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Adaptive Registration with Decentralized Kalman Filter Fusion Algorithm for Radar-ADS-B Data Fusion in Air Traffic Surveillance

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Abstract

Multi-sensor-Multi target tracking is an emerging technology which is an essential building block of 4-D trajectory based operation in next-generation air transport system. This study proposes an adaptive algorithm for filtering and fusion of multiple heterogeneous sensors, which includes secondary surveillance radars at different geographical location and ADS-B, whose measurements and sensor characteristics are different from one another. Decentralized fusion architecture based on 4D-dimensional (3-D plus time) Earth-Centered Earth-Fixed (ECEF) common coordinate system is adapted to process the data received asynchronously from multiple heterogeneous sensors. The proposed algorithm, removes sensor bias, by proper sensor registration process using LMS (Least Mean Square) algorithm and thereby increasing the quality of the track. A decentralized Adaptive filter with Decentralized Kalman Filter Fusion (ADKFF) method based on Mahalanobis distance is proposed to carry out the fusion task. This study also makes use of the Down-linked Aircraft Parameters (DAP) which can be obtained from mode-S radar and ADS-B for the computation-ally efficient fusion process. The simulation results indicate that the proposed adaptive filtering algorithm with decentralized Kalman filtering can remove sensor registration error, better tracking performance, eliminating ghost and more accurate position information using different types of surveillance sensors.

Keywords: Multi-radar-ADS-B fusion; Multiple heterogeneous sensors; Earth-centred earth-fixed

Introduction

With the advancement of civil aviation to cop up with increase in air traffic, accurate determination aircraft position and for providing safe separation, demand for reliable and precise air traffic control surveillance system increased. Multi-radar-ADS-B fusion processing offers an advance on target tracking by fusing the detections of multiple radars and ADS-B in areas of overlapping coverage, improving the probability of detection and the tracking of maneuvering aircraft. Multi-target multi-sensor target tracking is a form of estimation fusion, in its core processing feature of the Surveillance Data Processing System (SDPS) for Air Traffic Control (ATC) [1]. SDPS estimates the state of targets using the measurements or estimates that are obtained from multiple surveillance sensors. With the advancement of secondary radar technology and ADS-B more reliable information from aircraft are received on ground station, which includes Download Aircraft Parameters (DAP) like speed, heading altitude etc. ADS-B [2,3] is a dependent sensor, which uses satellite-based or inertial systems of aircraft to determine the position and other additional information. Contrary to typical independent sensors, such as radar, ADSB measurements are all dependent upon and calculated by the aircraft systems. ADS-B is known to have the following advantages: a high refresh rate (at least 1 Hz), small latency, high positioning accuracy, and availability of onboard surveillance as well as ATC [1]. On the other hand, the drawbacks include the following: dependency on the equipage of the aircraft and the Global Navigation Satellite System (GNSS), reliance on the data correction sent by the aircraft, time stamping error, and additional issues [4]. One of the most important characteristics of ADS-B, regarding target tracking and fusion, is that its measurements and corrections of these terms solely depend on each aircraft based on ADS-B transceiver used on it. This shows that the tracker may not be able to handle the ADS-B measurements properly if a particular aircraft processes data incorrectly and sends the wrong information to the tracker without any form of notification. Fusing the data from multiple sensors such as radar and ADS-B which have the most challenging ones heterogeneous characteristics.

A tracking function for air traffic control based on radar and ADS-B messages was proposed by Beseda et al. [5]. The use of both sensors can lead to a significant improvement both in track accuracy and overall system integrity. Baud et al. [2,4], described the experimental data fusion architecture, processes, and steps required for the air traffic control applications that were based on radar plots and ADS-B reports to enhance track accuracy and sensor coverage. ICAO (International Civil Aviation Organization) has published [3] Minimum Operational Performance Standards for ADS-B integration. A simple ADS-B data fusion method to incorporate ADS-B data into traffic control centers already operative was proposed by De Vela et al. presented. But the fusion was with the minimal intervention on the tracking filter already tuned and tested [6,7]. Da Silva et al., proposed both centralized and distributed fusion architectures with an assumption of synchronous radars and ADS-B sensors. Practically all the sensor synchronization is not possible because all are working on different geographical location with different delays. In the last three decades, both synchronous and asynchronous sensor registration problems have been studied [8-11]. Sensor registration entails two major objectives. The first objective is to align the different sensor platforms by removing the bias of each cooperating unit for the purpose of track association. The second is

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to estimate target positions with respect to geodetic coordinates. The common radar registration errors contained in radar measurements are range, azimuth, and altitude and time biases. The range bias is a constant deviation in range measurement while the azimuth bias is a misalignment of the radar north mark with respect to the true north mark or lateral position offset. Both biases are varied with distance from the radar site over the coverage area of each sensor. It is assumed to be almost nil for ADSB measurement. Clock offset could cause the radar and ADSB time bias, and/or processing, storage, and transmission delays.

A detailed study on the requirement of ADS-B integration to the existing surveillance system and future requirement next-generation air transport system was conducted by Strohmeier M et al., [12]. Later Jeon D et al. [1] proposed a system for the estimation fusion of multiple heterogeneous sensors, which includes radar and ADS-B, whose measurements and sensor characteristics are different from one another. Their proposal was a centralized fusion architecture based on three-dimensional Earth Centred Earth-Fixed (ECEF) common coordinate system is adapted to process the data received asynchronously from multiple heterogeneous sensors. Their study also proposes variable-sized measurement vectors and matrices for the tracking filter in order to dynamically reflect the availability of the additional measurements from the Downlinked Aircraft Parameters (DAP) which can be obtained from mode-S radar and ADS-B. But the system lack in the processing of ADSB data completely and correlating same with radar data. It also lacks effective bias estimation (pre-filtering) data from multiple sources. Bias estimation or sensor registration is an essential step in ensuring the accuracy of global tracks in multi sensor-multi target tracking. An algorithm capable of accurately estimating the biases even in the absence of filter gain information from local platforms was proposed by E. Taghavi [13] for distributed-tracking systems with intermittent track transmission. But the proposed algorithm does not take care fusion process to make use of all available information and its merit. Major drawbacks of the previous study [1] are that their main purpose is to improve tracking performance with the usage of ADS-B data without considering the target location with respect to the radar location. Thus didn't consider the major issue of the track is jumping in the same coverage area which affects standard separation between two aircraft. It also didn't take care of the radar bias error and correcting the same, which will result discarding radar data which having a constant bias. This study utilizes making use of both radar and ADS-B data and giving proper weight to data received from each sensor thereby smooth transition of track in the boundary of the cell grid. It also calibrates the radar sensor data with the data from ADS-B and vice-versa using LMS feedback algorithm in the preprocessing stage. A decentralized fusion architecture is designed to overcome the above-said drawbacks [1,13] which make efficient use of both radar and ADS-B data for accurate track prediction system.

