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Comparison of Filtering Techniques for Transfer Alignment of Air-Launched Tactical Guided Weapons

Sambhav Kumar Jain[#,*], Tapan K. Jain[$], Srikant Srivastava[#] and Saumya Shanker[#]

[#]*DRDO-Defence Research and Development Laboratory, Hyderabad - 500 058, India*
[$]*Department of Electronics Engineering, IIIT Nagpur - 440 006, India*
[*]*E-mail: sambhavjain@rediffmail.com*

ABSTRACT

The transfer alignment technique is very useful for the accurate initialization and calibration of gyroscopes and accelerometers of INS for air-launched tactical guided weapon systems. In the present war scenario, the initialization of INS should be accurate and rapid to launch the tactical weapon against air or land targets within the shortest available time. A lot of development has been carried out by researchers for INS transfer alignment in the field of state estimation. The study and method presented in the research are relevant to aerial launch vehicles. However, to meet present guidance requirements within less time for initializing weapons, more appropriate transfer alignment algorithms are needed. This paper discusses the relative performance of Kalman Filter (KF), Extended KF, and Unscented KF for aligning the weapon INS using the data from Master INS. New developments, limitations, applicability, and design methods for the Kalman filters, became a key component in the transfer alignment of air-launched tactical missiles. These methodologies are extensively utilized in Navigation and Control systems; therefore, this research work will be an informative and perfect guide to existing and potential readers.

Keywords: Master INS (Aerial Vehicle's Inertial Navigation System); Extended Kalman filter (EKF); Inertial Measurement Unit (IMU); Kalman filter (KF); Weapon INS or Slave INS (Weapon's Navigation System); Position Velocity and Attitude(PVA); Transfer Alignment(TA); Unmanned Aerial Vehicles (UAVs); Unscented Kalman filter (UKF)

1. INTRODUCTION

The Aircraft and Helicopter are conventional platforms for launching air-launched weapons. The latest advancement in this field is UAVs. In the advancement of the development of air-launched tactical weapons, the need arises to launch these weapons from various platforms like Aircraft, Helicopters, and UAVs. Figure 1 shows various platforms for air-launched tactical weapons. These air-launch platforms (Aircraft/Helicopter/UAV) and tactical weapons are fitted with their navigation systems.

Figure 1. Air-launched platforms.

Inertial Navigation Systems (INS) give the vehicle's Position and Velocity in 3 axes, and the attitude (PVA) solution of the Aircraft/Missile in the reference frame. It consists of 3 gyroscopes, 3 accelerometers for each direction, called Inertial Measuring Unit (IMU), and navigation electronics.

The INS is broadly classified into two different categories: stabilized platform INS and strap-down INS.

Inertial navigation systems are not only used in aviation, land, and submarine navigation, but it is also influencing the development of unmanned vehicle navigation.

Platform INS is one of the primitive setups that constructs a physical framework using electromechanical control components, which exerts minimal constraints on the navigation software. Its primary drawbacks consist of its intricate computational structure and relatively heavy equipment. The strap-down inertial system is now the most widely used INS transforming the conventional Platform INS due to advancements in micro-processor technologies and the evolution of optical gyroscopic methods. In contrast to stable platform techniques, the sensors in strap-down technology are mounted directly to the vehicle's body.

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The weapon INS is powered ON based on the requirement or need basis. The weapon INS (Slave INS) is aligned using the data of air-launch platform INS (Master INS).

The Transfer Alignment of INS is generally based on the Master-Slaveconfiguration[20] as shown in Fig. 2. The Master INS is a highly accurate navigation system that transfers reference navigation data such as a PVA solution, whereas the weapon navigation system is the less accurate navigation system of a tactical weapon that is to be aligned and calibrated[15]. Using this transfer alignment approach, the weapon INS misalignment w.r.t. the Master INS data is determined. It is observed tha tthe measurements derived by the weapon INS system are not accurate as compared to the actual values. Over the decades, great research has been done to improve the accuracy of the sensor values through various algorithms.

