ROBOT LOCALIZATION AND NAVIGATION (ROB-GY 6213)

PROJECT 1 - REPORT

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PROJECT -1 TOPIC: EKF FOR STATE ESTIMATION

TASK:

In this project, according to the descriptive handout given, the goal is to implement Extended Kalman filter to determine the state of a Quadrotor given the IMU and Vicon data. The Vicon being the world frame provides information about the position, orientation, linear and angular velocities. The IMU onboard, through the accelerometer and gyroscope provides the state values. The idea is to make use of the data, use them as control inputs, and determine the state estimates of the quadrotor.

PROCESS:

The process involves understanding the parameters involved in the prediction and update steps of the Extended Kalman filter process flow. Initially, the parameters for the prediction step must be initialized. These parameters include the following as per lecture 7:

- **STEP 1_PREDICTION STEP:**
  - The following parameters are to be initially calculated to proceed ahead with the prediction step.
  - For the process model ***F(x,u,n)*** the first thing that has to be calculated is the ZYX rotation matrix which according to our implementation is called R, which is calculated using symbolic variables so they can further be used for substitution.
  - The matrix G is also to be calculated with it being an Euler angle rotation about the Z-Y-X axes. In the execution, the matrix is precalculated after which the inverse is taken and stored in a symbolic variable matrix for further usage.
  - Once the parameters for the process model are ready, they're vertically concatenated.

$$\left.\begin{array}{l} \circ\ \dot{x} = f(x,u,n) \\ \circ\ n \sim N(0,Q) \end{array}\right\} \text{Assumptions}$$

$$\left.\begin{array}{l} \circ\ A_t = \left.\dfrac{\partial f}{\partial x}\right|_{\mu_{t-1},u_t,0} \\ \circ\ U_t = \left.\dfrac{\partial f}{\partial n}\right|_{\mu_{t-1},u_t,0} \end{array}\right\} \text{Linearization}$$

$$\left.\begin{array}{l} \circ\ F_t = I + \delta t\, A_t \\ \circ\ V_t = U_t \\ \circ\ Q_d = Q\, \delta t \end{array}\right\} \text{Discretization}$$

$$\dot{\mathbf{x}} = \begin{bmatrix} \mathbf{x}_3 \\ G(\mathbf{x}_2)^{-1}(\boldsymbol{\omega}_m - \mathbf{x}_4 - \mathbf{n}_g) \\ \mathbf{g} + R(\mathbf{x}_2)(\mathbf{a}_m - \mathbf{x}_5 - \mathbf{n}_a) \\ \mathbf{n}_{bg} \\ \mathbf{n}_{ba} \end{bmatrix} = f(\mathbf{x},\mathbf{u},\mathbf{n})$$

  - Further the Parameters for linearization are calculated post which the parameters for discretization are initialised.
  - The complete process occurs within the predict_step.m script. The Jacobian is taken, and the linearization and discretization variables are arrived at.
  - Upon every function call from the main code, the predict function is passed in with parameters, and a function call provides all the required parameters. With every iteration, the previous state's parameters are stored for updating.
  - Finally, after this the Prediction of the state estimate and the estimate of the Covariance are calculated.

$$\bar{\mu}_t = \mu_{t-1} + \delta t\, f(\mu_{t-1}, u_t, 0)$$

$$\bar{\Sigma}_t = F_t\, \Sigma_{t-1}\, F_t^T + V_t\, Q_d\, V_t^T$$

STEP 2_UPDATE STEP:

- Once the covariance estimate and state estimates are calculated through the function call the measurement model **z_t** is taken as the observation from the Vicon and the state and covariance estimates are given as input to the function call upd_step.
- As per lecture 7, the C in the observation model is taken as a horizontal concatenation between an identity matrix and zeros to match the dimensions being **6x15 for part 1 and 3x15 for part 2.**
- A matrix R is introduced as a 6x6 matrix indicating the sensor noise factor.

