ENAE788M Assignment 1 - Attitude Estimation using Complimentary Filter and Madgwick Filter

Estefany Carrillo, Mohamed Khalid M, and Sharan Nayak

I. INTRODUCTION

In this project, we have implemented the complementary filter and the Madgwick filter to estimate orientation values from IMU data. The complimentary filter does a linear combination of orientation estimates derived from gyroscope and accelerometer data. Both components provide an independent orientation estimate, and thus, by fusing these estimates together, we can improve estimation results.

The Madgwick filter uses a quaternion representation, allowing accelerometer and magnetometer data to be used in a gradient-descent based algorithm to compute the direction of the gyroscope measurement error as a quaternion derivative [1]. Then, this derivative is integrated to compute the final orientation estimate.

In the following sections, we present a description of our implementation of each filter and the parameter values used to tune the resulting estimation.

A. Estimating Orientation from Gyroscope Data

The provided gyroscope data has angular velocity data in the order ω_z, ω_x, ω_y respectively. To facilitate easy processing, the order is set to the usual convention of ω_x, ω_y and ω_z. The bias b_g is calculated by taking the mean of first 300 samples. The gyroscopic values are first converted to physical units of rad/s by using the equation

$$\tilde{\omega} = \frac{3300}{1023} \times \frac{\pi}{180} \times 0.3 \times (\omega - b_g)$$

where $\tilde{\omega}$ is the value of ω in rad/s.

B. Estimating Orientation from Accelerometer Data

In order to obtain attitude estimation from accelerometer data, we first converted the angular velocities provided by the IMU to be in physical units. Then, we derived the orientations by decomposing the angular velocities vector after removing the bias. As a final step, we implemented a low pass filter to reduce noise in the orientations. We set $\gamma_a = 0.5$ to weigh past and present values equally as this resulted in better estimation.

C. Estimating Orientation from Complimentary Filter

To improve on estimation from gyroscope data and accelerometer data, we implemented the complimentary filter. We first passed the orientation estimated values from the gyroscope data through a high pass filter with $\gamma_g = 0.6$ to weigh past values slightly more than current values in order to achieve better estimation. Once we passed estimated orientations from accelerometer data through a low pass filter and estimated orientations from gyroscope data through a high pass filter, we proceeded to do a weighted linear combination of both of these estimates setting $\alpha = 0.7$ in the following equation:

$$x_{comp} = (1 - \alpha) * x_{accelerometer} + \alpha * x_{gyroscope}$$

D. Estimating Orientation from Madgwick Filter

The first step to implement the Madgwick filter was to compute the linear acceleration bias and the angular acceleration bias from the IMU data. To do this, we average the first 300 acceleration values to compute each bias. Assuming the quadrotor is initially at rest, we represent the initial zero angle as a quaternion. Then, the orientation increment is computed from current gyroscope measurements values and previous quaternion values. To obtain an estimate of the orientation increment from the accelerometer data, we perform the gradient update by setting $\beta = 0.001$. We tuned β, which represents the gyroscope error in the direction of accelerometer measurements, in order to obtain better estimation with respect to the train data.

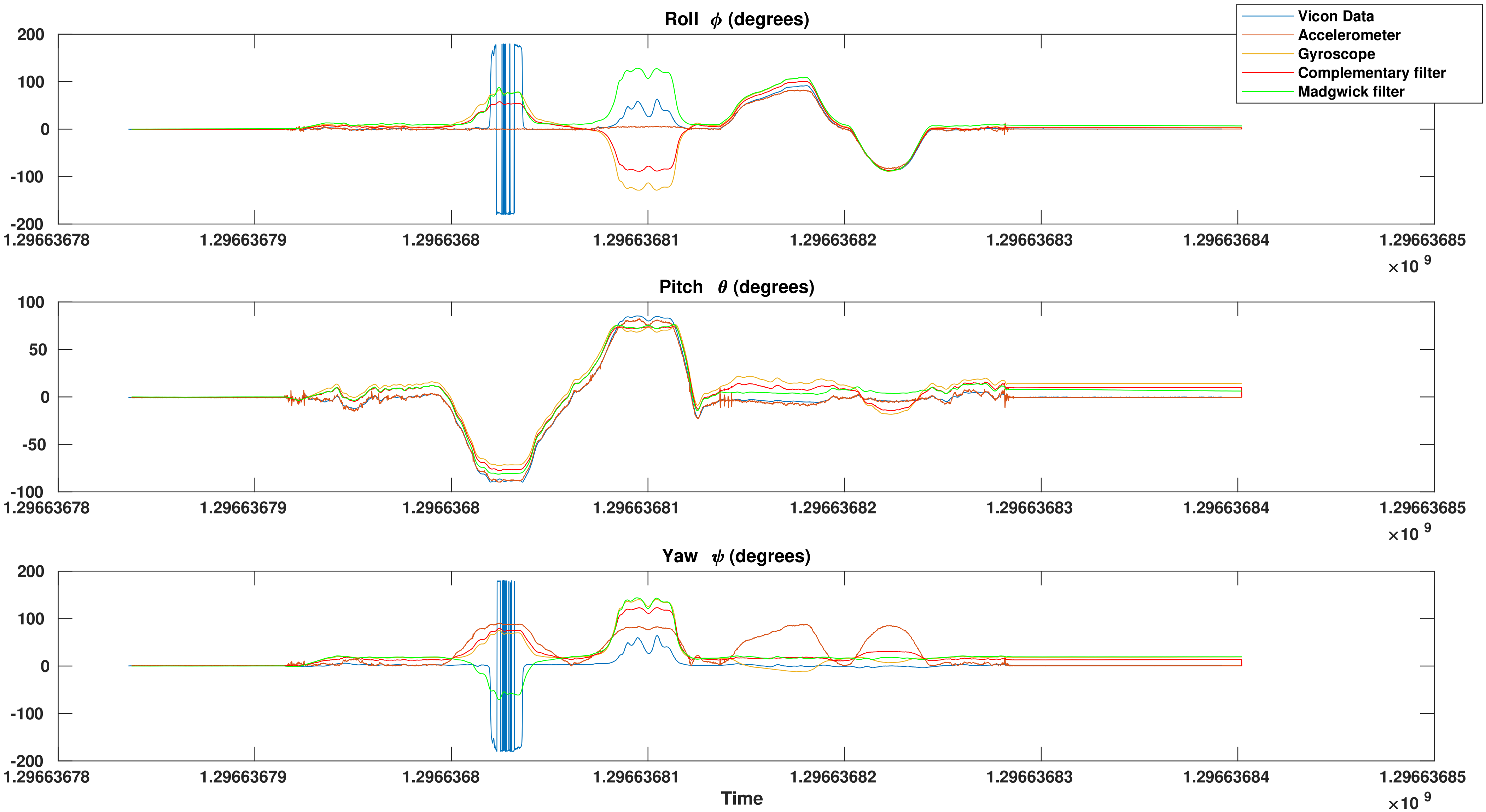
Finally, the orientation increments estimated from the gyroscope and accelerometer data are combined and integrated to output the orientation estimates.

