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Centralized Fusion of Radar and IRST on an Aircraft

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Abstract — **This paper presents a centralized sensor fusion approach for radar and an infrared search and track (IRST) system mounted on an aircraft. The target motion is modelled in relative kinematics with radar measuring range, azimuth and elevation while IRST measures only target line of sight direction of arrival. A detailed sensor fusion architecture is presented for target tracking and the performance of the same is analyzed in the simulation environment. The sensor operational modes viz. track while scan (TWS) and single target tracking (STT) modes of radar and IRST are analyzed and target tracking performance is presented. Further, Monte Carlo simulations are carried out and root mean squared error analysis has been used to analyze the proposed centralized sensor fusion algorithm.**

Keywords—KF, EKF, radar, IRST, TWS, STT, target tracking.

I. INTRODUCTION

Primary tactical sensor suite on a combat aircraft comprise of a radar, an infrared search and track (IRST) system, a missile approach warning system (MAWS) and a radar warning receiver (RWR). Beyond visual range (BVR) target tracking primarily involves in radar and IRST detecting targets and providing corresponding measurements to their respective processing units (PU). Both these sensors operate in two operational modes namely i) Track While Scan (TWS) mode and ii) Single Target Tracking (STT) mode. In TWS mode of operation the radar and IRST shall search for targets in their corresponding respective field of regards (FOR). Field of view (FOV) or foot print on these sensors depend on their respective intrinsic parameters. Primary measurements obtained from a radar typically comprise of target line of sight (LOS) range, azimuth and elevation angles, while IRST measurements typically comprise of LOS direction of arrival i.e. target azimuth and elevation. These measurements for all the detected targets are typically processed in the respective processing units using sophisticated target tracking algorithms giving rise to confirmed tracks from each sensor. These individual tracks are further processed at a fusion center to perform track to track (T2T) fusion. Such a track fusion is typically named as decentralized T2T fusion. Decentralized fusion approach is useful in the case if one does not have access to raw measurements from each of the sensor and are bound to rely on the track output provided by the sensors. Such a decentralized fusion approach is a sub-optimal T2T fusion and can be found in [1], [2] and [3]. In this paper, we present a centralized measurement fusion approach to fuse the measurements from radar and IRST. Such a fusion is termed as TYPE IV configuration in [4] and is termed as optimal in terms of providing the track accuracy. In our previous work [5], a decentralized T2T fusion approach was presented to fuse a radar and an IRST mounted on an aircraft. Ref [5] also presents a detailed sensor fusion architecture for a multi target tracking scenario with radar and IRST mounted on an aircraft. Ref [6] presents optimal track to track fusion approach and provides the optimality in maximum likelihood (ML) sense. Ref [7] presents track to track fusion for dissimilar sensor and also derives a closed form solution for cross correlation considering the common target process noise in each of the sensor tracking filters. Ref [8] presents various track to track fusion algorithms and has segregated into a total four types of track to track configurations depending on the data availability at the fusion center. In this paper, a centralized fusion approach is looked at considering the availability of raw sensor measurements from radar and IRST at fusion center. An extended Kalman filter (EKF) is presented in this paper for target tracking using measurements obtained from radar and IRST. The performance of the EKF algorithm in operational modes of these sensors i.e. TWS and STT modes are analyzed.

The rest of the article is structured as follows: section II presents the target tracking algorithm with state and measurement models for radar and IRST. This section also presents the nonlinear mapping of sensor measurement model to target tracking state model. Section III presents an extended Kalman filter algorithm and provides the sensor fusion architecture for centralized tracking using radar and IRST measurements. A detailed mathematical formulations involved in the EKF implementation are presented in this section. Section IV presents few simulation results involving in various operational modes of radar and IRST and presents the performance analysis of the proposed fusion algorithm with the help of Monte Carlo simulations and section V concludes the paper.