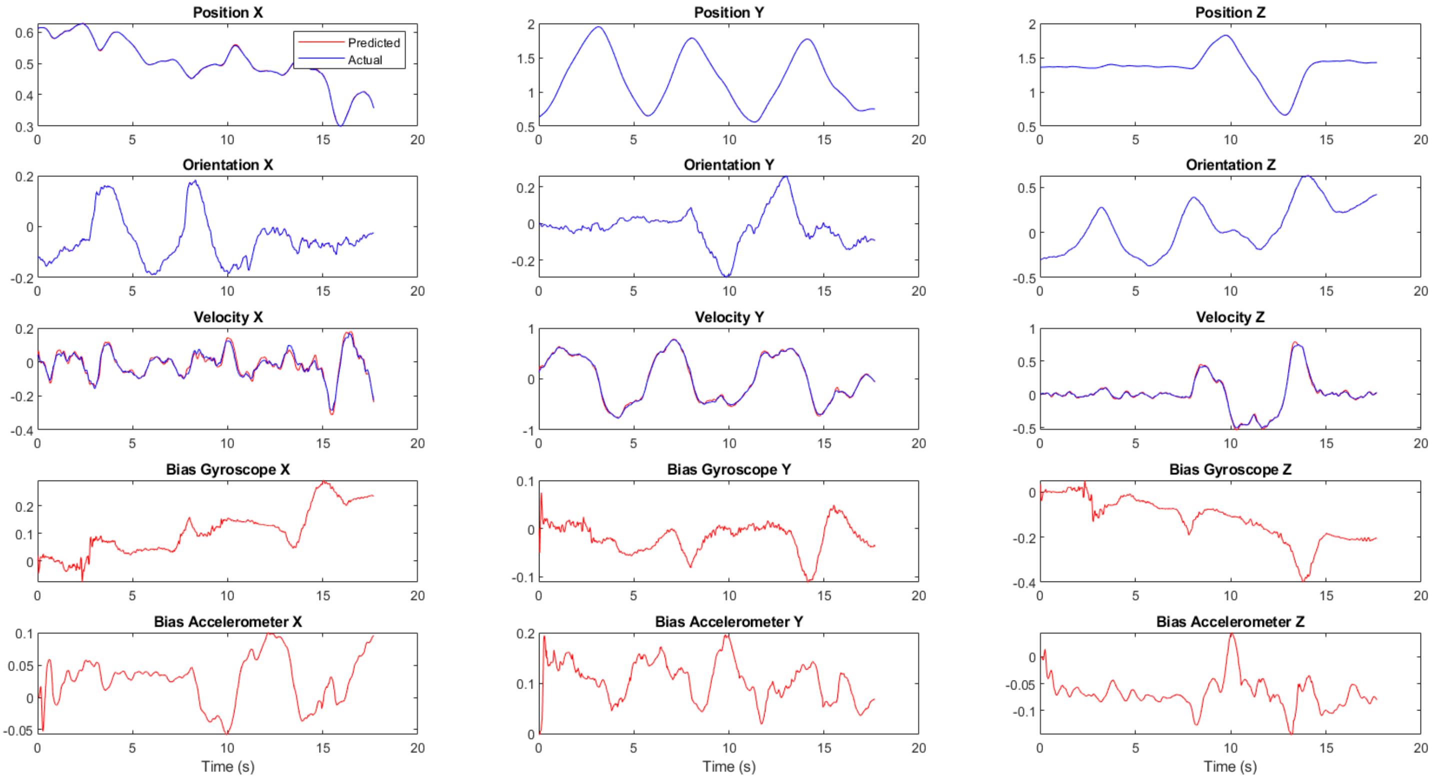
  - $\mu_t = \bar{\mu}_t + K_t(z_t - C\,\bar{\mu}_t)$
  - $\Sigma_t = \bar{\Sigma}_t - K_t\, C\, \bar{\Sigma}_t$
  - $K_t = \bar{\Sigma}_t\, C^T\, (C\, \bar{\Sigma}_t\, C^T + R)^{-1}$

- Further the Kalman gain is calculated in the update step accordingly keeping in mind that the update step in this model is linear.
- The current state of the quadrotor and current covariance are calculated and further updated in the main function as the previous states for further propagation of the Extended Kalman filter.