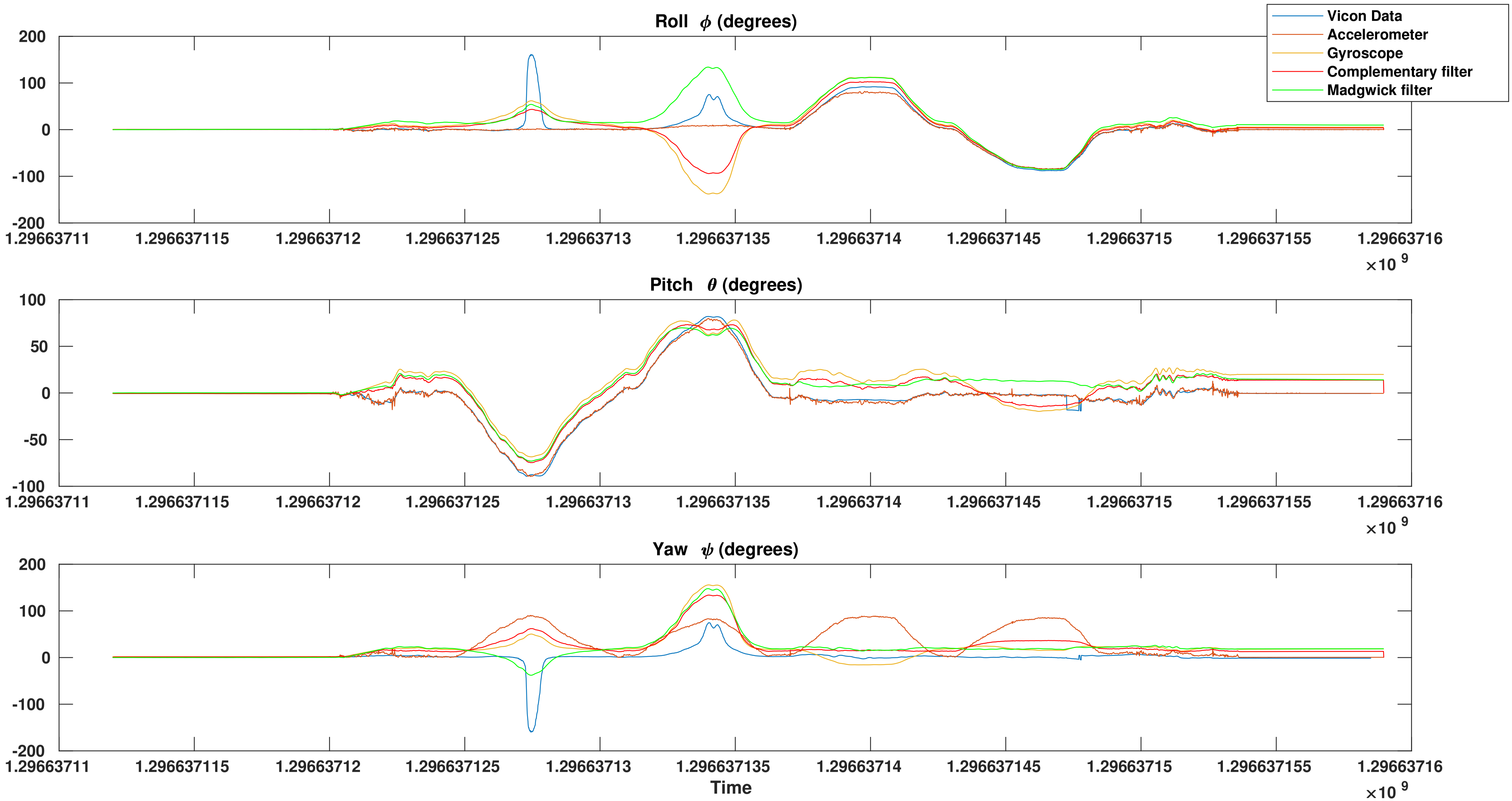
E. Implementation Details

Both filters were implemented in Python 2.7. We utilized the following libraries: numpy, io, the Rotation, math, pyplot, and pyquaternion to perform operations with quaternions in our implementation. Two very useful functions were implemented as well, $euler2quaternion$ and $quaternion2euler$, which helped us in going from one representation to the other.