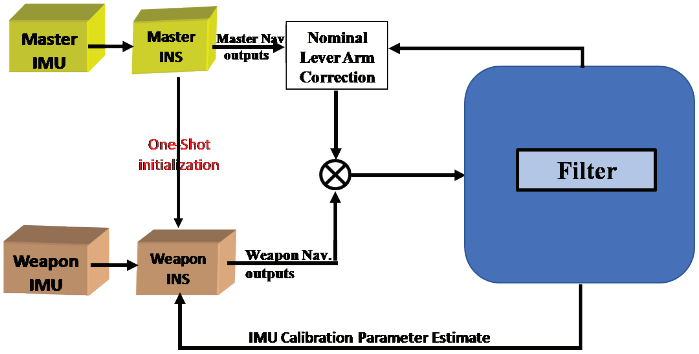

Figure 2. Block diagram of transfer alignment (TA).

Transfer alignment is a significant mechanism for utilizing data from the host aerial vehicle's navigation system to define and configure a weapon's INS. Transfer alignment procedures are divided into categories and are frequently known based on the kind of vectors used for comparison. They are position matching, velocity matching, position plus velocity matching, acceleration matching, and acceleration plus velocity matching[15].

Various filtering algorithms can be implemented for the Transfer Alignment (TA), which is the backbone of air-launched weapons. We explored three different filters for transfer alignment and compared the developed algorithms, merits, and drawbacks.

There are two basic problems encountered in the real-life implementation of the transfer alignment to initialize the slave INS (weapon INS) w.r.t. launch platform (Aircraft, Helicopter, and UAVs) Master INS. The first is, the mathematical modelling, cannot completely represent the exact system behaviour due to uncertainties. The second is, the measurements from the gyroscopes and accelerometers are not accurate due to launch platform vibration and sensor errors. Therefore, we need estimation filters to estimate the values close to the true values (Master INS measurements).

In the literature, various types of filtering algorithms are available for this purpose. Hence, the primary aim of this simulation study is the necessity of evaluating various filtering techniques for rapid and accurate alignment of weapon (Slave) INS, which is needed to neutralize the target by meeting guidance requirements.

A set of attributes have been used to evaluate the application and reliability of the filters. In this study, three different types of filter algorithms were implemented and simulations were carried out. The performances of these three estimation techniques were relatively studied and compared. The merits and demerits of each method were analyzed for the air-launched tactical weapon. The ease of implementation of each algorithm was also presented.

The paper is organized in various sections. Section 1 provides past research works in the field of TA. Section 2 covers the theoretical concepts regarding Inertial navigation systems, Transfer alignment, and the working algorithm of Kalman filters. Section 3 provides a detailed in-depth comparison of the three different types of Kalman filters, Transfer Alignment formulation, and realistic simulation environment, and the obtained results and conclusions are discussed in Section 4 and Section 5.

2. LITERATURE REVIEW

Implementation of the various Transfer Alignment algorithms using various filtering techniques for air-launched weapons INS is a challenging task, however, some great research work has been done in the progress and development of this field. Several researchers have used various methods to analyze and provide better-proposed algorithms for the same. The following paragraphs provide a concise overview of the key research and step-by-step development that has been done in this field so far.

Y. Yuksel[1] has introduced a simulation environment under realistic scenarios and conditions.

Joon, L.Y. & Lim, You-chol[4] have presented how to deal with problems that occur in the strap-down INS and the transfer alignment algorithms. Furthermore, they discuss a few common errors that affect attitude and velocity matching.

Chattaraj, S. & Mukherjee, A.[5-6], in their paper, talk about the different types of transfer alignment algorithms used based on the type of TA problem for tactical weapons from different platforms.

Liu, X.[7] begin with the problem that occurs due to the inconsistency among subsystems when it comes to the update frequency in a strap-down INS.

Kim, Y.J. & Bang, H.[8] in their paper mainly focus on giving a rudimentary explanation of the Kalman Filters and explaining their components and working.

Honghui, Q.[9], initially discuss the difference in error estimation of two types of Kalman filter formulations, that was indirect Kalman filter formulation and direct Kalman filter formulation. Furthermore, the main focus of the paper was the way these two formulations of the Kalman filters have influenced the complete system performance of a GPS/INS system used for aerospace applications.

Emer, N. & Ozbek, N.S.[10] presented a few recent trends, their applications, challenges faced, and the design methodologies of a Kalman filter for Unmanned Aerial Vehicles (UAVs).

György, K.[11], have focused on the working, usage, advantages, and applications of Extended and Unscented Kalman Filters (UKF).

These studies and works brought out the suitability of various filters with the aim of achieving accuracy after the completion of the alignment, but achieving this accuracy in the shortest possible time was not discussed in the related papers for launching the tactical weapon with desired accuracies.