In this paper, we propose an algorithm based adaptive filtering/gating process to remove bias error and thereby an accurate registration process achieved. The algorithm calculates these biases using quality ADS-B positions and velocities as approximate true quantities. The LMS adaptive filtering along with decentralized Kalman filtering make an optimal ADS-B radar data fusion. The paper is organized as follows. Section 2 defines system dynamics and formulates bias error correction or registration using LMS algorithm. In section 3 an algorithm for multi radar-ads b data fusion based decentralized Kalman filter. A set of simulations presented in Section 4, and the conclusions provided in Section 5.

Problem Definition and System Dynamics

Problem definition

Today, air traffic controllers in India utilize multiple radars to provide separation for en route surveillance. Terminal controllers in India are required to use a single radar to provide 5 NM (Nautical Mile) separation up to 60 nm range (terminal radar is a mono-pulse secondary surveillance radar/+ primary) from radar head. Likewise, en route controllers in India use a single radar (uses the single sensor from multiple inputs) for separation with 10 NM separation beyond 60 NM from radar head. This method, called mosaicking, displays the radar returns from preferred en route radar for a particular geographic area. If a radar return from the preferred radar is not available, then the radar report from the alternate radar is utilized, although this often causes track jumps. This will cause serious impact on separation which will increase or decrease abruptly which also contribute error in conflict prediction.

One reason for using single radar reports even when reports from multiple radars are available is to avoid errors introduced by biases uncorrelated between different radars. Each radar has several types of bias: location bias, azimuth bias, and range bias. Location bias results from uncertainty about where the radar is located and typically amounts to 200 ft in any direction independent of range. Azimuth bias results from incorrect alignment of the 000-degree mark (True North for en route radars and Magnetic North for terminal radars), and mechanical misalignments between the antenna and the hardware that interfaces the position encoder to the rotating antenna. This error has been found to be +=0:3 degree for some en route and terminal radars. Moreover, this bias is azimuth dependent and varies with time. Azimuth bias causes position error that increases with increasing range. Range bias (typically on the order of 300 ft) is introduced by the normal design limits imposed by the range sampling clock and the allowable turn around processing time of transponders.

Some of the existing fusion issue while using multi-sensor is shown in Figure 1. Two radar located at different geographical locations indicated as Radar 1 and Radar 2. The measurements on radar surveillance plot are shown on right side. The red and green marks are measurement received from two radar around 100 nm apart. Target detection and by two radar has shown as blue and red 'X' and '.' mark shows its position as ADSB position. A real-time radar data plot from Indra automation system is shown in Figure 2. The x is the corresponding previous measurement and square block with data block shows the identity of the aircraft, speed, and its altitude. It can be seen that the measurement error from radar 2 (red) is more and having constant bias error as the target the moves away from radar the measurement error varies. This is the radar plot of an aircraft on real-time flying at FL360 (36000 ft). It is observed that this error from 0.2 NM to 1 NM and cannot be easily identifiable when to put 260 NM resolution, which normally used in Area control surveillance.

Here we propose an Adaptive filtering algorithm for registration of multi-sensor data which will minimize the different bias error and optimize the fusion result. All bias correction computations take place in stereo plane coordinates so the reverse transformation of ADS-B data to radar coordinates is not required. A stereo plane is an imaginary plane where each Cartesian coordinate on the plane represents a point on the Earth's surface. Radar target reports are converted from polar coordinates to the stereo plane while ADSB target reports position and velocity in geodetic coordinates are also converted to the stereo plane. Each radar report is linked with an appropriate ADS-B report.

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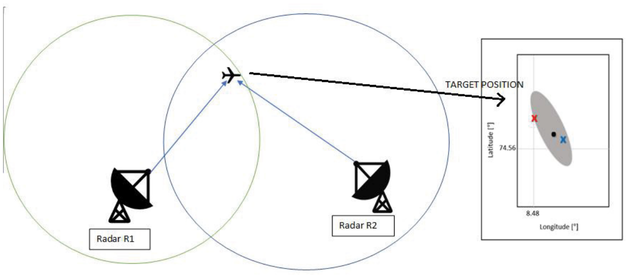

Figure 1: Multi radar target detection in common coverage area.

Figure 2: Radar plot from Indra Automation system.

This linked pair represents one target and, together with its velocity, provides the raw data for the registration calculations.

System dynamics

Sensor data received from the radar and ADS-B are all converted into ECEF X, Y, Z coordinates. This allows tracking in the same coordinate system. In the case of radar, the slant range (Rm) from the radar site to the target, azimuth (m), and altitude (hm) are typically obtained. When we consider the surveillance display the target are plotted in XY plane (2-D) with altitude and Identification information in data Block and position will be updated based on the time in a 2-D plane. If the radar has mode-S functions and the target reports include the Downlinked Aircraft Parameters (DAP), such as ground speed (V Gm), heading (m), and altitude rate (h), the measurements can be extended to carry the velocity terms. Thus, the ECEF-based radar measurement vector is defined as a 2D plane when Mode A/C radar data (1) or (2) based on the availability of DAP in the measurements when mode S information used.

Let's assume an aircraft that moves only on a plane (air traffic surveillance display), then its motion is entirely defined by 3 variables: translation on the x-axis, translation on the y-axis, and a rotation by an angle θ around the z-axis. If we want to track the movement of this object in a specified time interval T in the plane, we must know its pose (x,y,θ) at every moment of time within the time interval T. In this paper we consider the movement in (x,y) to study linear system and assume We can measure the position of this object at every instant of time. However; sensor's readings are usually noisy, and they cannot give us an accurate value of the object's position. One of the solutions for the above issue is to use a Kalman filter to estimate the position of the object at every time step in the time interval T. To use Kalman filtering to track an object in a plane, we first need to model the movement of this object. We cannot model the object's movement accurately, but we can have an acceptable approximation model of the object movement. Assuming that the motion on the x-axis is uncorrelated to the motion on the y-axis by ignoring the jerk and all the higher derivatives of the pose, we can write the following discrete equations that describe the object's movements in 2D constant velocity model as shown below:

$$x_{k+1} = x_k + T\dot{x}_k \tag{1}$$

$$y_{k+1} = y_k + T\dot{x}_k \tag{2}$$

$$\dot{x}_{k+1} = \dot{x}_k + Tax_k \tag{3}$$

$$\dot{y}_{k+1} = \dot{y}_k + Tay_k \tag{4}$$

where x_k and y_k are the position and $\dot{x}_k$ and $\dot{y}_k$ are the velocity. We can rewrite them as a state space model as following:

$$X_{k+1} = \begin{bmatrix} x_{k+1} \\ y_{k+1} \\ \dot{x}_{k+1} \\ \dot{y}_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_k \\ y_k \\ \dot{x}_k \\ \dot{y}_k \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ w_{1k} \\ w_{2k} \end{bmatrix} \tag{5}$$