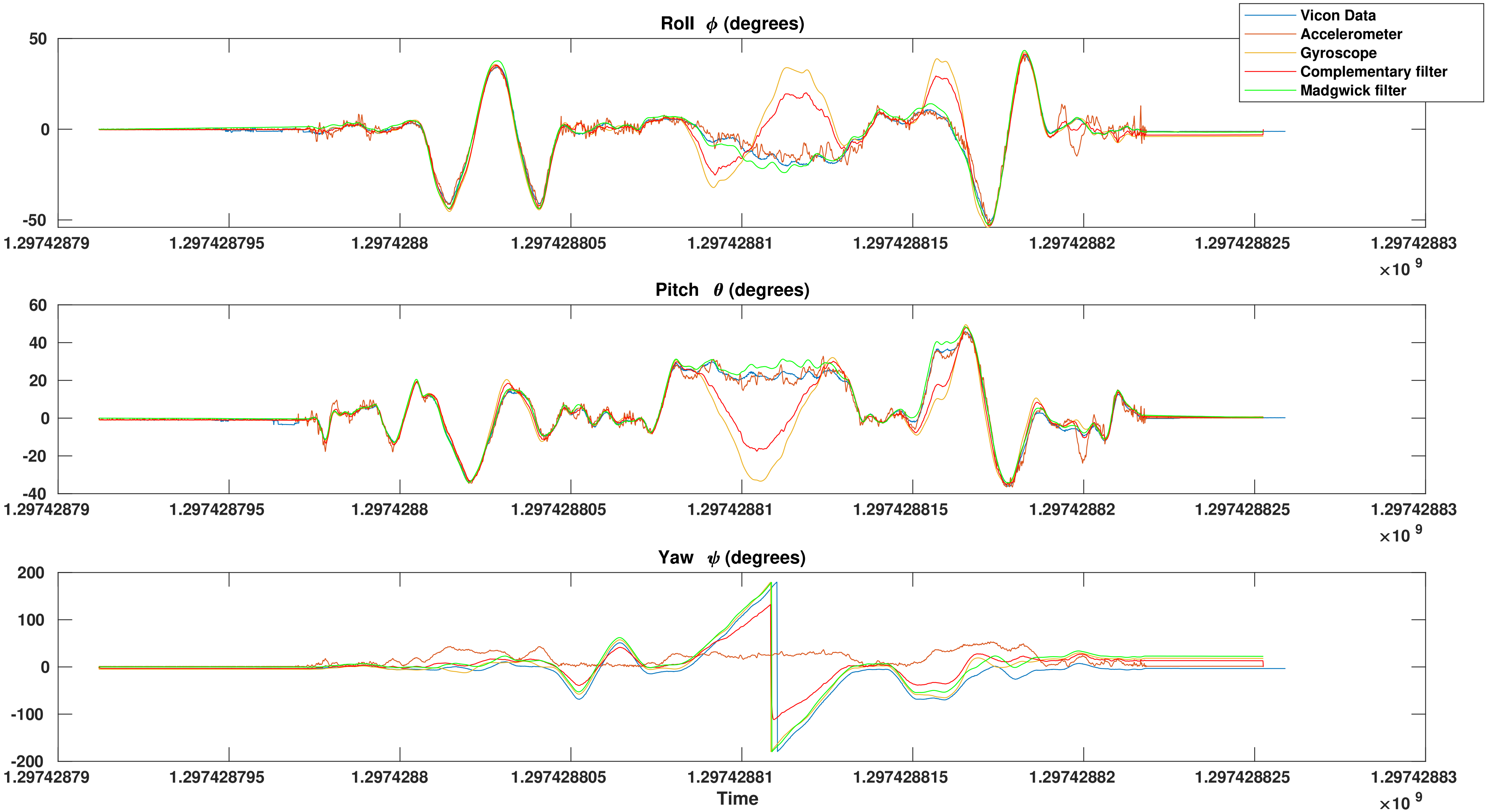
F. Analysis and Results

We have included plots of all training data sets and test data sets in the following pages starting with train data set 1 and ending with test data set 10. From these results, we were able to make a few observations. First, the Madgwick filter more consistently followed the Vicon data shape, whereas the complementary filter estimates were closer in amplitude to the Vicon data in the time instances where they matched the shape of the Vicon data. We would not recommend relying on the estimates obtained solely from accelerometer data as there are many time instances where the estimates deviate largely from the Vicon data. See for example the results for Data Set 2. By using the complimentary filter, resulting estimates were closer to Vicon data than using only gyroscope or only accelerometer measurements.