In this work, our focus is on selecting a particular filter based on the different types of Kalman filters for the estimation of weapon INS misalignment with minimum time and desired accuracy.

3. FILTERING APPROACHESAND MATHEMATICAL MODELING

The Kalman Filter is a highly distinctive algorithm since itis one of the few algorithms to be proven optimal and simple. Three types of Kalman approaches adapted here to find out a real-time accurate and rapid solution, the estimation of weapon INS misalignments, and one by one description has been provided.

3.1 Kalman Filter

Kalman Filter (KF) is a best linear unbiased estimator filter. This filter estimates the dynamic states of a system. Its primary goal is to use linear transition functions to transmit a state given by a Gaussian distribution. The operational state flow diagram of the KF is shown in Fig. 3.

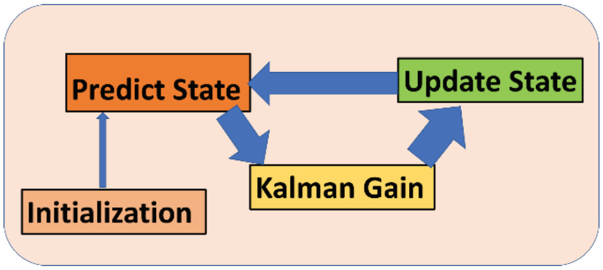

Figure 3. Operational state flow diagram of KF.

This filter assumes a certain number of assumptions. The first one is that the state transition appears to be in a linear form:

Kalman filter estimates states based on the system having linear dynamics. The process noise covariance matrix defines the formation of (k) time state from (k– 1) time state:

$$x_K = F_k x_{k-1} + B_k u_{k-1} + w_{k-1}$$

where,

F : State-transition model
x_{k-1} : Previous state vector
B : Control-input model, applied to control vector (u_{k-1})
w_{k-1} : Process noise

The process noise covariance matrix and measurement matrix describe the correlation between the state transition model and the measurement model at the time step (k) as:

$$Z_K = H_k X_k + v_k$$

where,

z_k: Measurement(Observation) vector
H: Measurement(Observation) matrix
v_k: Measurement(Observation) noise

The second assumption is that the system will always be continuous.

The basic thought of using this filter is to make use of the state transition function in projecting the state forward[13]. Hence the algorithm is built in a predictor and corrector form, where the system's observable quantities' measurements are incorporated such that, they correct the state.

3.2 Extended Kalman Filter

Real-world systems are mostly non-linear, therefore the Extended Kalman F (EKF) ilter was created with the limitations of a Kalman filter in mind. The problem we face with a Kalman filter is that it only applies to a set of scenarios where the problems have been defined – added Gaussian noise along with difficulties in linear and state transition and its measurements. This in turn, improvises the optimality of the Kalman filter in general[9]. The operational state flow diagram of EKF is shown in Fig. 4.

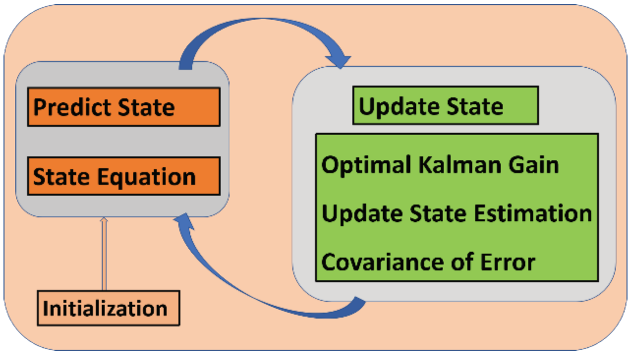

Figure 4. Operational state flow diagram Extended KF.

When it comes to the accuracy of an Extended Kalman filter, it depends on two factors. The behaviour of the observation models and the linear transition around the mean is one factor. Another factor is how the observation models will be affected by the modality of the transition. The detailed mathematical modelling of this is presented here:

A Gauss-Markov random process can be expressed in the state space representation form as

$$X_{K+1} = A_k X_k + w_k$$

The observations vector and the process vector is associated with the state vector of the linear transition as:

$$Z_k = H_k X_k + v_k$$

where,

A_K = State transition Model
X_K = Linear State Space of the system
Z_K = Observation (measurement) of the system states
H_K = Observation (measurement) model
w_K = Process Noise
v_K = Observation (measurement) Noise

3.2.1 Kalman Recursions

$$K_k = P_{k-1} H_k^T (H_k P_{k-1} H_k^T + R_k)^{-1}$$

$$\hat{X}_k = \hat{X}_{k-1} + K_k(Z_k - H_k \hat{X}_{k-1})$$

$$P_k = (1 - K_k H_k) P_{k-1}$$

Detailed analysis of the KF and mathematical formulations are explained in Gelb[11].