It can be rewritten as a state model

$$X_{k+1} = AX_k + W_k \tag{6}$$

On the above, we assume that random accelerations can happen between sensor samples, and define the dynamic noises as assuming is a Gaussian distribution noise with a mean zero $w_{1k} \sim \aleph(0,\sigma_{w1}^2)$ and $w_{2k} \sim \aleph(0,\sigma_{w2}^2)$

$$W_k = \begin{bmatrix} 0 \\ 0 \\ w_1 k \\ w_2 k \end{bmatrix} \tag{7}$$

We assume that we can sense the x and y positions (when DAP not available), denoting sensor measurements as observation equations.

$$\tilde{x}_k = x_k + n_{1k} \tag{8}$$

$$\tilde{y}_k = y_k + n_{2k} \tag{9}$$

we assume that both sensor readings are corrupted by noise n_{1k} and n_{2k} are Gaussian distribution noise with a mean zero $n_{1k} \sim \aleph(0,\sigma_{n1}^2)$ and $n_{2k} \sim \aleph(0,\sigma_{n2}^2)$ that can be modeled as

$$meannoise = V_k = \begin{bmatrix} n_{1k} \\ n_{2k} \end{bmatrix} \tag{10}$$

The above equations can be written in matrix form as

$$z_k = \begin{bmatrix} \tilde{x}_k \\ \tilde{y}_k \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_k \\ y_k \\ \dot{x}_k \\ \dot{y}_k \end{bmatrix} + V_k \tag{11}$$

Here we assume that the data received from a sensor having bias error which is static for a particular sensor and dynamic processing error in the measurement equation will modified the following section. Then V_k will be some of Bias and dynamic error. We assume that bias error will be constant for sensor and dynamic measurement error will vary. The covariance of the dynamic noises can be written as:

$$Cov(W_k) = Q = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{w_1}^2 & 0 \\ 0 & 0 & 0 & \sigma_{w_2}^2 \end{bmatrix} \quad (12)$$

$$Cov(V_k) = R = \begin{bmatrix} \sigma_{n_1}^2 & 0 \\ 0 & \sigma_{n_2}^2 \end{bmatrix} \quad (13)$$

Multi-Sensor Fusion Process

An adaptive filter with Kalman filter structure that is provided for the multiple sensor fusion is proposed in Figure 3. Here for the redundancy and minimizing biasing errors, we have a parallel process each sensor data, and master filter will combine this data. The primary sensor which used for reference measurement is selected from the available sensors and for a particular grid; it is selected dynamically according to the target location with respect to sensor and sensor accuracy and availability. A separate algorithm developed. Here we consider the decentralized fusion center where the processed data from different sensors combined. The data received from the various sensors include *ADS-B* Messages, *Modes-S* information, and secondary data since we consider terminal area navigation these are the primary source of the sensor. The data received from the multi-sensor can be correlated easily by the information from Down Aircraft Parameters (DAP) or *Mode-A/S* identity as we are considering only the cooperative target in civil aviation. Here we are assuming that no same target can be sensed by a single sensor or multiple sensors at different locations (outside course gate region) at the same time. The presence of the same target at a different position is due to sensor fusion error, identity error or ghost track due to the error in the radar processing unit. In this study, the reliability of each sensor used in the multiple sensor fusion is evaluated and weighted value is granted to select the main sensor after removing bias error, and the method that the error-weighted average with each sensor is compensated for finding the fusion sensor result value is presented. In this paper, we consider a single target which is identified by both radars and *ADS-B* correctly and correlated. The algorithm can be extended to multiple targets under similar conditions. The Radar characteristics of SSR and *ADS-B* considered here for modeling the system. Here we consider the corresponding sensor and target process the data received from the Radar and *ADS-B* are detected by the sensor in decentralized fusion. The data collected from the sensors are coordinate converted to make it in a common coordinate system so that coordinate conversion error can be minimized. Here we consider the scenario where heterogeneous (radar/ADS-B) sensor fusion. On that, practically two scenarios come when we receive the same target data from a single sensor and second, both receivers receive data on a particular grid cell. In the first case, the data will process directly and the second case, from the received data we can calculate the location of the target on a particular grid. For this, we calculate the Euclidean distance from the target and the received sensor (radar). Here we considered the Secondary surveillance radar and one ADS-B message. The distance between the target and radar calculated as followed. The first step of the algorithm is to find the closest radar which can be used as the primary source for the particular cell. The location of Radars is known. Let R_{x1}, R_{y1} be the geographical location of Radar 1 and R_{x2}, R_{y2} be the Radar 2 geographical location. Let D1 be the distance of the target from Radar 1 which can be found out by

$$D1 = \sqrt{(\tilde{X}_{\text{rdar1}}(t1) - R_{x1})^2 + (\tilde{Y}_{rdar1}(t1) - R_{y1})^2} \quad (14)$$

$$D2 = \sqrt{\left(\tilde{X}_{rdar2}(t1) - R_{x2})^2 + (\tilde{Y}_{rdar2}(t1) - R_{y2}\right)^2} \quad (15)$$

Similarly, $D2$ can be found out by in a particular cell if $D1 \leq D2$ then for the location prediction and updating the primary sensor data from will be data from $R1$ and maximum weight will be given from error calculated from the Radar $R1$ in Kalman filtering process updating. If $D1>D2$ then for the location prediction and update the primary sensor data will be data from Radar $R2$. If the distances are comparable the both having given equal weight for updating. If the ADS-B data available initially it will be used as the main sensor for calibrating other sensors adaptive filtering technique, which was explained in the following section. Here we consider one more situation as per different studies normally within 60 nm range the radar data is more accurate and reliable. The ADS-B data quality will vary according to ADS-B Tx/Rx equipment used in each aircraft. We can use Radar data as main sensor data according to error receiving from the main filter we will compare the radar data value and logically select the main source. In