II. TARGET TRACKING

In this section, the target tracking state and measurement models are presented primarily focusing towards a centralized sensor fusion approach. The target motion kinematics in three dimensions are represented in Cartesian frame of reference while the measurements obtained from radar and IRST are represented in spherical frame of reference. The state and measurement models for target tracking is as follows:

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A. State Model

Target motion is modelled in Cartesian frame of reference with target kinematics in horizontal plane being a near constant turn (NCT) while that in vertical plane being near constant velocity (NCT). Let X_T represent the target absolute state in North-East-Down (NED) frame of reference as shown below:

$$X_T = \begin{bmatrix} x & y & z & \dot{x} & \dot{y} & \dot{z} & \omega \end{bmatrix} \quad (1)$$

Where, $\begin{bmatrix} x & y & z \end{bmatrix}$ and $\begin{bmatrix} \dot{x} & \dot{y} & \dot{z} \end{bmatrix}$ represent the target positon and velocity in NED frame of reference, ω represent the target turn rate in horizontal plane. The discrete-time target kinematics is given by:

$$X_T(k) = F_T X_T(k-1) + G_T(k-1) w(k-1) \quad (2)$$

Where, $w(k)$ is zero mean white piecewise constant process noise with variance of $\sigma_{a_x}^2, \sigma_{a_y}^2, \sigma_{a_z}^2, \sigma_{\omega}^2$, G_T represents the process noise scaling matrix and F_T represents the discrete time near constant turn (NCT) motion model in horizontal plane and near constant velocity (NCV) in vertical plane and is given by:

$$F_T = \begin{bmatrix} I_{3\times3} & A & O_{3\times1} \\ O_{3\times3} & B & O_{3\times1} \\ O_{1\times3} & O_{1\times3} & 1 \end{bmatrix}$$

$$A = \begin{bmatrix} \dfrac{\sin(\omega_t \delta t)}{\omega_t} & -\dfrac{1-\cos(\omega_t \delta t)}{\omega_t} & 0 \\ \dfrac{1-\cos(\omega_t \delta t)}{\omega_t} & \dfrac{\sin(\omega_t \delta t)}{\omega_t} & 0 \\ 0 & 0 & \delta t \end{bmatrix}$$

$$B = \begin{bmatrix} \cos(\omega_t \delta t) & -\sin(\omega_t \delta t) & 0 \\ \sin(\omega_t \delta t) & \cos(\omega_t \delta t) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Where, δt represent the sampling interval and ω_t represents the target turn rate in horizontal plane. $I_{x\times y}$ and $O_{x\times y}$ represent the identity matrix and null matrix respectively with x rows and y columns. Thus the target relative kinematics in Cartesian frame of reference can be modelled as shown below:

$$\begin{aligned} X(k) &= X_T(k) - X_A(k) \\ X(k) &= (F_T - F_A)\left(X_T(k-1) - X_A(k-1)\right) \\ &\quad + G_T(k-1) w(k-1) \end{aligned} \quad (3)$$

Where, X_A represents the absolute kinematic state of own ship aircraft where the sensors are mounted. In this paper, the aircraft motion is assumed to be deterministic at every instance in time comprising of its position, velocity and turn rate in NED frame of reference. In the above equation it is to be noted that the state $X(k)$ is target relative kinematic state in NED.

B. Measurement Model

The measurements from radar and IRST are in spherical frame of reference with radar measurements being line of sight range, azimuth and elevation while IRST measurements are only line of sight azimuth and elevation angles. In this paper, radar and IRST measurements are assumed to be corrupted with additive white Gaussian noise (AWGN) [4]. Thus the measurement models for radar and IRST are given by:

$$\begin{aligned} Y_r(k) &= h_r(X(k)) + \eta_r(k) \\ Y_{ir}(k) &= h_{ir}(X(k)) + \eta_{ir}(k) \end{aligned} \quad (4)$$

Y_r and Y_{ir} represent the measurements obtained from radar and IRST. $h_r(.)$ and $h_{ir}(.)$ represent the nonlinear mapping between the target relative kinematics and the measurements obtained from radar and IRST respectively. η_r and η_{ir} represent the additive white Gaussian noise (AWGN) in radar and IRST respectively.

C. Nonlinear Mapping

This sub section of the paper presents the nonlinear mapping between the relative target state kinematics and measurements obtained from radar and IRST. The LOS range (r), azimuth (ψ) and elevation (θ) of the target with respect to the own ship aircraft is given by:

$$Y = \begin{bmatrix} r \\ \psi \\ \theta \end{bmatrix} = h(X) = \begin{bmatrix} \sqrt{x^2 + y^2 + z^2} \\ \tan^{-1}\left(y/x\right) \\ \tan^{-1}\left(-z/\sqrt{x^2 + y^2}\right) \end{bmatrix} \quad (5)$$

Where $\begin{bmatrix} x & y & z \end{bmatrix}$ in the above expression represents the target relative position with respect to the own ship aircraft.