3.3 Unscented Kalman Filter

Unscented Kalman Filter (UKF) does not use the Riccati equations (for continuous time) or the covariance propagation and update laws (for discrete-time).

As we know, when any system has highly non-linear behaviour, the Extended KF becomes inefficient and the tuning becomes difficult. The Unscented transform method is used here on a random variable, to get the statistics, after it undergoes a transformation.

The Unscented KF is a non-linear sub-optimal filtration algorithm. It uses an unscented transformation instead of the linearization of non-linear equations with the Taylor series. UKF is the best-known non-linear estimator. To implement the UKF in practical applications, the following steps are carried out:

- Calculate a set of sigma points
- Weights are assigned to all sigma points
- Transform the sigma points through a non-linear function.
- From weighted and transformed points, Calculate the Gaussian
- Calculate the Variance and Mean of the new Gaussian.

Transfer Alignment Formulation

A nine (9) state KF is designed for the simulation studies to estimate the misalignment of Slave INS w.r.t. Master INS.

3.4 State-Transition Model (A_k)

The A_k matrix contains three (3) attitude errors of the weapon INS w.r.t. reference navigation frame, three (3) gyroscope drift of the weapon INS, and three (3) Attitude errors of weapon INS w.r.t. Master INS. To construct the A_k matrix, the kinematics of these nine (9) states are to be established. The final state dynamics

$$\dot{X} = \begin{pmatrix} -\omega_{ie}^{e}\times & -DCM_b^{ecef} & 0_{3x3} \\ 0_{3x3} & 0_{3x3} & 0_{3x3} \\ 0_{3x3} & 0_{3x3} & 0_{3x3} \end{pmatrix} X$$

$$\dot{X} = AX$$

3.5 Misalignment Model

The missile will experience a high value of acceleration during the initial launch phase. This high acceleration increases the misalignment. This results in an increase in miss distance[20]. Hence, the estimation of the attitude misalignments must be accurate.

The reference navigation frame for weapon INS and Master INS can be treated the same for both locations. Therefore, the correlation between the weapon INS body frame to reference frame Direction Cosine Matrices can be represented as follows:

$$DCM_s^n = DCM_M^n DCM_s^M \tag{1}$$

Differentiating the Eqn. 1 gives

$$\dot{DCM}_s^n = \dot{DCM}_M^n\, DCM_s^M + DCM_M^n\, \dot{DCM}_s^M \tag{2}$$

where,

$$\dot{DCM}_s^n = DCM_s^n\, \omega_{ns}^s X \tag{3}$$

$$\dot{DCM}_M^n = DCM_M^n\, \omega_{nM}^M X \tag{4}$$

$$\dot{DCM}_b^M = DCM_s^M\, \omega_{Ms}^s X \tag{5}$$

ω_{ns}^s : Angular rate of Slave INS frame (s frame) w.r.t navigation frame (n frame)

ω_{nM}^M : Angular rate of Master INS frame (M frame) w.r.t navigation frame (n frame)

ω_{MS}^S : Angular rate of Slave INS frame (s frame) w.r.t Master INS frame (M frame)

These angular rates are:

$$\omega_{ns}^s = \omega_{is}^s - DCM_n^s \omega_{in}^n \tag{6}$$

$$\omega_{nM}^M = \omega_{is}^s + \varepsilon - DCM_n^M \omega_{in}^n \tag{7}$$

$$\omega_{MS}^S = \dot{\psi} \tag{8}$$

where, ε is gyro drift, the misalignment of Slave INS w.r.t. virtual master INS is represented by ψ , ω_{is}^s is the angular rate vector of the weapon INS system w.r.t. inertial frame.