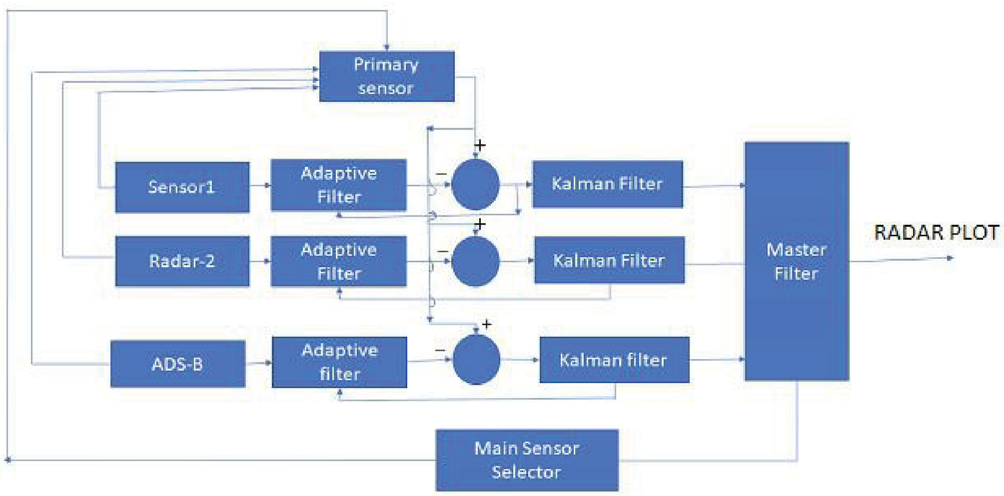

Figure 3: Adaptive filter with Kalman filter block diagram.

this study, the method is proposed on having the Surveillance radar as the primary sensor since it derives the target range and velocity derived from the radar beam. ADS-B as the main sensor for calibrating the radar data especially outside the particular range (60 nm) away from the sensor head. If the proper time synchronization is done both SSR and ADS-B has to give the same location for a single target at a time.

Pre-processing (Registration process)

Here we propose an LMS based adaptive filtering algorithm to minimize bias error of each sensor on the next update for the particular cell for which bias was minimized. The above is a recursive process and bias will vary according to cell and primary sensor used. The bias will be zero minimum when the primary sensor and sensor under consideration are same. Consider the position of data received from each sensor, Let For two-dimensional radar reports, the adaptive filter takes the format of a 2-D Finite Impulse Response (FIR) filter, h_j (m_1,m_2). Here we consider primary source data location for the current time $t=0$ is $P1_{t0}$ (m_1,m_2). We consider that the data received from primary is reference data either will be ADS-B or will be a radar data from radar which is close to the target as per grid cell location.

$$P1_{to}(m_1,m_2) = T_{t0}(m_1,m_2) + B_1 + \delta_{P1}(m_1,m_2) \quad (16)$$

Where T_{t0} (n_1,n_2) be the target original position at time t_0 and B_1 is the bias error for the second sensor1 and δP1 is the measurement error due to other factors. For the reference sensor, we initially assume that error approximately zero or negligible i.e $B_1 \simeq 0_{P1}(\mathrm{m}_1,\mathrm{m}_2) \simeq 0$ is the data received from the second sensor. We assume that the data received from the second sensor having bias error which is static for the sensor and dynamic processing error in the measurement. Begin

$$P1_{to}(m_1,m_2) = T_{t0}(m_1,m_2) + B_1 + \delta_{P1}(m_1,m_2) \quad (17)$$

Where B_2 is the bias error for the second sensor and δP2 (m_1,m_2) is the measurement error due to other factors. For finding the filter coefficient which will minimize error here we use a least-Mean-Square (LMS) adaptation algorithm, the adaptive filtering process is given as follows the 2-D.

LMS adaptation algorithm can be written as:

Filter output (Prediction phase):

$$P2_{t0}\ (\mathrm{m}_1,\mathrm{m}_2) = \hat{h}_j\ (\mathrm{m}_1,\mathrm{m}_2) * P_2 t0(\mathrm{m}_1,\mathrm{m}_2) \quad (18)$$

Estimation error:

$$e(m_1, m_2) = P1_{t0}(m_1, m_2)\ P2_{t0}(m_{11}, m_{22}) \quad (19)$$

Filter adaptation (Update phase):

$$\hat{h}_{j+1}(m_1,m_2) = \hat{h}_j\ (m_1,m_2) + \beta e(m_1,m_2) P2_{to}(m_1,m_2) \quad (20)$$

Initializing the filter for the next data at time t_1:

$t_1\ \hat{h}_j+1(\mathrm{m}_1,\mathrm{m}_2)$

Where (m_1,m_2) denotes x and y position of target and β is the adaptation step-size. $\hat{h}_j\ (m_1,m_2)$ denotes filter coefficient at j^{th} iteration. Under the appropriate conditions, (i.e, the right step-size and the right filter size) $\hat{h}_j\ (m_1,m_2)$ converges to the system model and bias error will be eliminated. Kalman filter will take the measurement error care on the next stage. Here for finding suitable filter coefficient, LMS algorithm is used. For that, we have to minimize the mean square error. For making computation efficient and parallel, we process x and y coordinates independently using the same. Here we use steepest descent algorithm due to low computational complexity, simple to implement and to allow real-time operations. It also doesn't require statistics of the data like correlation and covariance.

Decentralized adaptive kalaman filtering

At the start of the process, the Kalman filter must be given a correct initial state and an initial covariance matrix. In this work, an adaptive filter with decentralized Kalman filter fusion (ADKFF) method based on Mahalanobis distance is proposed to carry out the fusion task. This approach can adaptively adjust the measurement noise covariance matrix of the local Distributed Kalman Filters (DKFs) and thereby, determine the weight of each sensor more accurately in the fusion procedure. Then, the fused result will benefit from the source sensors with higher confidence. When performing this fusion method, the predicted states $\hat{x}_{mk|k1}$ are first obtained from the estimated state $\hat{x}_{mk-1|k1}$ at time k1, where m=1,2,...M denotes the number of source sensor. Then, with the observations z_k^m and sensor confidence based on MD_k^m, these predicted states are corrected and the corrected estimate $\hat{x}_{k|k}^m$ at time k is obtained. The correct estimate fed back to the prediction step for the next iteration. Finally, a fused state $\hat{x}_k$ at time k is generated with the local estimates. We assume that the local DKF process has $\hat{x}_{k|k}^m$ a state vector $x \in \Re_n$ and the process is governed by