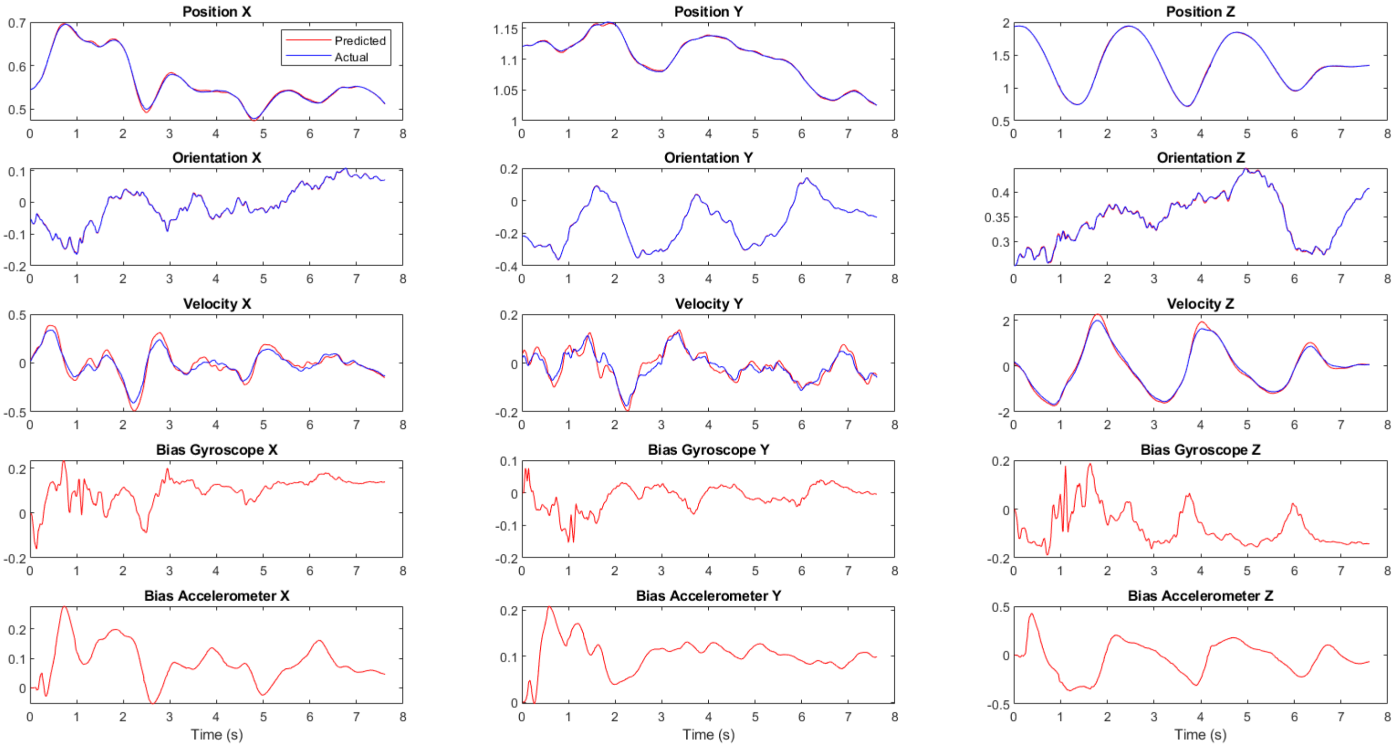
A clear explanation of variable declaration is commented sequentially in the code

RESULTS:

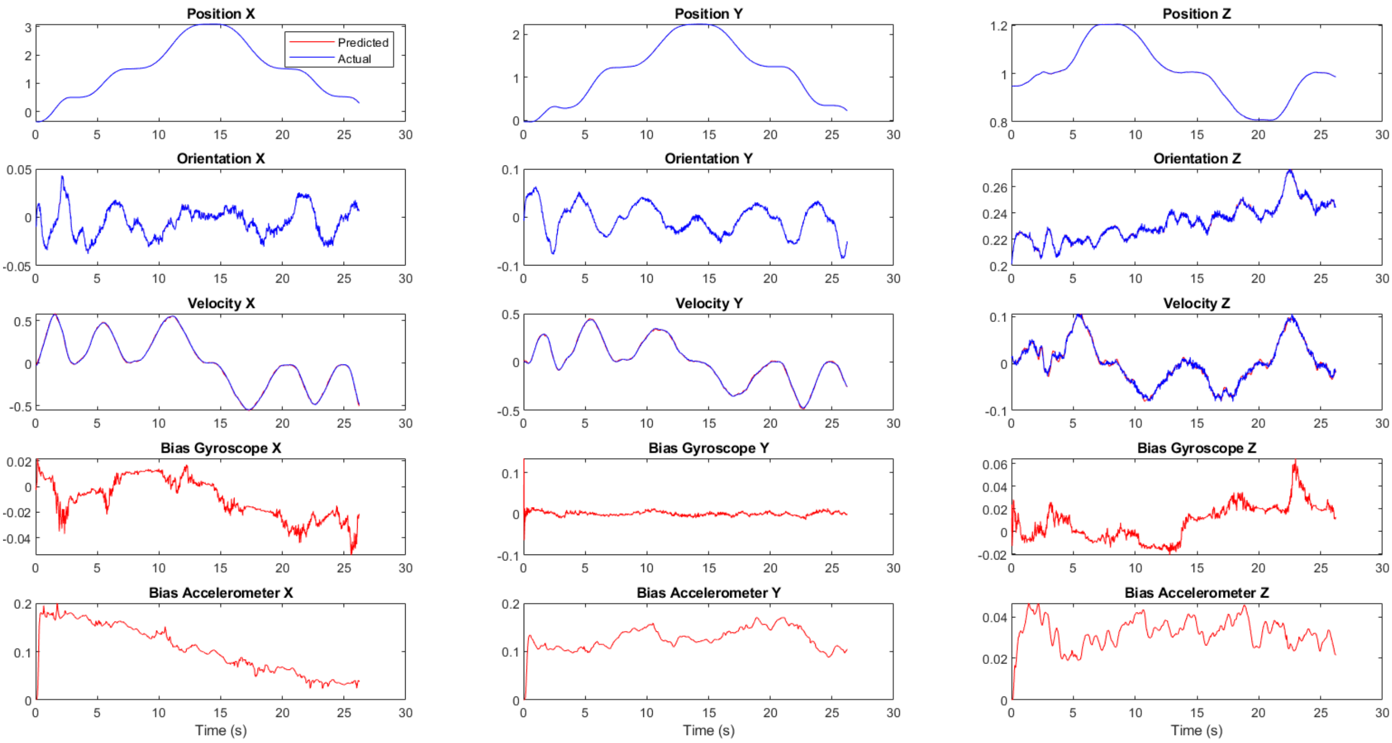
- **PART-1:**
  - The results from part one of the project are conclusive with the values of Q=0.01 and R=eye(6)0.00009.
  - We can observe that with position and orientation as the control inputs the graphs about position and orientation are perfectly aligned despite considering a healthy sensor noise. The velocity graphs have minor shifts along the Y axis given that this has been estimated purely out of the previously mentioned control inputs, making it a decently good estimation.
  - The Gyroscope and accelerometer bias is graphed to observe how biased the sensors are concerning the model.
  - All three data sets have decent to particularly good state estimation as per the tuned values based on trial and error.
  - Thus, as per the legend, the prediction and actual have coincided well for data sets 1, 4, and 9 based on the Extended Kalman filter algorithm for PART-1.



