Factors Affecting Data Fusion Performance in an Inertial Measurement Unit

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Abstract- **Implementation of a data fusion system is a multifaceted task that involves application of single or many techniques. The factors affecting the performance of data fusion system depends on many parameters such as selection of technique, selection of sensors and type of data and introduction of noise. In this paper, Kalman filtering technique is used to fuse the data obtained from accelerometer and gyroscope in an inertial measurement unit (IMU). The study explores the effect of measurement noise and process noise on data fusion performance.**

Keywords– Data Fusion; Kalman Filter; Inertial Measurement Unit; Process Noise; Measurement Noise

I. INTRODUCTION

An inertial measurement unit (IMU) is an electronic device that measures and reports on a craft's velocity, orientation, and gravitational forces, using a combination of accelerometers and gyroscopes. IMUs are typically used to maneuver aircraft, including unmanned aerial vehicles (UAV), among many others, and spacecraft, including shuttles and satellites. Recent developments allow for the production of electromagnetic interference (EMI) enabled global positioning system (GPS) devices. An IMU works by detecting the current rate of acceleration using one or more accelerometers, and detects changes in rotational attributes like pitch, roll and yaw using one or more gyroscopes. A detail description of principle, working and application of IMU could be found in [1-2].

Data fusion techniques can combine data from multiple information sources to achieve improved accuracies and more specific inferences than by the use of a single source alone [3]. Most critical issues related to the data fusion implementation are requirements analysis, sensor selection, architecture selection, algorithm selection, software implementation and testing & evaluation. Sensor fusion is concerned with distributed detection, sensor registration, data association, state estimation, target identification, decision fusion, user interface and database management. It uses many techniques such as the method of least squares, Bayesian method, Dempster-Shafer's method, Fuzzy logic, Kalman filtering and neural networks etc [4]. One of the most important factor on which the performance of data fusion system depends is the selection of appropriate technique. The choice of the most appropriate algorithm depends on the complexity of the target problem, obviously the more complex the problem is, the algorithm also becomes more complex. As commented by Hall and Garga [5], there is no perfect algorithm that is optimal under all conditions.

In this paper, the authors have used Kalman filtering technique to fuse data from accelerometer and gyroscope in an IMU. Kalman filter output and estimation error are evaluated. Simulation is carried out under various conditions of process and measurement noises. The effect of process noise and measurement noise on estimation error is tested. It is investigated that the measurement noise has significant role to increase estimation error in data fusion process.

II. KALMAN FILTER

Kalman filtering [6] is a well-established methodology for model-based fusion of sensor data [7-9]. The traditional Kalman filter requires exact knowledge of the plant model and the statistics of the process noise and measurement noise. Varieties of methods have been developed to simultaneously estimate the covariances with the state [10].

Shi et al [11] presented an alternative approach to consider the influence on the estimation from unknown but fixed errors in the noise statistics. The bounds were given on the estimation error both for the conventional Kalman filter but also for a sensor fusion scheme suitable for a sensor network implementation. A new performance bound is derived for a sensor fusion scheme that explicitly takes the model uncertainty of the underlying processes and sensors into account. Based on the classical Kalman filter, the estimation error covariance is computed for given uncertainties of the process and measurement noise covariances.

Kosanam and Simon [12] discussed robustness of Kalman filtering against uncertainties in process and measurement noise covariances. A new filter was proposed which addresses the uncertainties in process and measurement noise covariances and gives better results than the standard Kalman filter. The filter was used to estimate the health parameters of an aircraft gas turbine engine.

Most of the recent research in the robust filtering field has dealt with bounded parameter uncertainty or Kalman filtering with an H-infinity norm constraint. Petersen [13] designed robust state feedback controllers and steady state robust state estimators for uncertain linear systems with norm bounded uncertainties. In this method, a guaranteed cost quadratic controller was proposed and a quadratic guaranteed estimator was developed based on the duality. The uncertainties in this work had known upper bounds. Lihua [14] proposed a state estimator which guarantees a bound on estimation error covariance for all admissible uncertainties in the state and output model. Haddad [15] considered parametric uncertainties in plant model. An estimation error bound suggested by multiplicative white noise modeling is utilized for guaranteeing robust estimation over a specified range of parameter uncertainties.