III. EXTENDED KALMAN FILTER (EKF)

As the target relative kinematics presented in the previous section is nonlinear with target turn rate driving the nonlinearity and also the measurement model is nonlinear, an extended Kalman filter (EKF) based target tracking algorithm is presented in this section of the paper. The discrete time extended Kalman filter time update and measurement update equations with nonlinear state and measurement model is presented below:

A. Time Update

In the recursive update, let the target relative state output from EKF at $(k-1)$ time instance be represented by $X(k-1|k-1)$ with corresponding state error covariance matrix $P(k-1|k-1)$. Then the prediction step or time update step in the EKF is given by:

$$\begin{aligned} X(k|k-1) &= (F_T - F_A)\,X(k-1|k-1) \\ P(k|k-1) &= J(k)P(k-1|k-1)J(k)^T \\ &\quad + G(k)Q(k|k)G(k)^T \end{aligned} \tag{6}$$

Where, $X(k|k-1)$ and $P(k|k-1)$ represent the predicted state and state error covariance matrix at k[th] time instance. $Q(k|k)$ represents the process noise covariance matrix. $J(k)$ represents the gradient $\left(\nabla_X (F_T - F_A)\right)\big|_{X=X(k|k-1)}$ i.e. $J(k)$ is obtained from linearization of state propagation matrix $(F_T - F_A)$ at predicted state $X(k|k-1)$.

B. Measurement Update

The available measurements at any given instance in time shall depend on whether the target falls in radar and IRST instantaneous field of view (IFOV). In other words, at any given instance in time radar alone could detect the target, IRST alone could detect the target or both sensors could detect the target. Thus the EKF measurement update shall be based on the available measurements and source of the measurements. A typical measurement update expression in an EKF with nonlinear measurement model is shown below:

$$\begin{aligned} X(k|k) &= X(k|k-1) \\ &\quad + K\left(Y(k) - h\left(X(k|k-1)\right)\right) \\ K &= P(k|k-1)H^T(k|k-1)S^{-1}(k|k-1) \\ S(k|k-1) &= H(k|k-1)P(k|k-1)H^T(k|k-1) \\ &\quad + R(k) \\ P(k|k) &= P(k|k-1)\left[I - KH(k|k-1)\right] \end{aligned} \tag{7}$$

Where, $X(k|k)$ and $P(k|k)$ represent the updated state and state error covariance matrix at k[th] time instance. K is the Kalman gain and H represents the measurement jacobian evaluated at $X(k|k-1)$ i.e. the gradient $\left(\nabla_X h(X)\right)\big|_{X=X(k|k-1)}$. And $R(k)$ represents the measurement noise covariance matrix. The nonlinear function $h(X)$ for radar measurements has full mapping with the state model, while for IRST measurements there does not exist full mapping between state model and measurement model. The nonlinear mapping for radar $h_r(X)$ contains range, azimuth and elevation as presented in eq.(5), while for IRST $h_{ir}(X)$ contains only azimuth and elevation as shown below:

$$h_{ir}(X) = \begin{bmatrix} \psi \\ \theta \end{bmatrix} = \begin{bmatrix} \tan^{-1}\left(y/x\right) \\ \tan^{-1}\left(-z/\sqrt{x^2+y^2}\right) \end{bmatrix} \tag{8}$$

The measurement jacobian for radar (H_r) and IRST (H_{ir}) have the matrix sizes of 3×7 and 2×7 respectively. The measurement noise covariance matrices for radar and IRST are represented by $R_r(k)$ and $R_{ir}(k)$ respectively.

C. Fusion Approach

The measurement update of the target track from the measurements of radar and IRST are made in a sequential fashion as shown in the Figure 1.