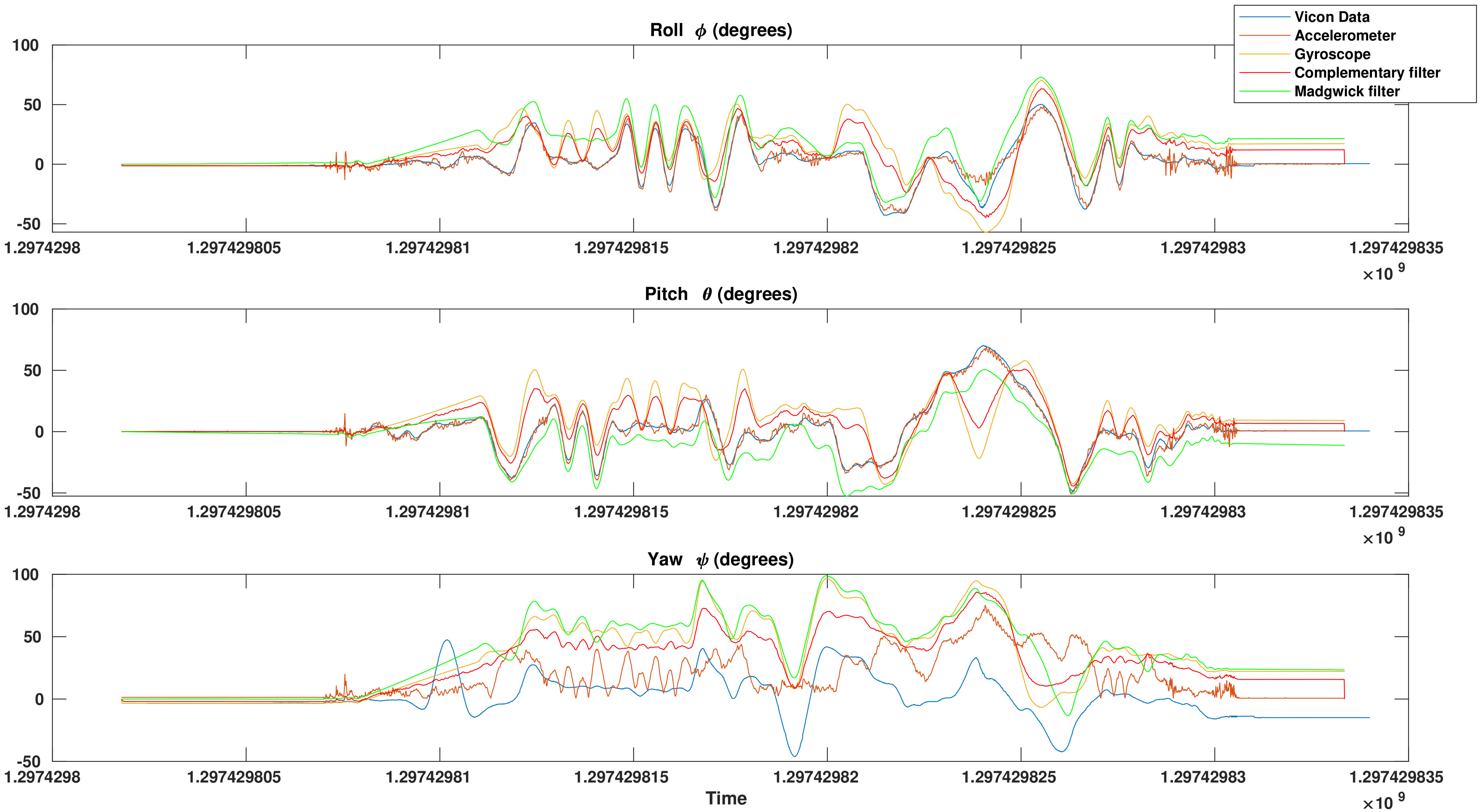

Roll ϕ (degrees)
Pitch θ (degrees)
Yaw ψ (degrees)
Time
$\times 10^9$
Vicon Data
Accelerometer
Gyroscope
Complementary filter
Madgwick filter