$$x_k + 1 = A_k - 1x_k + w_{k-1} \quad (21)$$

With a measurement $z \in \Re_r$ that is defined by

$$z_k = H_k x_k + v_k \quad (22)$$

In the above equations, the random variables wk and υ_k represent the process and measurement noise with the covariance Q_k and R_k, respectively; they are zero mean. Gaussian white noise having zero cross-correlation with each other. The state transition matrix A_{k1} relates the state at the previous time step k_1 to the state at the current time step k with process noise w_k. H_k represents the observation transition matrix and relates the state x_k to the measurement z_k. In a practical object, tracking $x_{k-1|k-1}^m$ denotes the state of sensor m ($m=1,2,..., M$) at time $k-1$. Then the prediction $x_{k|k-1}^m$ is generated by (24) and the corresponding prior estimate error covariance $P_{k|k-1}^m$ is given by (25):

$$x_{k|k-1}^m = A_{k-1} x_{k-1|k-1}^m \quad (23)$$

$$x_{k|k-1}^m = A_{k-1} x_{k-1|k-1}^m \quad (24)$$

$$P_{k|k-1}^m = A_{k-1} P_{k-1|k-1}^m A_{k-1}^T + Q_{k-1} \quad (25)$$

With these predictions, the estimate of the next time $x_{k|k}^m$ is obtained as follows:

$$x_{k|k}^m = x_{k|k-1}^m + K_k^m (z_k^m\ H_k^m x_{k|k-1}^m) \quad (26)$$

$$K_k^m = P_{k|k-1}^m (\mathrm{H_k})^{\mathrm{T}} \left[H_k P_{k|k-1}^m (\mathrm{H_k})^{\mathrm{T}} + R_k^m \right]^{-1} \quad (27)$$

$$P_{k|k-1}^m = \left[I - \mathrm{K}_m^k \mathrm{H_k} \right] P_{k|k-1}^m \quad (28)$$

Where K_m^k denotes the local DKF gain matrix for sensor m at time k and $P_{k|k}^m$ represents the corresponding posteriori estimate error covariance.

Adjustment of measurement error covariance matrix using MD: In the procedure described above, the measurement error covariance matrix R models the uncertain and inaccurate information of the filter. It reflects the precision of the source sensors and plays an important role in the state estimate. In the traditional method, this matrix is usually set a fixed value, which implies that the corresponding sensor is also set a fixed confidence. This will significantly affect the fusion result. For solving this problem, in this study, the sensor confidence is applied to adaptively adjust the measurement error covariance matrix. It is defined by

$$R_k^m = \begin{bmatrix} R_{m,k}^{xx} & 0 \\ 0 & R_{m,k}^{yy} \end{bmatrix} \quad (29)$$

It is assumed that the measurement error is not cross-correlated. Thus, we set R^{xy} and R^{yx} to 0. The function for the c^{xx} and c^{yy} is defined as follows:

$$R_{m,k}^{xx} = c^{xx} w_{i,j}\,[c^{xx}] \quad (30)$$

$$R_{m,k}^{yy} = c^{yy} w_{i,j}\,[c^{yy}] \quad (31)$$

For calculating weight, we use Mahalanobis distance are calculated. The Mahalanobis Distance (MD) [14,15] is one of the fundamental and widely used techniques as a distance measure for classification. Therefore, the Mahalanobis distance should be used as a basis of our new weighted distance metric. The features which are distorted by noise have, on average, a higher influence on the distance measure than the less distorted features as they are further away from the feature mean of the class. Therefore, we aim to lower the influence of these features by reducing their weight. To find the features which have the strongest influence on the distance we solve the Mahalanobis distance equation for every single feature c overall input samples i and classes j and store the value in M: $\forall(c,i,j)$:

$$M_{i,j}[c] = (x_i[c]\mu_j[c]) \sum_j [c,c]^1 (x_i[c]\mu_j[c]) \quad (32)$$

The goal now is to give less weight to the features with high distance and vice versa to avoid the masking of the features with small distances $\forall(c,i,j)$:

$$D_{i,j}^{weighted} = \sum_{(c=1)}^{N} w_{i,j}[c] * \mathrm{M}_{i,j}[c] \quad (33)$$

Under the two constraints: $\forall c$: $w[c] \geq 0, \sum(c=1)^N w_{i,j}[c] = N$ another approach could give more weight to features which are similar to other features than to features which are very different. The idea here is that noisy features should be significantly different from noise-free features, as long as only a small number of features are distorted by noise. We can calculate the difference $d[c]$ for the features as $\forall(c,i,j)$:

$$D_{i,j}^{weighted} = \sum_{(c=1)}^{N} w_{i,j}[c] * M_{i,j}[c] \quad (34)$$

Normalize and invert to calculate the individual weights $\forall(c,i,j)$:

$$w_{i,j}[c] = \sum (a=1)^N [d_{i,j}[a]]) / (Nd_{i,j}[c] \quad (35)$$

These weights could be directly used in equation 29. The matrix R_k^m will finally affect the fused estimate by influencing the corrected estimate $\hat{x}_{k|k}^m$, the local Kalman filter gain matrix K_k^m, and their corresponding estimate error covariance matrix $P_{k|k}^m$, as shown in equation 25 and 27.

Fusion centre

When the local prediction $x_{k|k-1}^m$, corrected estimate $x_{k|k}^m$, the corresponding error covariance $P_{k|k1}^m$ and $P_{k|k}^m$ is ready, a fused estimate $\hat{x}_k$ can be generated from the fusion centre. The fusion centre also has two steps, namely the prediction step, and a correction step. The prediction step is performed on the basis of the previous corrected estimate as follows:

$$\hat{x}_k^- = A_{k-1}\hat{x}_{k-1} \quad (36)$$

$$\mathrm{P_k} = A_{k-1}P_{k-1}A_{k-1}^T + Q_{k-1} \quad (37)$$

The final fusion result $\hat{x}_k$ is obtained from the correction step, which is calculated on the basis of the local estimates as in (38) and (39). It will be fed back to the next prediction step [8].

$$\hat{\mathrm{x}}_\mathrm{k} = P_\mathrm{k}[(P_\mathrm{k}) - 1\hat{x}_\mathrm{k} + \sum_{(m=1)}^{M} (P_{k|k}^m) - 1x_{k|k}^m \sum_{(m=1)}^{M} (P_{(k|k-1)}^m)^{-1} x_{[k|k-1]}^m \quad (38)$$

$$(P_k)^{-1} = (\mathrm{P}_k^-)^{-1} + \sum_{m=1}^{M} (P_{k|k}^m)^{-1} + \sum_{m=1}^{M} (P_{k|k-1}^m)^{-1} \quad (39)$$

In the fusion procedure described above, the posteriori estimate error covariance $P_{k|k}^m$ is affected by sensor confidence and thus, adaptively adjusts the weight of each source sensor. Finally, the fusion result will contain more information from the sensors with greater confidence.