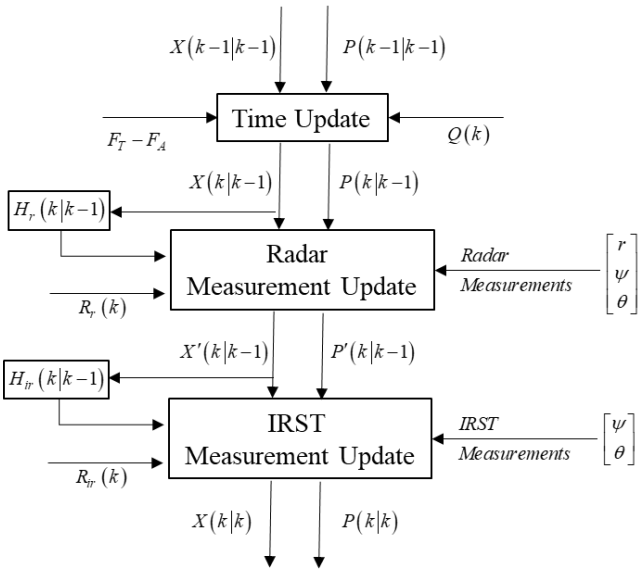


Figure 1: Sequential Fusion of Radar and IRST

The sequential fusion approach presented in Figure 1 is in general applicable when both the sensors detect a particular target of interest at a given instance in time, thus leading to EKF update from both the sensor measurements. Such a scenario is termed as synchronous measurement update of both the sensors. Such a scenario is very much possible when both radar and IRST are tracking same target in single target tracking (STT) mode of operation. On the other hand, when

sensors are operational in track while scan (TWS) mode of operation, there would be an asynchronous measurement update scenario for any given target track. Thus at any given instance in time the measurement update can be given by:

$$\begin{aligned} X(k|k) &= X(k|k-1) \\ &\quad + \lambda_r K_r \left(Y_r(k) - h_r\left(X(k|k-1) \right) \right) \\ &\quad + \lambda_{ir} K_{ir} \left(Y_{ir}(k) - h_{ir}\left(X(k|k-1) \right) \right) \\ P(k|k) &= P(k|k-1) \\ &\quad - \lambda_r P(k|k-1) K_r H_r\left(k|k-1\right) \\ &\quad - \lambda_{ir} P(k|k-1) K_{ir} H_{ir}\left(k|k-1\right) \end{aligned} \tag{9}$$

Where

$$\lambda_r = \begin{cases} 1 & \textit{if radar track update at time k} \\ 0 & \textit{otherwise} \end{cases} \tag{10}$$

$$\lambda_{ir} = \begin{cases} 1 & \textit{if IRST track update at time k} \\ 0 & \textit{otherwise} \end{cases} \tag{11}$$

In the above measurement update expression one should note that, the Kalman gain K_r is computed with radar measurement jacobian matrix $\left(H_r\right)$ and radar measurement noise covariance matrix $\left(R_r\right)$. Similarly, the Kalman gain K_{ir} is computed with IRST measurement jacobian matrix $\left(H_{ir}\right)$ and IRST measurement noise covariance matrix $\left(R_{ir}\right)$

D. Fusion Performance Analysis

In this paper, the performance analysis of the proposed centralized fusion of radar and IRST are analyzed by performing 100 Monte Carlo Simulations. The performance metrics viz. root mean square position error (RMSPE), root mean squared velocity error (RMSVE) and root mean squares turn rate error (RMSTRE) are computed from 100 Monte Carlo simulations. At any given instance in time the position, velocity and turn rate error from the estimated target state of EKF is given by:

$$\begin{bmatrix} \delta x \\ \delta y \\ \delta z \end{bmatrix} = \begin{bmatrix} x - \hat{x} \\ y - \hat{y} \\ z - \hat{z} \end{bmatrix} \& \begin{bmatrix} \delta \dot{x} \\ \delta \dot{y} \\ \delta \dot{z} \end{bmatrix} = \begin{bmatrix} \dot{x} - \hat{\dot{x}} \\ \dot{y} - \hat{\dot{y}} \\ \dot{z} - \hat{\dot{z}} \end{bmatrix} \tag{12}$$