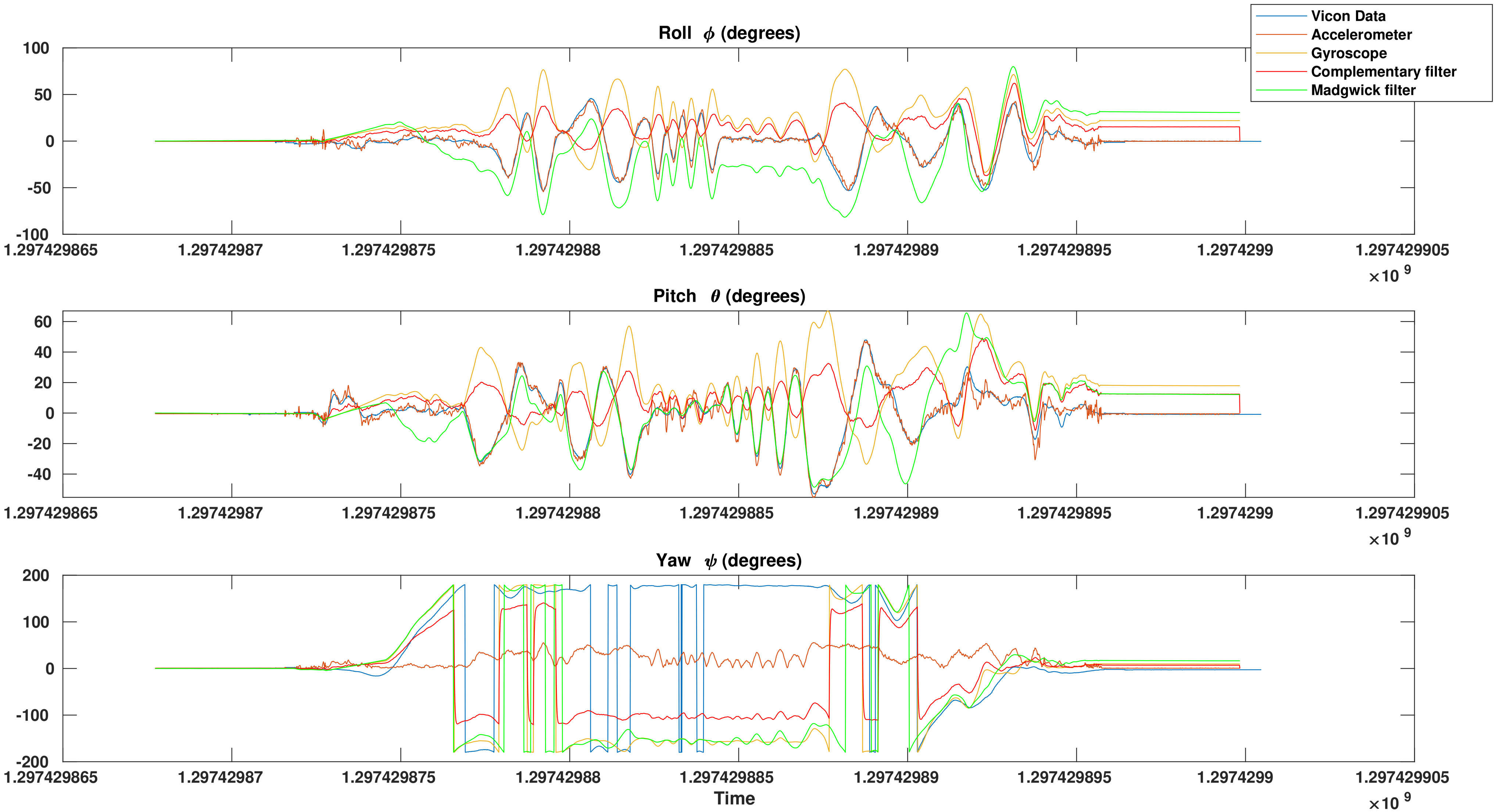


Roll ϕ (degrees)
Pitch θ (degrees)
Yaw ψ (degrees)
Vicon Data
Accelerometer
Gyroscope
Complementary filter
Madgwick filter
Time
$\times 10^{9}$

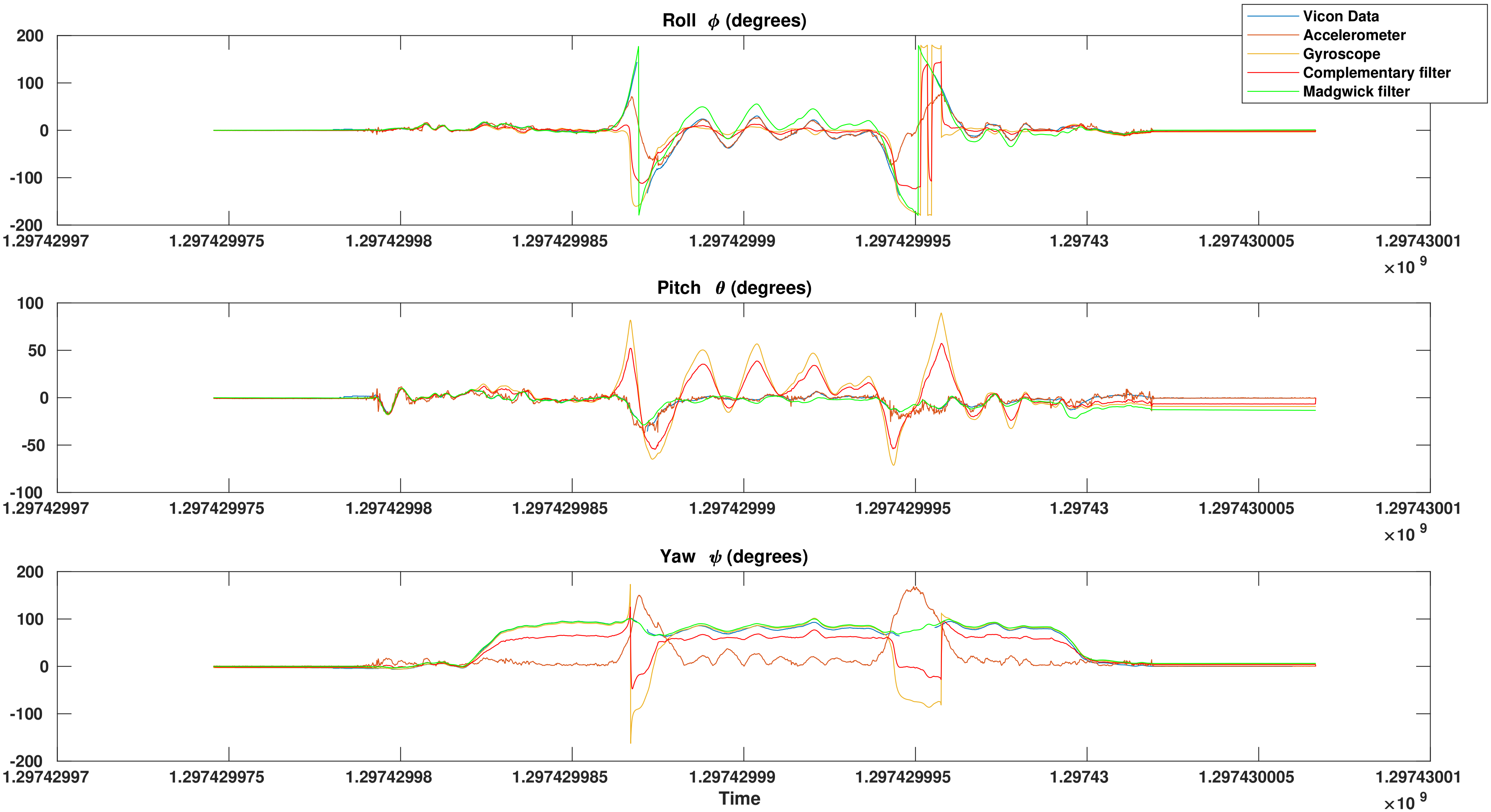


Roll φ (degrees)
Pitch θ (degrees)
Yaw ψ (degrees)
Vicon Data
Accelerometer
Gyroscope
Complementary filter
Madgwick filter
50
0
-50
60
40
20
-20
-40
200
100
-100
-200
1.29742879
1.297428795
1.2974288
1.297428805
1.29742881
1.297428815
1.29742882
1.297428825
1.29742883
×10^9
Time