Data fusion architecture

The data received the multi-radar tracking function will processed and converted UTC time-stamped plots (e.g. EUROCONTROL ASTERIX standard Category 001 message [16,17]. Measurements from different radars are then allocated so as to update radar tracks (e.g. EUROCONTROL ASTERIX standard Category 030 message). The ADS branch takes ADS-B reports (e.g. EUROCONTROL ASTERIX standard Category 021 [17] as inputs. If the DAP (mode information like aircraft identity, squeak etc) available with radar and ADS-B data the correlation between Radar and ADS-B data can be done using Aircraft identity to form a Multi-Sensor Target track (the track which has filtered at least one ADS-B reports and/or one radar plot). This step is based on kinematics window and aircraft address matching (in a predominant way). The association process provides the best pairs report-track to the track management process. In ADS-B reports, contains aircraft position in the geodesic frame. All processing is done in System Cartesian frame in which WGS84 position is converted to ECCF [15]. The fusion architecture is shown in Figure 4.

The data received from each radar station will be processed separately in decentralized fusion. This data will first be passed to coordinate transformation covariance module. The sensor measurements from the radar and ADS-B transformed into a common coordinate, and measurement covariance is updated accordingly. This study adopts the Earth-Centred Earth-Fixed (ECEF) three-dimensional Cartesian coordinates instead of the local coordinates based on a stereographic projection [15,17]. The mosaic display used for Air traffic surveillance purpose and those target movements projected in the 2D plane with Altitude, identification and other DAP information as a DATA block. Here the data received after coordinate conversion and covariance matric formation selected based on the sector will be processed. In the mosaic display, the plot is divided into segments. Upon reception of the plot sector N, the following actions performed. Handling of sector N confirmed tracks using sectors N and N-1 plots by activating following functions: correlation and, the association of each track in the different sensor using track identity (aircraft identity or squak which is available in SSR and ADS-B data).

This association will reduce computation and remove processing of same aircraft data at different locations and be displaying it (ghost). If the aircraft identity not available the association function is based

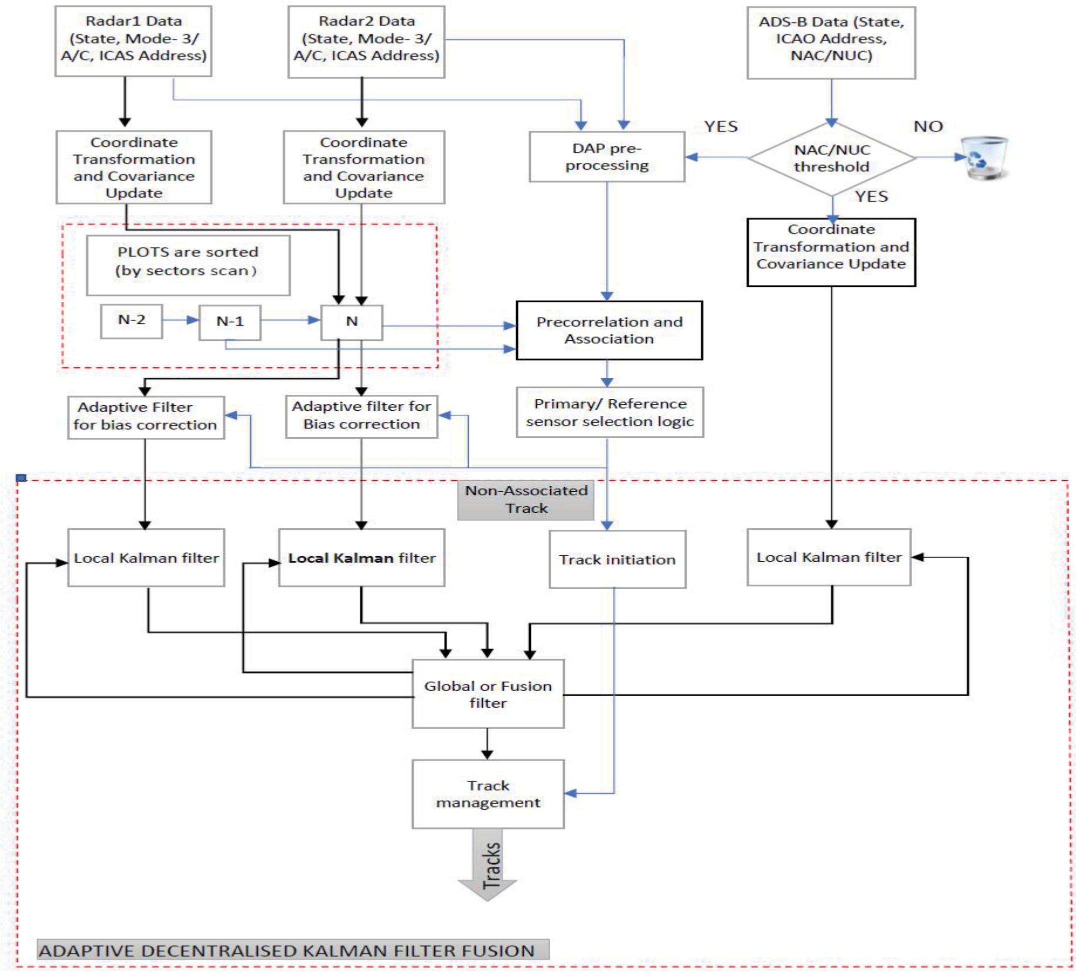

Figure 4: Proposed fusion architecture.

on a Global Nearest Neighbor (GNN) approach: it solves correlation conflicts and searches among correlated measurements for the one, which corresponds best to the aircraft detection.

After the precorrelation and association, each sensor data processed separately. Here we propose an LMS adaptive filter for preprocessing of data from each sensor to remove bias error in each sector. Finite Impulse Response (FIR) Least Mean Square (LMS) adaptive filter has been very popular due to its simplicity and good convergence characteristics. The purpose of introducing adaptive filter is the remove the sensor error so that future predictions of Kalman filter will be more accurate due to the feedback mechanism involved. Here the filter coefficients are adaptively changed for each sensor so that data received from another sensor calibrated so that the minimum means square error produced. The sensor selection logic module will select the primary or reference sensor for the sector and mostly the ADS-B data will be chosen as a reference due to multiple numbers of position information available for a particular time interval. The data received from the ADS-B can be calibrated by SSR data when the target is close to the radar. The initialization function aims to generate new tracks when aircraft appears in the system domain of interest, and no previous tracks are available. The initialization can be secondary radar or from ADS-B data.