$$\delta\omega = \omega - \hat{\omega}$$

Where, $\left(\delta x \quad \delta y \quad \delta z\right)$, $\left(\delta \dot{x} \quad \delta \dot{y} \quad \delta \dot{z}\right)$ and $\delta\omega$ represent the estimated target position error, velocity error and turn rate error respectively. Thus for 'N' Monte Carlo simulation the RMSPE, RMSVE and RMSTRE are given by:

$$\begin{aligned} RMSPE &= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\begin{bmatrix} \delta x & \delta y & \delta z \end{bmatrix}_i \begin{bmatrix} \delta x \\ \delta y \\ \delta z \end{bmatrix}_i \right)} \\ RMSVE &= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\begin{bmatrix} \delta \dot{x} & \delta \dot{y} & \delta \dot{z} \end{bmatrix}_i \begin{bmatrix} \delta \dot{x} \\ \delta \dot{y} \\ \delta \dot{z} \end{bmatrix}_i \right)} \\ RMSTRE &= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\delta\omega_i^2 \right)} \end{aligned} \tag{13}$$

IV. Simulation Scenario & Results

In this paper, performance of the centralized fusion approach of radar and IRST is analyzed by carrying out various simulation scenarios with single target placed in field of regard (FOR) of radar and IRST. Firstly, the own ship aircraft is simulated such that it is heading towards the north with a near constant velocity (NCV) of 250 m/sec. A single target is simulated such that it has NCV motion for initial 10 seconds and then enter into a NCT motion in horizontal plane with $\omega = 10$ deg/sec and also descend in vertical plane with a near constant vertical speed of 10 m/sec. During the entire simulation the horizontal velocity of the target simulated is 350 m/sec. The NCT motion of the target simulation is for a duration of 70 seconds and followed by another 30 seconds of NCV motion. The entire target trajectory is shown in Figure 2. Further, the radar and IRST sensors are simulated to have an update rate of 50 Hz, while both sensors can operate in TWS and STT modes of operation. In this paper, TWS modes of radar and IRST are simulated with a scan rate of 60 deg/sec and 50 deg/sec while the search volumes/FORs are at ± 30 degrees and ± 25 degrees respectively. At a given instance in time, Figure 2 shows the IFOVs of both radar and IRST with $\left(3^o \times 3^o\right)$ and $\left(5^o \times 7^o\right)$ foot print in TWS modes of operation shown at approximately 100 km from the aircraft. Further, IRST being a camera based sensor it does have a finer resolution in azimuth and elevation corresponding to the sensor detector size. Along with the specific resolution in each measurement for both sensors, the measurements are corrupted with zero mean white noise. The angular accuracy for radar is simulated to be 5 mrad and range accuracy is at 300m, while for IRST the angular accuracy is at 0.5 mrad. Monte Carlo simulations are carried out and the performance of the centralized fusion approach is analyzed with both the sensors operational in TWS mode and STT mode. In the STT mode of operation it is ensured that the IFOVs of both the sensors are directed such that the target is detected though out the simulation. The target RMSPE, RMSVE and RMSTRE of fusion algorithm obtained from 100 Monte Carlo simulations are bench marked with the metrics obtained from standalone radar operational scenario. Figure 3 shows the RMSPE, RMSVE and RMSTRE of the fused track obtained while both the sensors are operated in TWS mode and compared against

the standalone radar track output. This clearly shows how the fusion is improving the track accuracy with respect to each of the sensor operating in TWS mode. Figure 4 shows the performance of fusion algorithm while both the sensors are operating in single target tracking (STT) mode. RMSPE, RMSVE and RMSTRE are significantly improved with the fusion of radar and IRST sensors. Further, simulations are carried out to analyze the performance of the fusion algorithm when the sensors are operated in various operational modes. Following combinations of operational modes of the radar and IRST are simulated and performance of fusion algorithm is analyzed.

i. Radar (TWS) & IRST (TWS).
ii. Radar (TWS) & IRST (STT).
iii. Radar (STT) & IRST (TWS).
iv. Radar (STT) & IRST (STT).