Although Kalman filter is optimal and robust filter used in various real time data fusion applications, but introduction of noise and other inaccuracies have their own futile effect on the performance. The authors have focused on estimation error encountered during fusion process.

III. THE STATE ESTIMATION PROBLEM

This analysis is based on [16] and [17], which applies to the continuous time systems, in this paper to discrete time systems and applied to IMU system.

Consider a linear stochastic system represented by

$$x_{k+1}=Ax_k + B_u u_k + B_w w_k \qquad (1)$$
$$y_k = Cx_k + v_k$$

Here x is the system state, y is the measurement vector, u is the input vector, w is the process noise vector and v is the measurement noise vector. A, B_u, B_w and C are matrices of appropriate dimensions. W and v in this case are assumed to be mutually independent and zero mean white noise. The covariances of w and v are given as

$$E[w_k w^T_k] = Q \qquad (2)$$
$$E[v_k v^T_k] = R$$

The state estimate equations before and after the measurements are processed are given as [7]

$$\hat{x}^-_{k+1} = A\hat{x}^+_k + B_u u_k$$
$$\hat{x}^+_{k+1} = \hat{x}^-_{k+1} + K_k(y_{k+1} - C\hat{x}^-_{k+1}) \qquad (3)$$

Where K_k is the Kalman filter gain.

The estimation error is defined as follows:

$$e_{k+1} \equiv x_{k+1} - \hat{x}^-_{k+1}$$

From Equations (1) and (3) the estimation error satisfies the equation

$$e_{k+1} = (A - AK_k C)e_k + B_w w_k - AK_k v_k \qquad (4)$$

Using the noise characteristics in Equation (2) the steady state error covariance P becomes solution to the following equation [18]:

$$P = (A - AKC)P(A - AKC)^T + B_w Q B_w^T + (AK)R(AK)^T \qquad (5)$$

Where P is defined as

$$P = E[ee^T] \qquad (6)$$

When R = 0 (no measurement noise), Equation (5) becomes

$$X_1 = (A\text{-}AKC)\, X1(A\text{-}AKC)^T + B_w Q_k B_w^T \qquad (7)$$

Where X_1 is the estimation error covariance due to process noise only.

When Q = 0 (no process noise), Equation (5) becomes

$$X_2 = (A\text{-}AKC)\, X_2(A\text{-}AKC)^T + (AK)R(AK)^T \qquad (8)$$

Where X_2 is the estimation error covariance due to observation noise only.

Adding Equations (7) and (8) gives the following:

$$(X_1+X_2) = (A\text{-}AKC)(X_1+X_2)(A\text{-}AKC)^T + B_w Q B_w^T + (AK)R(AK)^T \qquad (9)$$

This shows that when Q, R are not zero at the same time, the solution P of Equation (5) becomes:

$$P=X_1+X_2 \qquad (10)$$

This is the estimation error covariance in the presence of both the process and measurement noise. Thus, it is shown to a linear combination of the estimation error covariance when only one of the noises is present.

This linear combination helps in realizing the performance index of the Kalman Filter, which would be a linear combination of functions of X_1 and X_2. Therefore, in the standard Kalman filter, the filter gain K minimizes the following performance index [19]:

$$J=tr[E(e_k e^T_k)] =tr(P)= tr(X_1) + tr(X_2) \qquad (11)$$

Where $tr(\ )$ denotes the trace of a matrix. If there are no uncertainties in the process and measurement noise covariances the performance index J attains a global minimum using the standard Kalman filter. However, if there were uncertainties in Q and R, J would not attain a minimum.

IV. SIMULATION AND RESULTS

Let us now consider the cases where we measure estimation error by plugging and unplugging process noise and measurement noise in the simulation environment. Here we shall consider four cases:

Case 1: Kalman output and measurement of estimation error normally.