Substituting Eqn. (3) to (8) in Eqn. (2):

$$\dot{\psi} = (I - DCM_M^S)\omega_{is}^s - DCM_M^S \varepsilon \tag{9}$$

We know that,

$$DCM_M^S = I - \psi X \tag{10}$$

Substituting Eqn. (10) in (9), we get

$$\dot{\psi} = \omega_{is}^s X \psi - \varepsilon + \psi X \varepsilon$$

Since, $\psi X \varepsilon$ is very small and has no effect on $\dot{\psi}$. Hence, Neglecting $\psi X \varepsilon$ gives

$$\dot{\psi} = -\omega_{is}^s X \psi - \varepsilon \tag{11}$$

Eqn. (11) is the INS transfer alignment misalignment model. It consists of

- The misalignment of the s frame w.r.t. M frame.
- The drift of weapon INS frame w.r.t. reference frame during the TA.

4. SIMULATION RESULTS ANALYSIS AND DISCUSSION

4.1 Attitude Initialization

It is assumed that the weapon (Slave) INS ('S') and Master INS ('M') are installed on a hard surface (rigid body) and with undetermined angular separation DCM_S^M exists between the two systems. At the beginning of TA, Master and weapon navigation systems were initialized with same Euler angles $D\hat{C}M_S^n(0) \equiv DCM_M^n(0)$. This'^' operator indicates the erroneous initialization of Slave INS ('S') to Navigation frame Direction Cosine Matrix. For misalignment, the initial Direction Cosine Matrix is initialized as $D\tilde{C}M_S^M \equiv I_{3x3}$. The Direction Cosine Matrix $D\tilde{C}M_S^M$ is the misalignment between the Master and weapon INS attitude. The operator

'~' refers to uncertainties in the matrix. The misalignment error is estimated using attitude-matching algorithm. The Direction Cosine Matrix relating the weapon INS frame (S frame) to the navigation frame (n frame) is initialized as $D\tilde{C}M_S^n = DCM_M^n D\tilde{C}M_S^M$.

Weapon INS navigation parameters are different from Master INS navigation parameters since both navigation systems are separated by Lever Arm (LA). Lever Arm compensated Master INS data is provided to the Weapon INS. The angular relations between Master and Weapon INS change with time due to the dynamics of the aircraft. A virtual Master navigation system is designed at a weapon location for comparing the weapon INS data with the virtual Master INS data.

One of the outcomes of this simulation study is to evaluate the misalignment error between the virtual Master and Weapon navigation systems in the presence of weapon INS sensor errors.

4.2 TA Simulation Environment

The following assumptions have been made for the simulation of the proposed filtering schemes:

- Detailed error modelling is needed to design an optimal KF. Many error parameters cannot be modelled by mathematical formulations.
- The transfer alignment scheme uses rates and accelerations sensed by Master INS during aircraft take-off. This led to, No requirement for specific manoeuvres by aircraft.

To assess the performance and correctness of estimation for the three proposed filtering schemes and the time required for the convergence of each scheme. A six-degree-of-freedom (6-DoF) simulation setup was used to assess the performance under different test conditions. The 6-DoF simulation setup consists of air-launched platforms trajectory simulator model, Master, and weapon INS sensor specifications simulator model. The simulation setup is shown in Fig. 5.

The specifications of a typical Master[19] INS and weapon INS are simulated using the sensor specifications given in Table 1 for air-launched platforms INS (Master INS) and Table 2 for weapon INS respectively. The flexure[7,9] of the aircraft body and effect of lever arm (LA) is simulated for weapon INS only, as Master INS is not affected by flexure motion. By matching the Master INS and weapon INS parameters to obtain the states of TA, all three types of Kalman Filters are used for the estimation of misalignment.

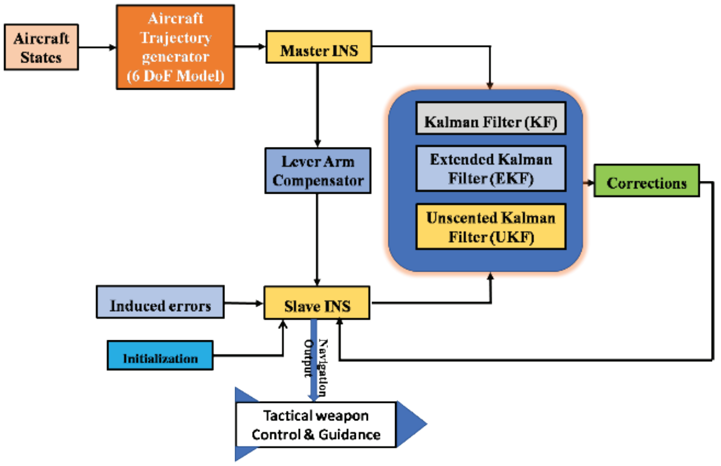

Figure 5. Block diagram of transfer alignment simulation environment and Initialization.

