unit (IMU). Besides, the scene where the platform is is also tracked and provides as one set of RGB images. In this project, an UKF algorithm was implemented to provide more accurate 3D orientation data and one real-time mosaicing of the tracking scene was also created after computing three dimentional orientation by the filter. The algorithm, the results and even the mosaicing image are presented in details below.

2. Preprocessing of data

At an input, the training data were taken from an IMU at different time stamps. In the preprocessing stage, the bias and scalability of sensors are computed by averaging the raw IMU data over the first static 150 sample time stamps. The bias of the gyroscope is just mean of the angular velocity readings, while for accelerometer, the mean of the first 150 static samples needs to be scaled to a vertical vector g pointing down. Here I used $[0; 0; 1]$ which will lead to the negative sign multiplication on the z value in gyroscope and also when we estimate the measurement model we set the quaternion of g is as $[0\ 0\ 0\ 1]$. With reference to the data sheet, we can easily compute the scale factor for both the accelerometer and gyroscope and preprocess them into 3D vectors [2].

3. Time Synchronization

Considering the various time difference from sensors, we need to synchronize the timestamps from the IMU unit, Vicon and also the camera. Here one brute-force method was used to compare difference between each group of timestamps and finding the smallest one or find some similar timestamps within one threshold. Here, since the IMU and the vicon both works approximately at the frequency 1000 Hz. We can just find the nearest timestamps among them. And for the camera we use the latter method to synchronize.

4. UKF Algorithm

As mentioned in the introduction part, UKF is a variant of the Kalman filter so as to solve nonlinear process and measurement models. UKF uses a sampling method to choose a set of Sigma points to propagate the distribution. The UKF in this project mainly consists of the measured acceleration of the rigid body and the body angular velocity. Both of them can be used to provide 3D spatial information about the body with respect to the local world frame. Here I both tried the 7 state UKF and 4 state one, since the data from the gyroscope was quite good. I mainly implement one 4 state UKF and the angular velocity data was directly obtained from the IMU.

The UKF algorithm can be also summerized as below [1]:

1. Initialize Covariance Matrix: Here three main covari-

ance matrices we referred to:

(a) State Covariance Matrix P

(b) Process Noise Matrix Q

(c) Measurement Noise Matrix R

All of them are diagonal matrix with different scale. Generally, the Q is not a large number, while R is relatively large (values are all within the range of [0, 1]).

2. Process Model: The gyroscope here was comparatively less noisy and can directly be used in the process model. A set of sigma points were obtained through Cholesky decomposition of the summation of state noise covariance P and the process noise covariance Q.

3. Measurement Model: The oberservation stage was primarily used to find the difference ν between the directly mesured accelerometer data and the predicted measurement from the dynamic model.

5. Image Mosaicing

The stitching result is not so good only use the brute force method. Here is the result of the stitching part.

Figure 1. Result 1 from train dataset 1

6. Results

Here are the results of several train datasets. See the results from both datasets 1 and 2, the UKF did a good job. However, there are still some scenarios such as the dataset 9 the result is not so good.

7. Conclusion

In this project, one UKF algorithm was implemented to estimate the 3D orientation data from the IMU with good estimation result comparing to the vicon data. However in some cases, the rotations went slightly out of control. Beside, there should also be kind of learning algorithm for the covariance paramters so as to avoid overfitting in some extreme cases, but due to the insufficient time I didn't do that, it can be one of the improvement in the future work.

8. Acknowledgement

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References

[1] E. Kraft. A quaternion-based unscented kalman filter for orientation tracking. Physikalisches Institut, University of Bonn, Germany.

[2] D. Lee. Lecture notes for ese 650: Learning in robotics, 2014.

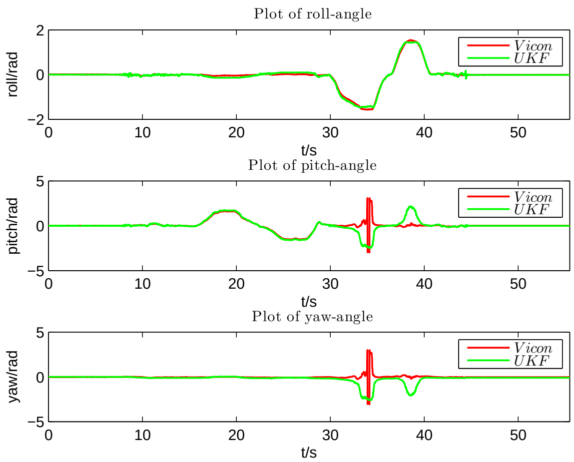

Figure 2. Result 1 from train dataset 1

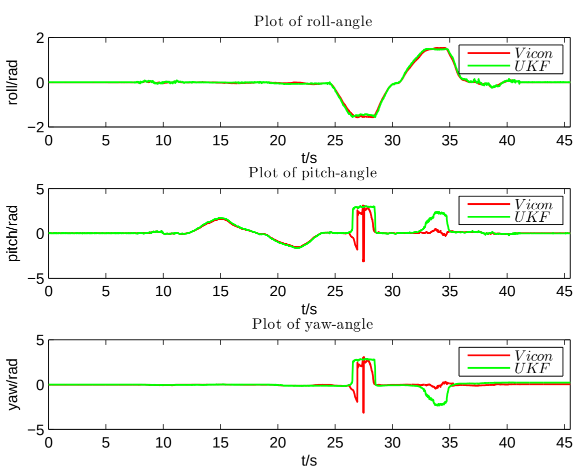

Figure 3. Result 2 from train dataset 2

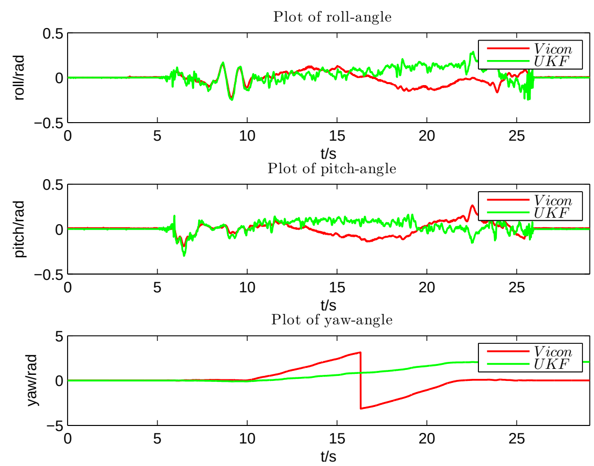

Figure 4. Result 3 from train dataset 9