Figure 5, Figure 6 and Figure 7 show the RMSPE, RMSVE and RMSTRE for the above operational scenarios with single target in the field of regard of both the sensors. It is clearly observed that the position, velocity and target turn rate estimation accuracy is superior when a target is tracked by both the sensor together in STT mode of operation. This is attribute to the fact that, the track gets measurement update at each and every instance in time from both the sensors leading to a superior estimation accuracy. Similarly, the track estimation accuracy deteriorates as and when the target is tracked by any sensor operating in track while scan mode. This leads to a least accurate scenario of both the sensors tracking a particular target in TWS mode of operation. This can be clearly observed in Figure 5, Figure 6 and Figure 7. Thus to accurately localize the target it is desirable that both the sensors lock on to the particular target of interest thus leading to a best positional accuracy.

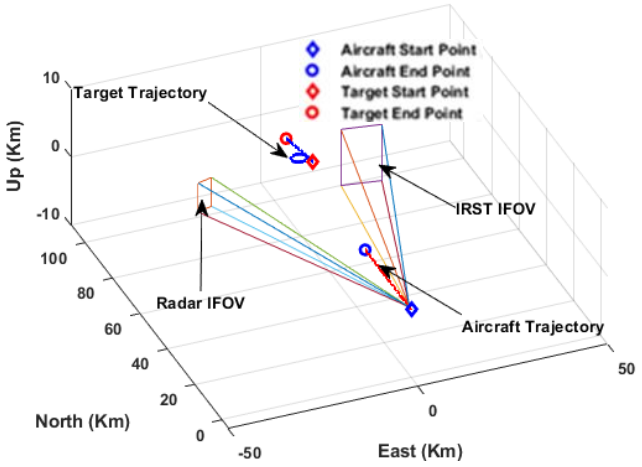


Figure 2: Simulation scenario showing target trajectory and own ship aircraft mounted with radar and IRST.

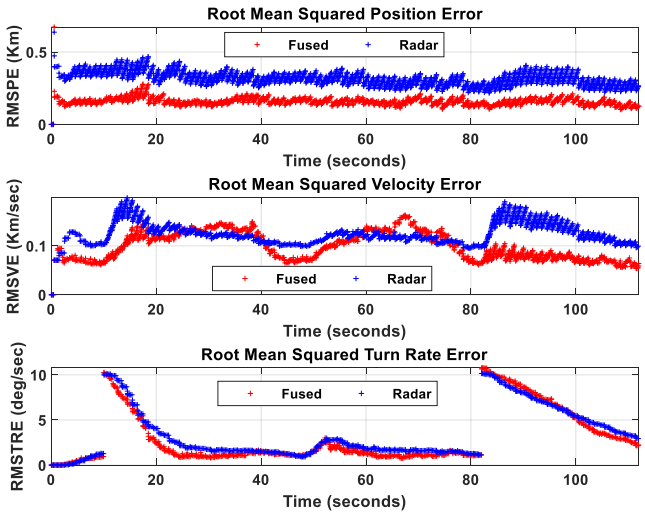


Figure 3: Fusion performance metrics while Radar and IRST are operated in TWS mode.

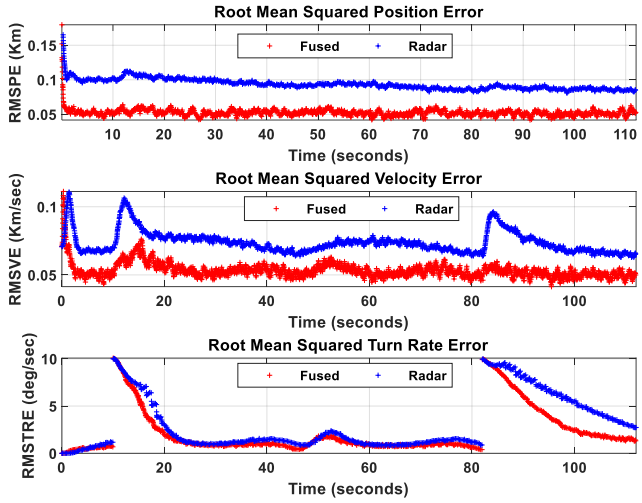


Figure 4: Fusion performance metrics while Radar and IRST are operated in STT mode.