Data read from 1000 samples of the accelerometer had a variance of 0.07701688 and gyroscope had a variance of 0.00025556 [20]. Measurement noise and process noise are plugged in the code based on [21] and [22]. Data obtained from accelerometer and gyroscope and their fusion using Kalman filter are shown in Figure 1. Kalman output and estimation error are shown in Figure 2.

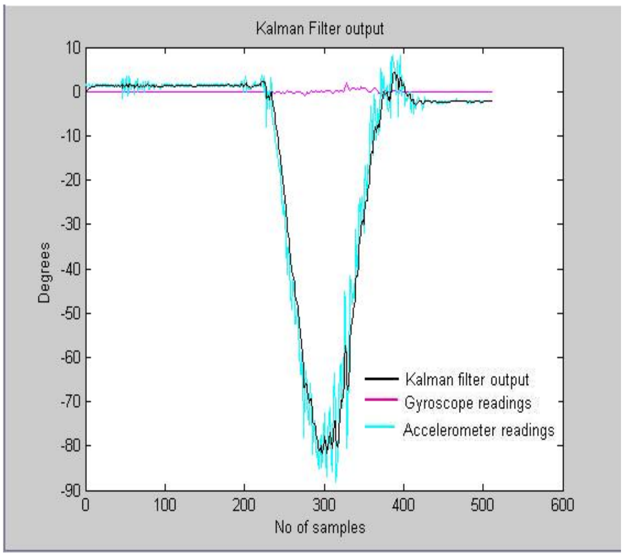

Fig. 1 Kalman filter output

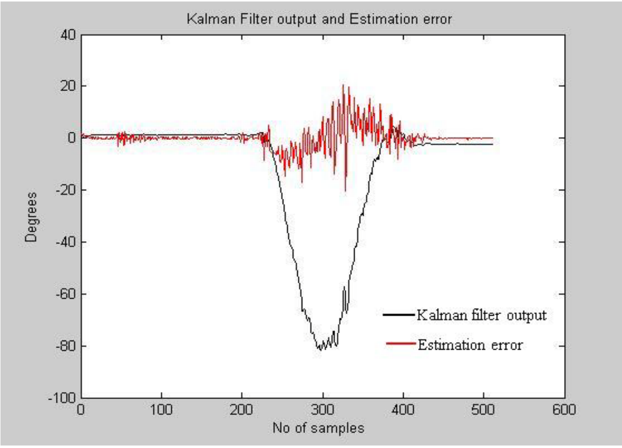

Fig. 2 Kalman filter output and estimation error

Case 2: Measurement of estimation error without plugging measurement noise and process noise.

Figure 3 shows estimation error almost negligible, as measurement noise and process noise are kept zero (ideal case).

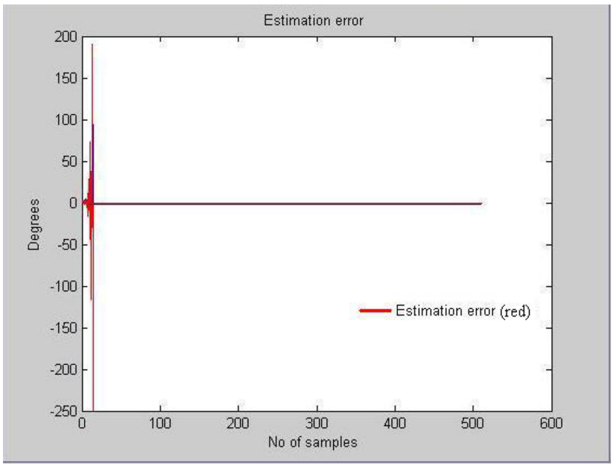

Fig. 3 Estimation error without noises (ideal case)

Case 3: Measurement of estimation error plugging process noise (measurement noise is kept zero)

Figure 4 shows the effect of process noise on estimation error.