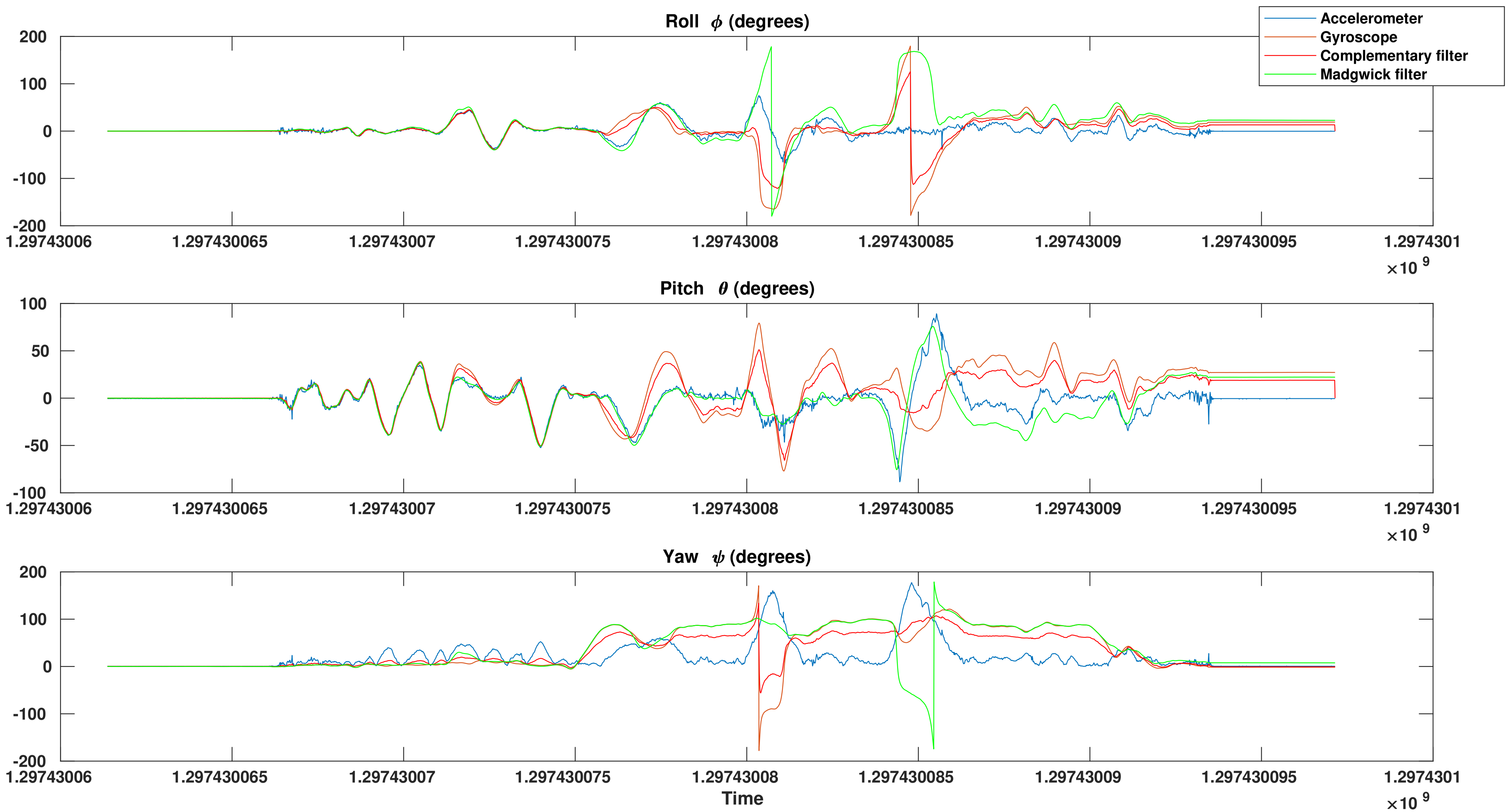

Roll ϕ (degrees)
Pitch θ (degrees)
Yaw ψ (degrees)
Vicon Data
Accelerometer
Gyroscope
Complementary filter
Madgwick filter
100
50
0
-50
1.2974298
1.297429805
1.29742981
1.297429815
1.29742982
1.297429825
1.29742983
1.297429835
$\times 10^9$
Time