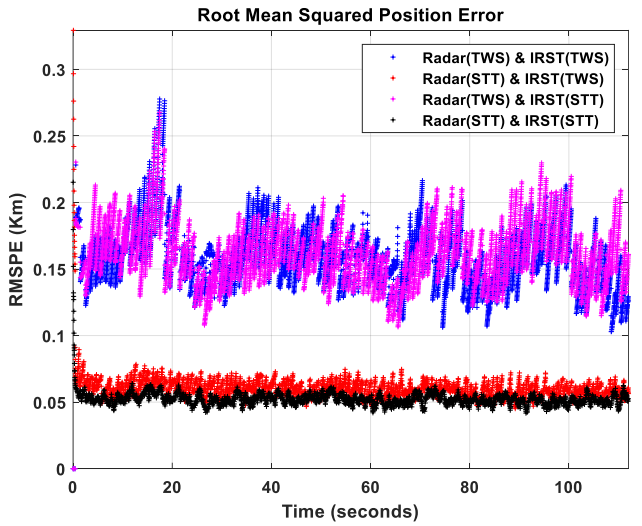


Figure 5: Comparison of RMSPE from fused track for various sensor operational modes.

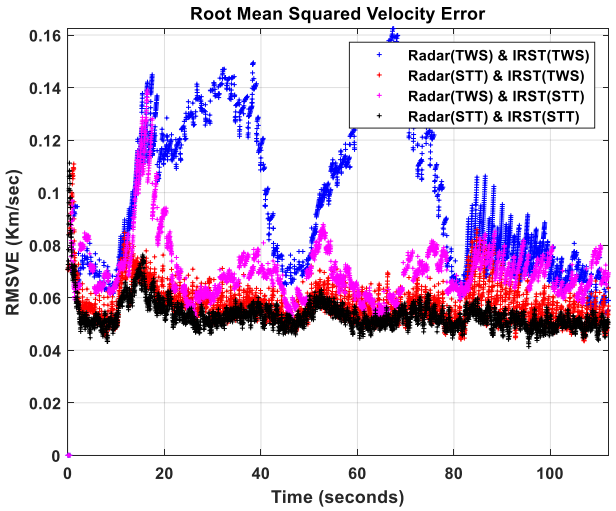


Figure 6: Comparison of RMSVE from fused track for various sensor operational modes.

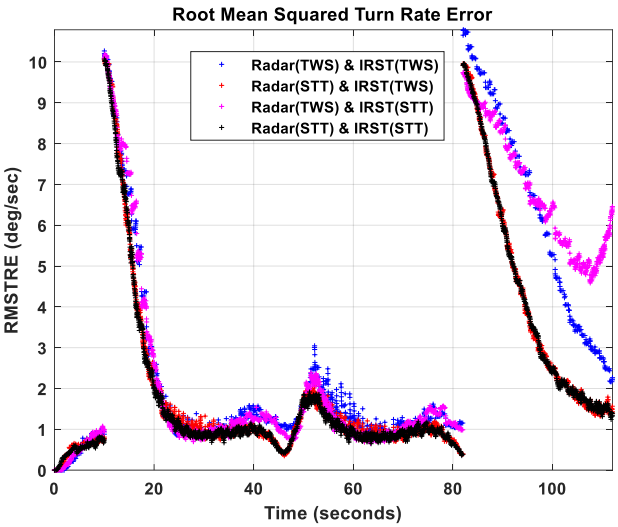


Figure 7: Comparison of RMSTRE from fused track for various sensor operational modes.

V. CONCLUSIONS

This paper presents a centralized sensor fusion approach for fusion of radar and IRST mounted on an aircraft. The measurements obtained from each of the sensor at any given instance in time are directly used in the measurement update of the target track using an extended Kalman filter (EKF) algorithm. In this paper, the target state model is in Cartesian frame of reference while sensor measurement model is in Spherical frame of reference. This paper also emphasizes on the nonexistence of full one to one mapping of target state and IRST measurement. A complete mathematical formulations involved in the measurement update of EKF with radar and IRST sensors are clearly presented. The performance of the centralized fusion approach of radar and IRST is analyzed using root mean squared position error, root mean squared velocity error and root mean squared target turn rate error obtained from 100 Monte Carlo simulations. In this paper a single target tracking scenario is considered and the performance of the fusion algorithm is analyzed while the sensors are operated in various operational scenarios. The performance metrics of the fusion algorithm clearly brought out the significance of fusing radar and IRST in terms of localizing a particular target.

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