P1: Outcomes of EKF for Dataset-1

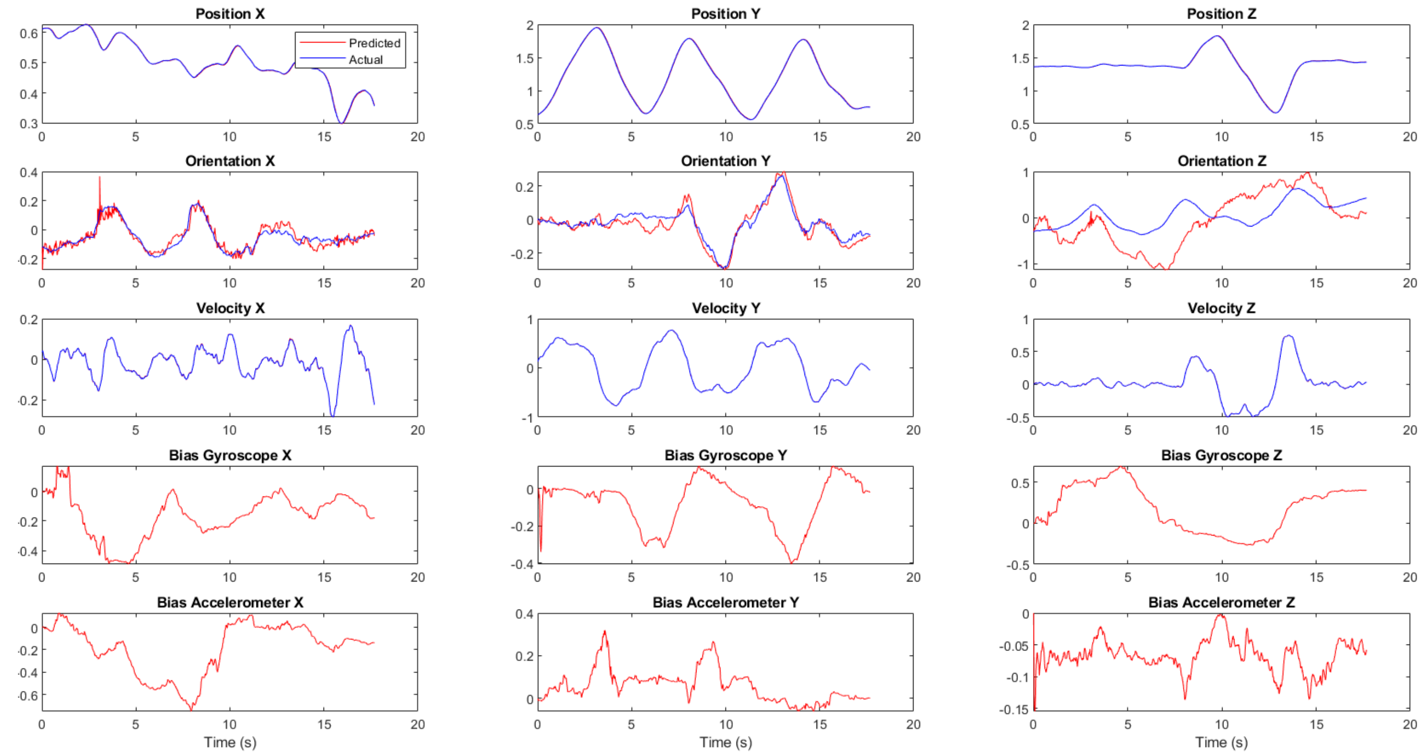


P1: Outcomes of EKF for Dataset-4

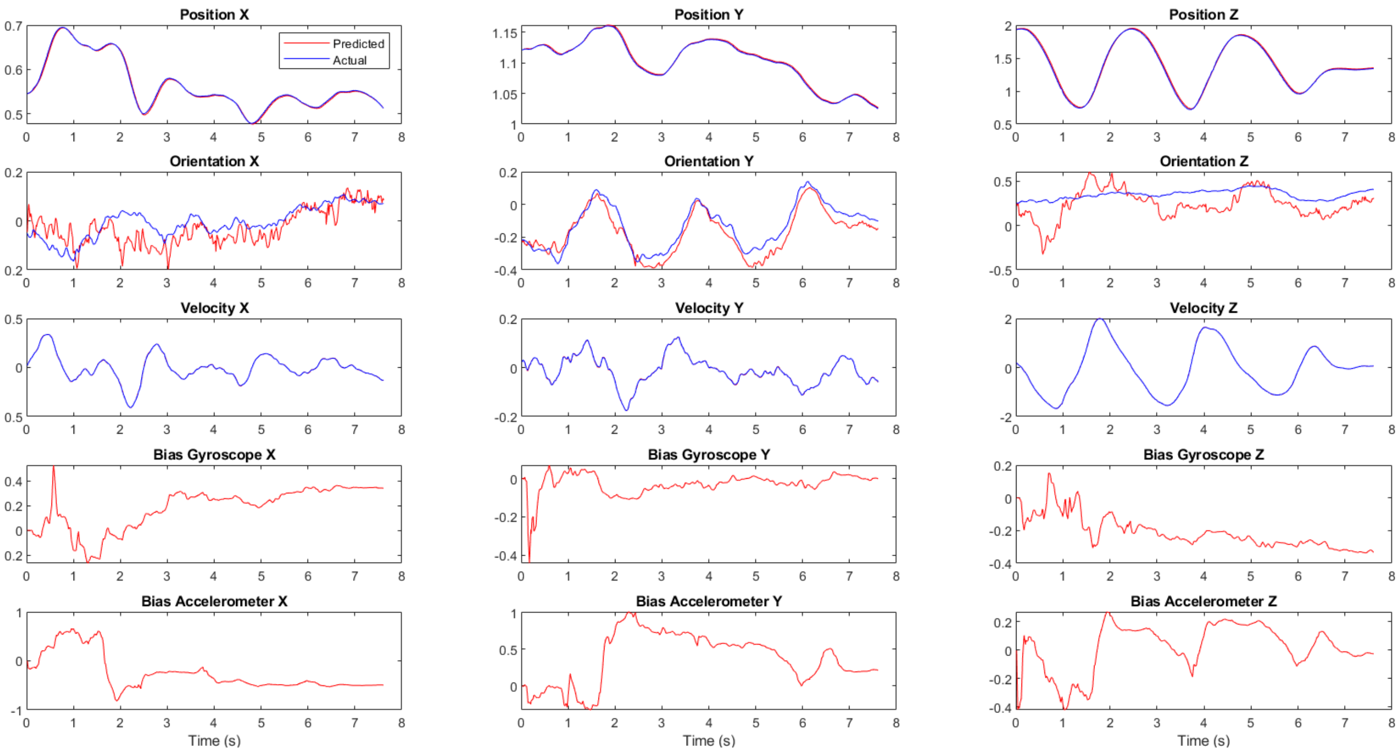


P1: Outcomes of EKF for Dataset-4

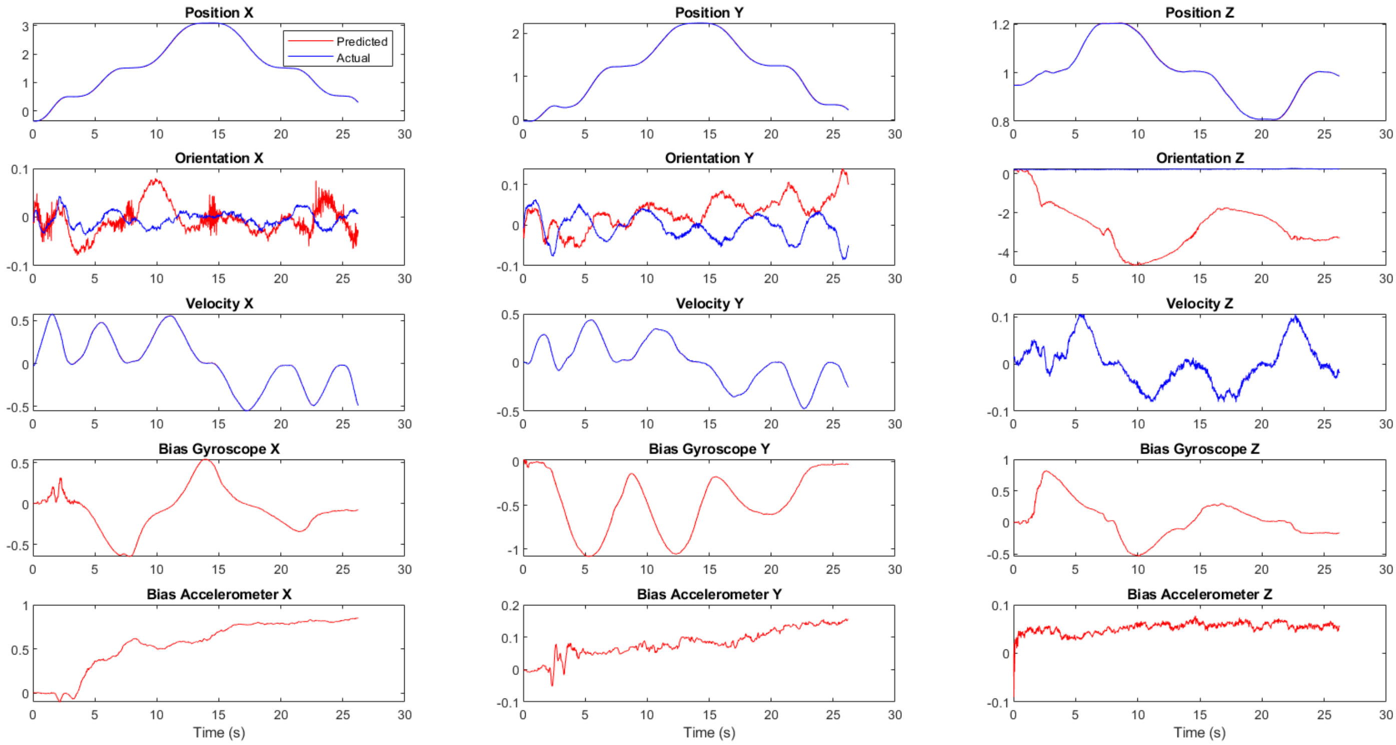
- **PART-2:**
  - The results from part two of the project are conclusive with the values of Q=0.01 and R=eye(3)0.00009.
  - With the measurement update being the velocity from the Vicon, the estimates have coincided well with the actual position and the velocity itself.
  - The only major changes in PART-2 of the project are the values of z_t are only taken to be the velocity from the Vicon and the dimension of R becomes **3x15.**
  - The steps in the process model and the update step remain the same.



P2: Outcomes of EKF for Dataset-1



P2: Outcomes of EKF for Dataset-4



P2: Outcomes of EKF for Dataset-9

CONCLUSION:

The Extended Kalman filter algorithm has proven to be effective in the case of non-linear systems, in our case the IMU-based system. The results of part 1 have proved the effectiveness of the estimate and how well the Kalman Gain evolves and changes the values of position, orientation, and velocity.

One aspect to notice is that the measurement update has a decent impact on the estimates since it has a direct effect on the outcome of dependent parameters. This can be observed well in the velocity graphs of part 1 and the position and orientation graphs of part 2 for which the measurement updates are non-existent corresponding to each part. This outcome supports the fact that the EKF is an unimodal filter and multiple hypotheses could only increase the uncertainty.