The estimation performance of the three Kalman Filters is evaluated for large value of 5 degrees of misalignment angle conditions to evaluate the effectiveness of the approach for meeting weapon systems Guidance and control[21-22] objectives and requirements.

Table 1. Master INS sensor specifications[19]

Parameter	Unit	Specifications
Gyro:		
Gyro drift	Deg/Hr	0.01 – 0.03
dynamic range	Deg/sec	±300
Scale factor stability	ppm	10
Random walk	Deg/√Hr	0.003
Accelerometer:		
Acceleration Range	'g'	50
SF stability	ppm	30

Table 2. Weapon INS sensor specifications

Parameter	Unit	Specifications
Gyro:		
Gyro drift	Deg/Hr	5-15
Dynamic range	Deg/sec	±500
SF stability	ppm	50 - 100
Random walk	Deg/√Hr	0.4
Accelerometer:		
Acceleration range	'g'	50
Bias Stability	mg	1
SF stability	ppm	50

4.2.1 Simulation Results and Analysis

This section illustrates the simulation results to assess the comparative simulation results performance of the three types of filters for transfer alignment of air-launched tactical weapon. Simulation results are shown in Fig. 6 to Fig. 9. Practically less than 3 deg of misalignment, is observed between Master INS and weapon INS. We have carried out simulations for the large mis alignment of 5°. This value of misalignments is not expected between Master INS and weapon INS. However, the convergence of the filtering algorithm for 5° of mis alignment, demonstrates the performance of the scheme for worst case of misalignment.

To assess the performance of the three algorithms, rates and accelerations in pitch and yaw axes sensed by Master INS and weapon INS during air-launched platform take-off were used. The misalignment angles in pitch and roll axes are estimated accurately in a short time, whereas misalignment estimation is less accurate in the yaw axis.

5. COMPARATIVE DISCUSSION

Through this research, we outlined three highly prominent methods in the domain of Bayesian state estimation.

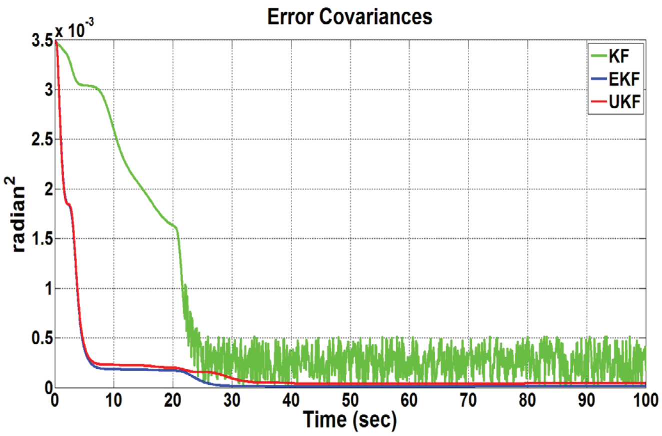

Figure 6. Error covariance for KF, EKF and UKF.

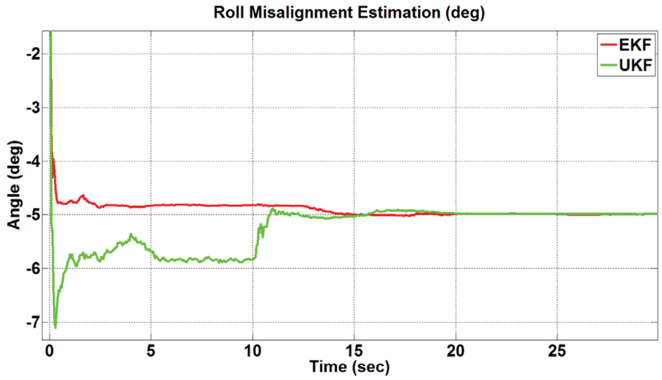

Figure 7. -5° misalignment in roll axis.