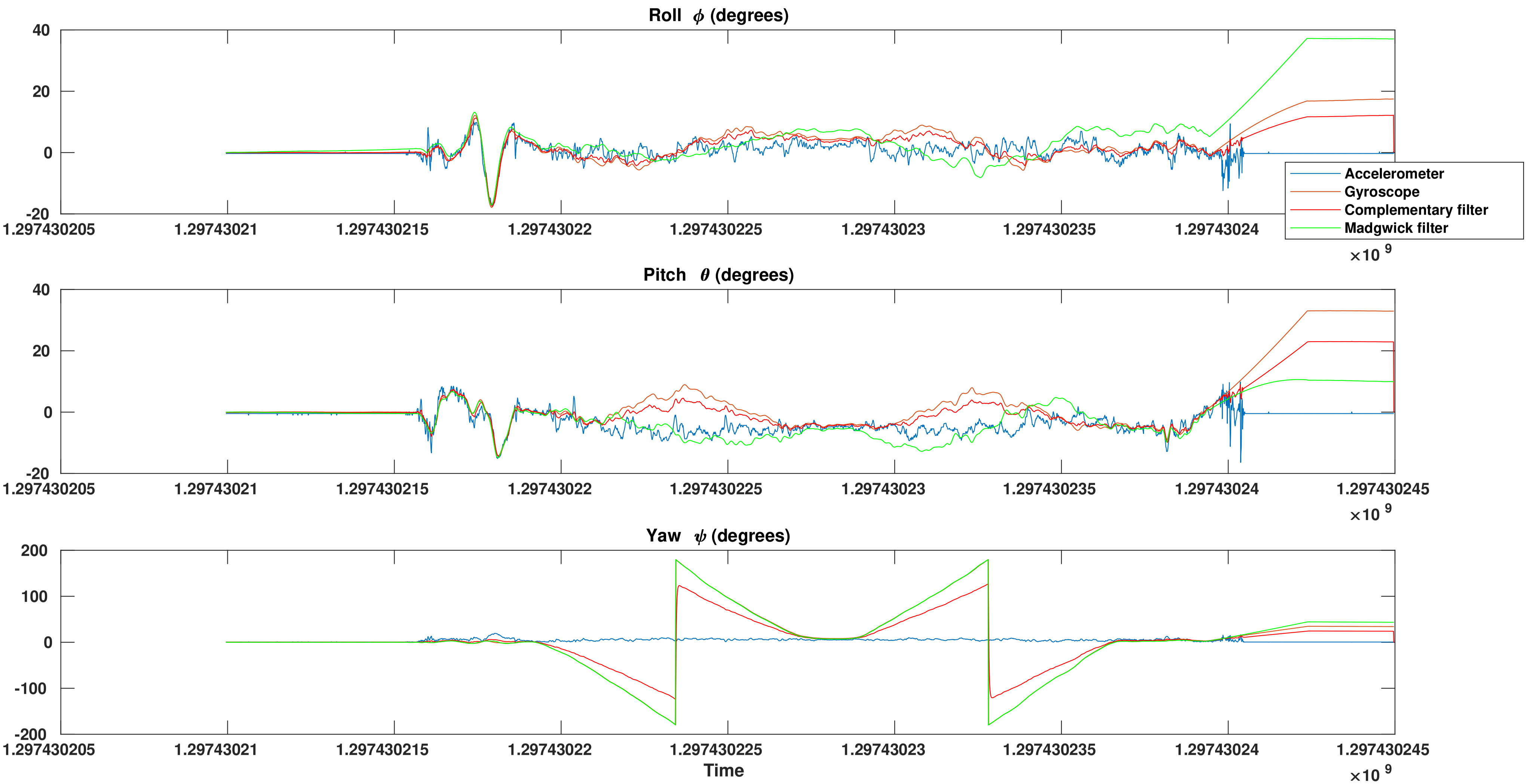


Roll ϕ (degrees)
Pitch θ (degrees)
Yaw ψ (degrees)
Time
Vicon Data
Accelerometer
Gyroscope
Complementary filter
Madgwick filter

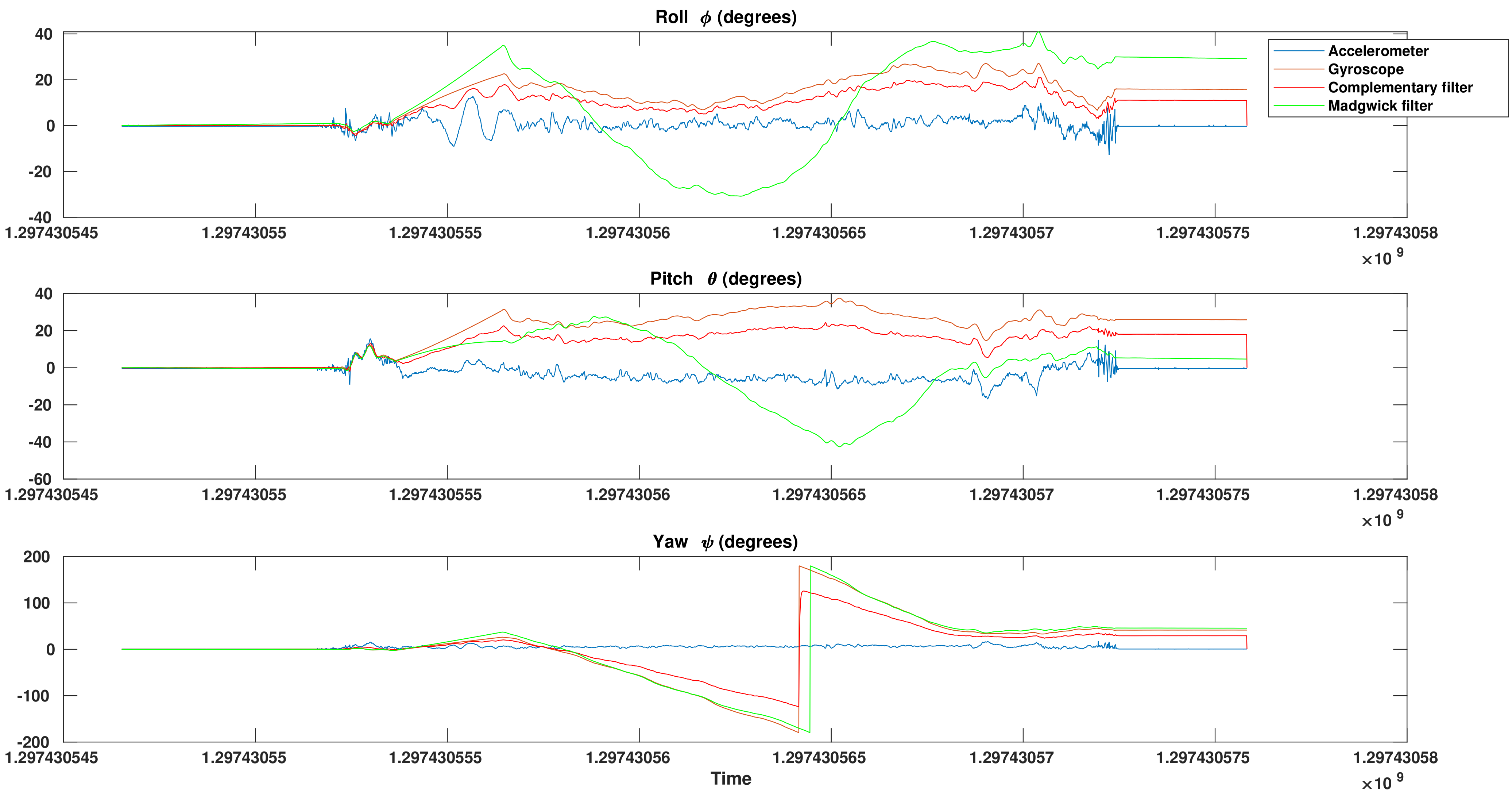


Roll ϕ (degrees)
Pitch θ (degrees)
Yaw ψ (degrees)
Time
$\times 10^{9}$
Vicon Data
Accelerometer
Gyroscope
Complementary filter
Madgwick filter