The confirmation of tentative tracks is based on a Bayesian approach to avoid false track creation. Adaptive Distributed Kalman filter structure that is provided for the multiple sensor fusion. The master filter outputs the final sensor value minimized with the sensor effect occurred with fault based on the error estimate value on each sensor value inputted from each local Kalman filter. The local Kalman filter estimates the measurement value of each sensor and the error value with the main sensor, and the primary filter calibrates this to be used as the estimated value $\hat{x}_k$ of each sensor. The reliability of the estimated value of each sensor is defined by the total deviation on the estimated value for each sensor used in the fusion as shown in equation 40. The local Kalman filter selects the sensor with maximum reliability as the primary sensor to be used as the standard signal, and the error on the standard signal of each sensor is estimated.

$$SD_k = \sum_{(i=1)}^{n} \hat{x}_k - \hat{x}_i \tag{40}$$

$k = 1,2,....N$ where SD_k is the reliability of sensor k, and x^i shows the estimated value of sensor i. Thus the sensor adaptively changes the measurement estimates based on the output of the master filter. The master filter reflects the reliability SD_k defined in Equation 40 in the estimated value of each sensor as the weighted value to acquire the weighted Mahalanobis distance as shown in Equation 29, and then, determines the final estimate value X_{k+1}. The proposed multiple sensor fusion models express the reliability of each sensor measurement value as the relative deviation and select the sensor with high reliability as the sensor with low possibility of a fault with high measurement accuracy to have the adaptive Kalman filter structure of calibrating the error on each sensor.

Result and Discussion

In the simulation, we consider the measurements are from ADS-B, radar1, and radar-2. For generating the radar1 and radar 2 data we have added bias value and random noise to the ADS-B signal (shown as an actual signal). The adaptive filter will adjust the filter values. Here FIR filter used for the filtering the input signal. Figure 5 shows the test results in a graph, comparing the ADS-B data, radar data filtered directly and estimated through the fusion filter proposed in this paper. As shown in Figure 5, the ADS-B data in black boxes and measurement have errors irregular shown in red*. The filtered value separate radar after applying base and random noise denoted by blue and cyan crosses (Figure 6). The figure shows the filtered values are having some bias exist along with noise. When we use our algorithm, the filtered values are very close to the ADSB values. It can be seen from the graph the after applying bias to both radar values it is reflected in the filtered results. The practical situation is shown in Figure 1 similar to this. Proposed method used gives an excellent output for bias removal and measurement error. Figure 7 shows the various measurements input

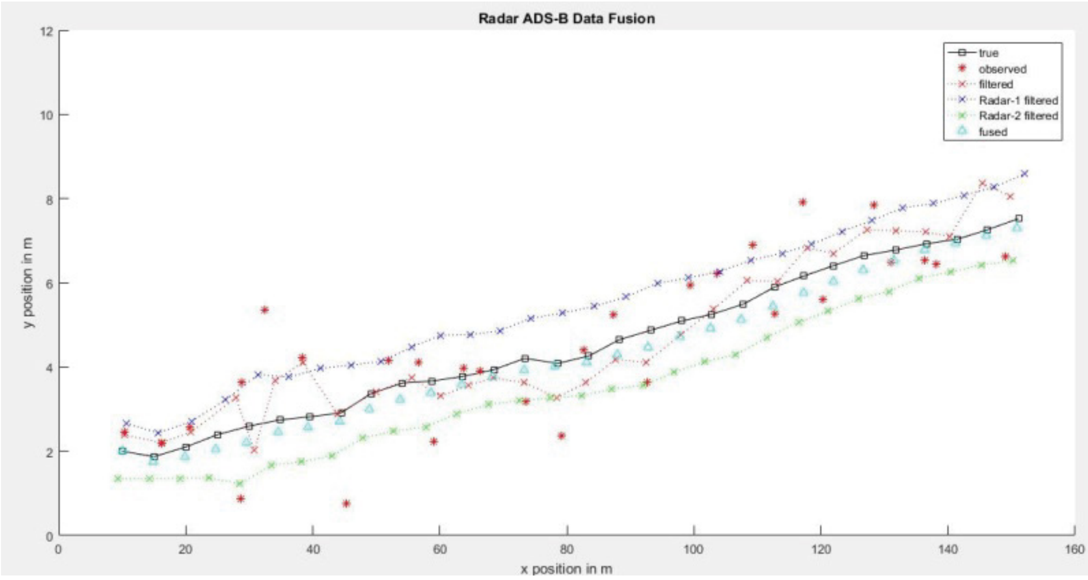

Figure 5: Comparison of results.

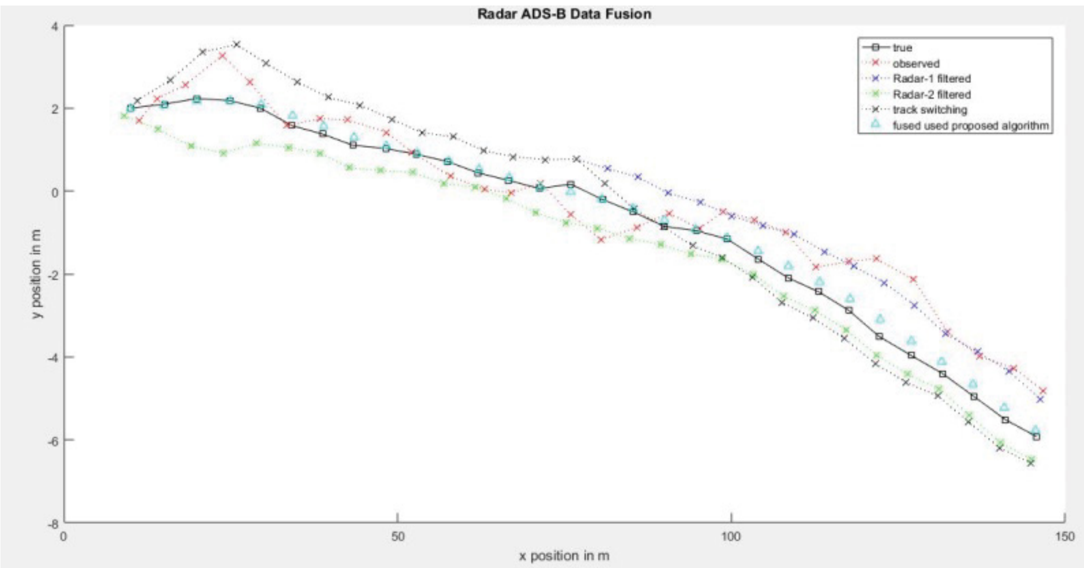

Figure 6: Results for input with track switching.