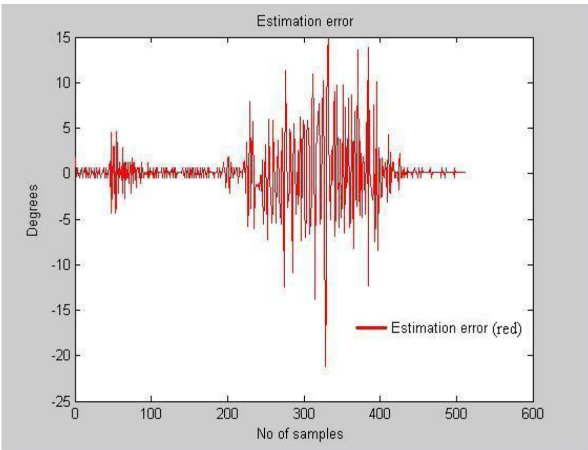

Fig. 4 Estimation error due to process noise

Case 4: Measurement of estimation error plugging measurement noise (process noise is kept zero)

Figure 5 shows effect of measurement noise on estimation error.

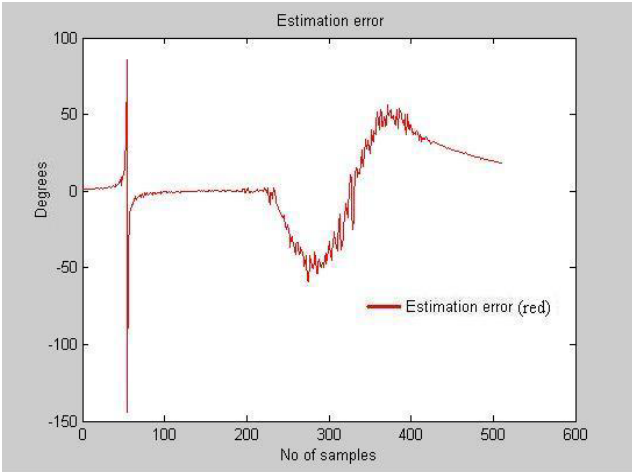

Fig. 5 Estimation error due to measurement noise

Finally, estimation error graph for Case 3 and Case 4 is plotted using least square method (LSM) [23] to precisely compare effects of process noise and measurement noise on estimation error.

As per state estimation analysis discussed above, the value of Kalman gain K_K decreases with increase in value of R, thus increasing estimation error. Measurement noise has significant impact on estimation error as compared to process noise that can be clearly seen in Figure 6.

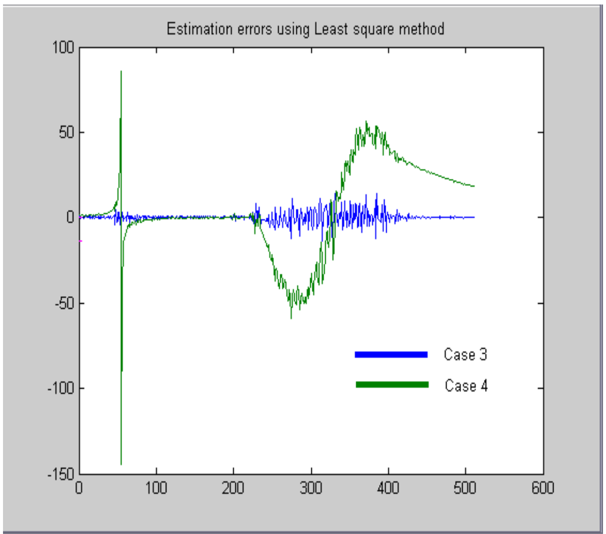

Fig. 6 Comparison of estimation errors

V. CONCLUSION

Data-fusion techniques have been investigated by many researchers and have been used in implementing several engineering applications. Exploring the factors, which affect data fusion performance by extensive analysis of data and technique applied, is an active research area for the researcher's community. The papers presents application of

Kalman filtering technique to fuse data obtained from accelerometer and gyroscope in an IMU. Kalman filter output and estimation error are evaluated. The effect of process noise and measurement noise on estimation error is tested. Finally, it is explored that the measurement noise has significant role to increase estimation error in data fusion process. The future work is to test and compare affects of various other techniques like Dempster-Shafer's method and fuzzy logic technique in data fusion process.

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