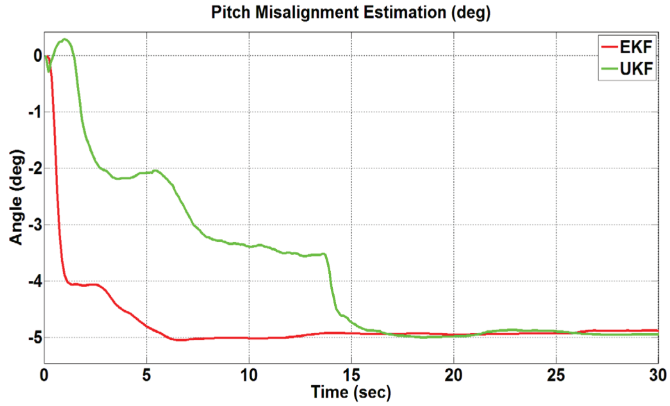

Figure 8. -5 deg misalignment in pitch axis.

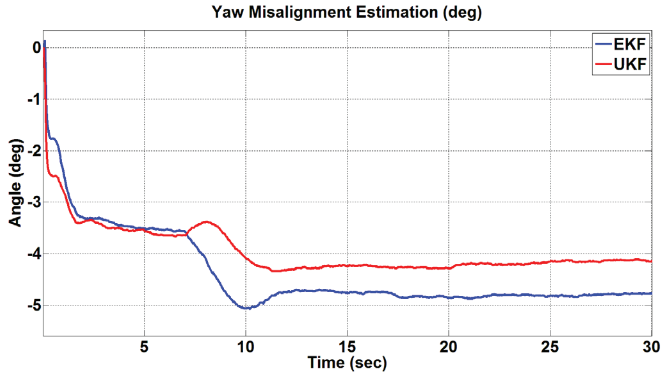

Figure 9. -5° mis alignment in yaw axis.

From Fig. 6, we observe that simple Kalman Filter error covariance is not converging and oscillations are seen. Based on this, further simulations were carried out for EKF and UKF. Figure 7 and Fig. 8 show that both filters (EKF & UKF) are estimating the misalignment accurately but EKF is converging faster than UKF.

Figure 9 shows that yaw misalignment estimation is less accurate as compared to Pitch and roll misalignment. The time taken for convergence of both filters is comparable but EKF is more accurate in yaw angle misalignment estimation. Table 3 gives the comparison of these three filters for various parameters.

Table 3. Comparison of different filters for transfer alignment

Type	Model	Rapid	Accurate
Kalman filter	Linear	Yes	Low
Extended lalman filter	Locally linear	Yes	Yes
Unscented kalman filter	Non-linear	No	Yes

6. CONCLUSION

Various factors affect the performance of the transfer alignment like modelling, estimator technique, initial measurements, and observation models. The parameter that is considered in this study is the speed of convergence and accuracy of misalignment estimation for practical misalignment values between Master and weapon INS.

In this paper, the advantages and disadvantages comparison of KF, EKF, and UKF filters are brought out for accurate and rapid transfer alignment of air-launched tactical weapons. The filters use the data of Master and weapon INS, to estimate the mis alignment of weapon INS. The simulation tests were made simulating the specifications of a typical Master and weapon INS. The results show that the EKF and UKF perform almost identically in the case of estimation accuracy. EKF converges faster than the UKF. Moreover, EKF and UKF appear to be more robust as compared to KF.

However, in these simulations, the time taken by UKF was more than the EKF.

Considering the above analysis in a practical implementation, the use of the EKF is more suitable for the transfer alignment of air-launched tactical weapon.

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CONTRIBUTORS

Mr Sambhav Kumar Jain completed his post-graduation in Telecommunication Technology & Management from Department of Electrical Engineering, IIT Delhi.
In the current simulation study, he has carried out a literature survey and made detailed modelling of various filters for tactical air-launched missiles, and prepared the manuscript.

Dr Tapan Kumar Jain did his PhD from JUIT, Solan. He has been currently working as Head of Department in the Department of Electronics Engineering IIIT Nagpur.
In this current study, he reviewed the work, gave the idea at various stages, continuously provided guidance, and gave many valuable inputs.

Dr Srikant Srivastava did his post-graduation from IIT Kharagpur in Electrical Engineering and PhD from NIT, Warangal. He has been working in DRDO, Hyderabad.
In the current study, he reviewed the manuscript and provided many valuable inputs at various stages of work.

Mr Saumya Shanker did his post-graduation from IIT Delhi in Computer Technology. He has been working in DRDO, Hyderabad.
In the current study, he has helped in analysing and validating the results.