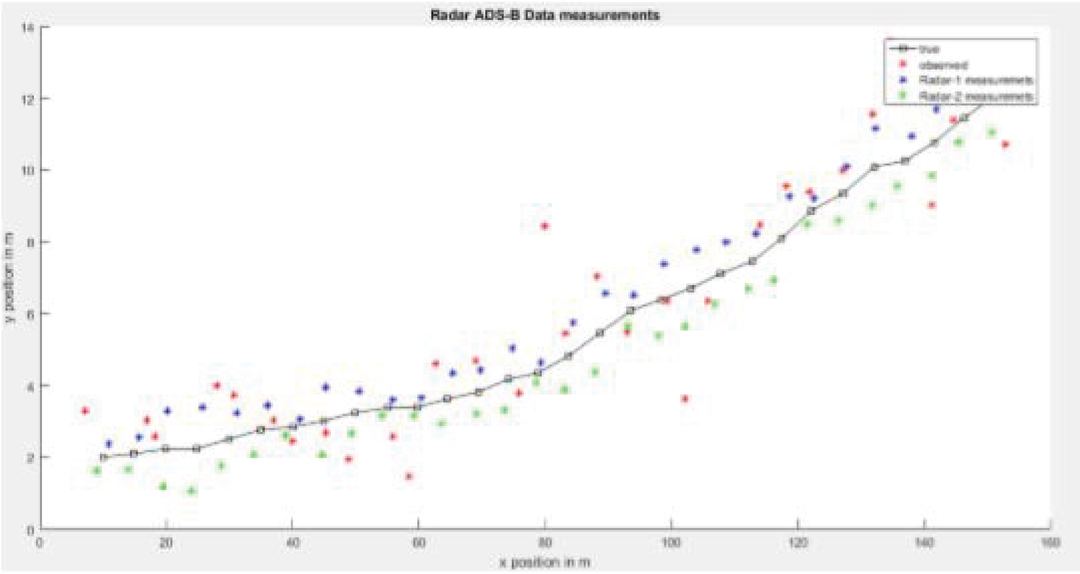

Figure 7: Radar-ADS-B measurements.

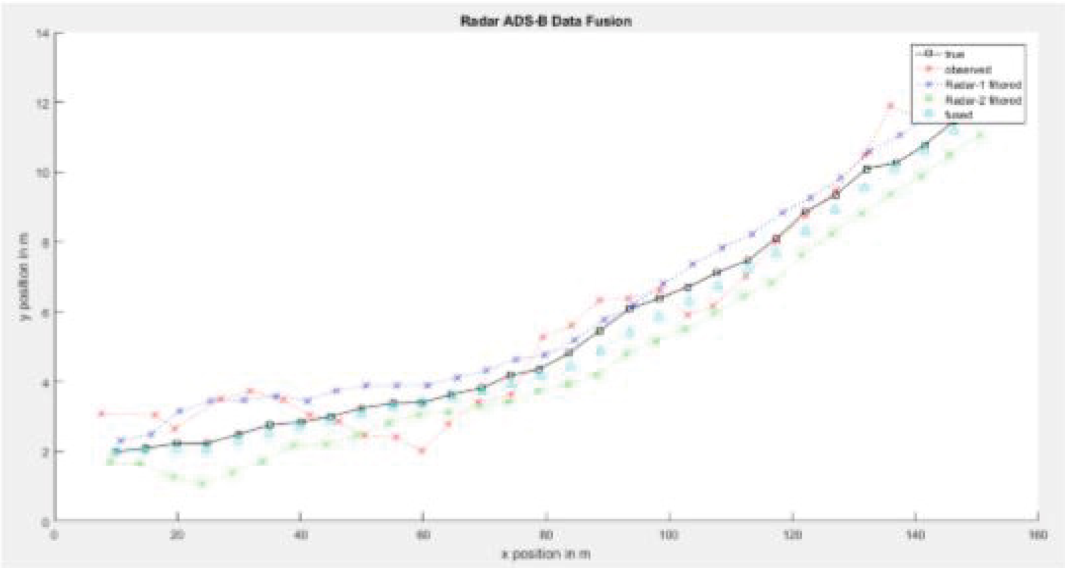

Figure 8: Radar, ADS-B and fusion results.

and Figure 8 shows the corresponding results. From Figure 8 it clearly shows the proposed algorithm having a very good output compared with single sensor results.

Table 1 shows the comparison of Means Square Error (MSE) of different inputs. It can be seen from the results the Mean square error of the proposed method is lesser than the standard Kalman filtering. When the bias added to both radar separately, and the tracking did with separate radar, output the MSE value is higher side. In the case of the proposed method simulations has been conducted for the different random input (Figure 6) all the time proposed method showed significant improvement in the MSE and it improves the overall efficiency of fusion process using all the information. The bias was able to remove by the proposed method. As Figure 6 shows the proposed method smoothly handles track shifting, ie when the primary sensor switch over Radar1 to Radar 2 data there is a sudden shift of track from one to another this was one of the major issues with existing fusion method. MD based weight makes the transit smooth. The proposed method overcame the practical difficulties of previous methods and managed to obtain excellent results in various inputs, which improves conflict prediction in air traffic surveillance system.

Input	MSE
Only Random Noise to ADS-B	5.8552
Radar1 only (Bias+random noise)	8.4269
Radar2 only (Bias+random noise)	8.2285
Fused (Bias+random noise)	2.1347

Table 1: Comparison of MSE.

Conclusion

The proposed architecture gives very good results concerning MSE and tracks accuracy. This method is making use of the LMS feedback mechanism to remove bias error and thereby acting as calibration for the radar measurements. The decentralized adaptive Kalman filter uses information from different sensors and using Mahalanobis distance based weight assigned to Kalman filter gain which enables accurate track prediction and updates more accurately and removes sudden change of track when radar data changes. Future work includes the other DAP information like to heading and velocity from the ADS-B measurement to predict more accurate fusion results and radar caliberation.

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