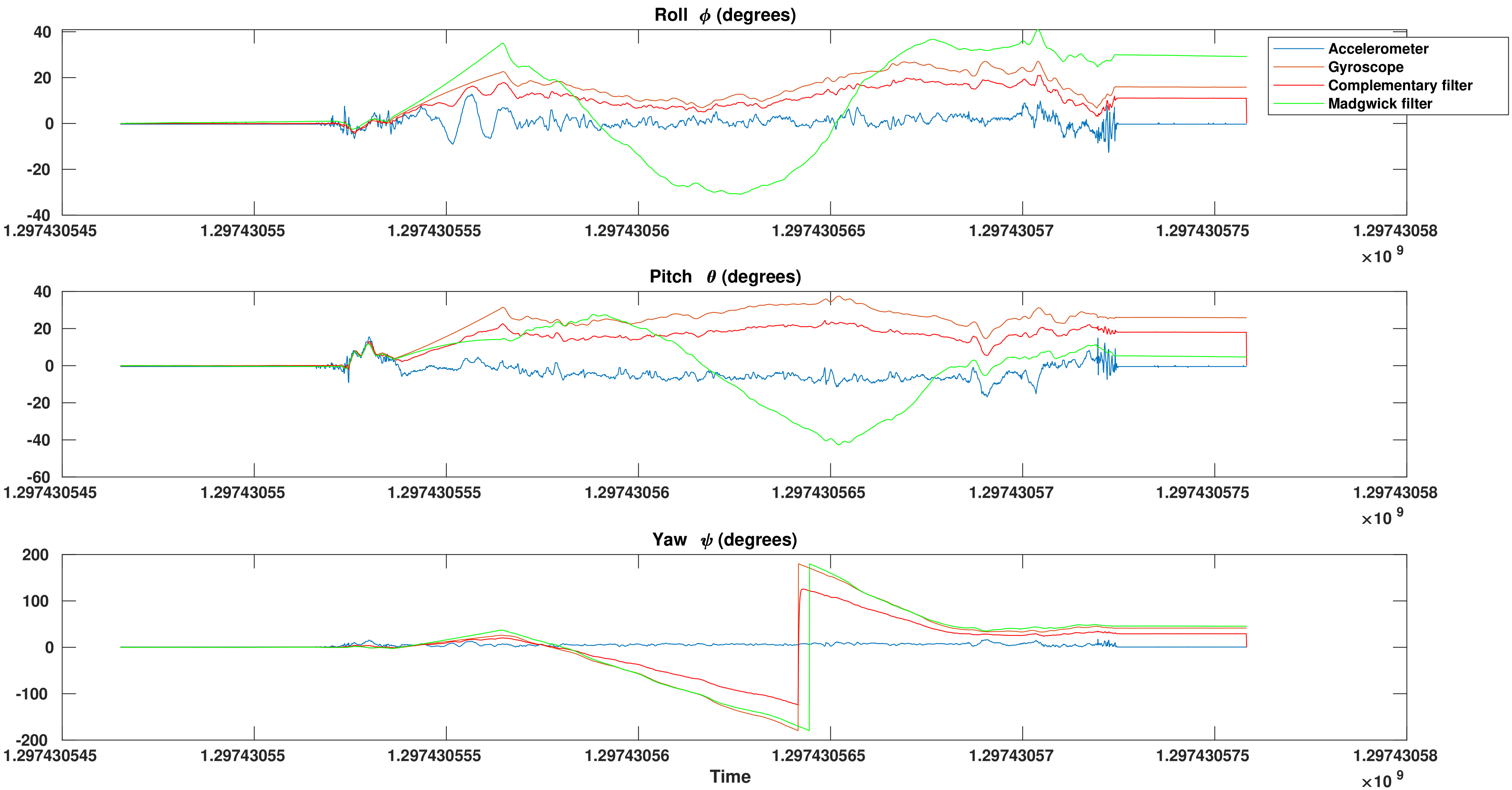

Roll ϕ (degrees)
Pitch θ (degrees)
Yaw ψ (degrees)
Accelerometer
Gyroscope
Complementary filter
Madgwick filter
Time
$\times 10^{9}$



Roll φ (degrees)
Pitch θ (degrees)
Yaw ψ (degrees)
Accelerometer
Gyroscope
Complementary filter
Madgwick filter
Time
×10 9



Roll φ (degrees)
Accelerometer
Gyroscope
Complementary filter
Madgwick filter
Pitch θ (degrees)
Yaw ψ (degrees)
Time
×10^9
40
20
0
-20
-40
-60
200
100
-100
-200
1.297430545
1.29743055
1.297430555
1.29743056
1.297430565
1.29743057
1.297430575
1.29743058



Roll ϕ (degrees)
Accelerometer
Gyroscope
Complementary filter
Madgwick filter
40
20
0
-20
-40
1.297430545
1.29743055
1.297430555
1.29743056
1.297430565
1.29743057
1.297430575
1.29743058
$\times 10^9$
Pitch θ (degrees)
40
20
0
-20
-40
-60
Yaw ψ (degrees)
200
100
0
-100
-200
Time

REFERENCES

[1] Sebastian Madgwick. An efficient orientation filter for inertial and inertial/magnetic sensor arrays. *Report x-io and University of Bristol (UK)*, 25:113–118, 2010.