Design of an A-SMGCS prototype at Barajas airport: 
Airport surveillance sensors bias estimation

Juan A. Besada, Andrés Soto, Gonzalo de Miguel, Javier Portillo
Universidad Politécnica de Madrid
juanalberto.besada@upm.es

Abstract – This paper describes the design and implementation of a bias estimation system for airport surveillance. If not correctly calibrated, systematic errors may lead to track instability, and even to track splitting. Airport safety demands for very stable and accurate tracking, and so addressing this problem is mandatory if a data fusion system is to be used in operational procedures. The paper describes the design of an innovative sensor bias estimation system, and the practical issues related with its integration in the data processing chain. The simulation based results show estimators rapid convergence, and how the inclusion of these methods improves overall tracking performance.

Keywords: Calibration, bias estimation, airport surveillance.

1 Introduction

Airport surveillance is a key function for airport control and management in present and future A-SMGCS systems. In this contribution, it is assumed airport surveillance is performed through Surface Movement Radars (SMR) [2], Multilateration Mode-S sensors (MMS), and Secondary Surveillance Radars (SSR), which are the sensors currently deployed in Barajas Airport, or under investigation. Sensor calibration is a prerequisite to data fusion. In airport surveillance, systematic errors may be dominant, due to the processing of low noise measures. If not correctly calibrated, several terms as antenna-centroid displacement, transponder delays, and others systematic errors may lead to track instability, and even to track splitting. In this contribution we are addressing this problem.

Some of these error terms are equal for all targets, but some others are target dependent, which makes necessary the use of on-line bias calibration systems, compromising the possibility of using reference targets such as corner reflectors, reference transponders, etc. and demanding the joint operation of tracking and bias estimation methods. In order to avoid a high computational load increase, both processes (tracking and bias estimation) are performed independently, enabling for an independent design and for future refinements. Other approaches, with a coupled state vector for target cinematic state and bias terms, have been neglected, following previous remarks.

The paper is divided into four sections. Section 2 describes the design of a novel bias estimation system. It is based on the use of additional information (airport map) and of appropriately organized measurements differences. Its architecture is depicted in Figure 1. Section 3 is devoted to the implementation of this on-line bias estimation system in the A-SMGCS prototype and of the practical issues arising during the integration of this block in the whole data fusion system. Finally, conclusions and results of the surveillance system are presented in section 4. Those results were obtained through simulation in the A-SMGCS prototype at Madrid-Barajas Airport.

![General bias estimation architecture](image)

Figure 1. General bias estimation architecture

* This work has been funded by the Spanish CICYT contracts TIC2002-04491-C01/02 and INDRA S.A.
2 Bias Estimation System design

Our aim is to obtain a real time calibration system in order to align all the desired available sensors. This process is going to be divided into two steps. The first step takes charge of calibrating a reference sensor (SMR in our sample airport) exploiting airport map information. The following step performs the alignment of other sensors using the unbiased measures provided by the former step. For the latter step, methods based on measurement differences between the position provided by one of the sensors and the one coming from an unbiased sensor will be implemented [3]. Next we will define the calibration method for SMR, MMS and SSR, in that order.

2.1 SMR Bias Estimation Method

The first step, SMR measures bias removal, is based on the assumption that aircraft follow taxiways axes. Thus, using the information contained in a precise airport map, we could calculate a “separation distance” (d). This distance measures how far is the estimated position of the aircraft is located. There is a relationship between this distance and SMR biases, which allow their estimation and subsequent cancellation. The following picture shows how the “separation distance” is obtained.

![Segment](image)

Figure 2. Obtaining the “separation distance”

First of all, the SMR error model is presented. In this model [1], i-th range-azimuth measurement \((R_{measure}(i), \theta_{measure}(i))\) include the following terms:

\[
R_{measure}(i) = R_{ideal}(i) + b_R + n_R(i) \tag{1}
\]

\[
\theta_{measure}(i) = \theta_{ideal}(i) + b_\theta + n_\theta(i) \tag{2}
\]

where \((n_R(i), n_\theta(i))\) are measurement noise errors, considered realizations of a random white process with associated constant covariance matrix \(N\). \(n_R(i)\) is the range noise, \(n_\theta(i)\) is the azimuth noise and \(N\) is:

\[
N = \begin{bmatrix}
\sigma_R^2 & 0 \\
0 & \sigma_\theta^2
\end{bmatrix} \tag{3}
\]

where \(\sigma_R\) is the standard deviation of the range noise and \(\sigma_\theta\) is the standard deviation of the azimuth noise.

Additionally, \((b_R, b_\theta)\) are sensor bias terms which are equal and constant in time for all targets. \(b_R\) is the range bias and \(b_\theta\) is the azimuth bias. Finally, \((R_{ideal}(i), \theta_{ideal}(i))\) are the ideal target centroid position for the i-th measurement.

After presenting the SMR model, the fundamentals of our method can be explained. There is a consideration to bear in mind which is that targets need to be automatically localized in only one segment, so the “separation distance” can be calculated without ambiguity. The next step is to analyze how biases are projected into this distance, in order to build an estimator. In this case, we have chosen a Best Linear Unbiased Estimator [4] (BLUE). The “separation distance” can be expressed in the following way:

\[
d(i) = H(i) \begin{bmatrix} b_R \\ b_\theta \end{bmatrix} \tag{4}
\]

where \(H(i)\) is the projection matrix, whose expression is:

\[
H(i) = \left[ \sin(\alpha(i) - \theta_{measure}(i)) \quad -\cos(\alpha(i) - \theta_{measure}(i)) \right] \tag{5}
\]

and \(\alpha(i)\) is the segment orientation. \(d(i)\) is defined positive if the measurement is on the right side of the segment axis (looking from segment origin to segment end), otherwise negative.

Considering eqn. 4, it is easy to implement a BLUE, as it is shown and in recursive form:

\[
\begin{bmatrix} \hat{b}_R \\ \hat{b}_\theta \end{bmatrix} = \left( \sum_i H^T(i) S^{-1}(i) H(i) \right)^{-1} \sum_i H^T(i) S^{-1}(i) d(i) \tag{6}
\]

where \(S(i)\) is the projected covariance matrix of the noises on “d” direction (\(d(i)\) variance), which can be calculated as:

\[
S(i) = H(i) N H(i)^T \tag{7}
\]

Once the “separation distance” \((d(i))\) is known without ambiguity, the projection matrix \((H(i))\) and the projected covariance matrix \((R(i))\) should be calculated. After that, they can be included in the BLUE. For our convenience we have named the summations as:

\[
A = \sum_i H^T(i) S^{-1}(i) H(i) \tag{8}
\]

\[
B = \sum_i H^T(i) S^{-1}(i) \cdot d(i) \tag{9}
\]

Thus, several updates or inclusions can be done before the estimator is resolved, which can be carried out on demand whenever the estimator has converged enough. Therefore, it does not represent an important computer load for the fusion system. The method to resolve the estimator, in terms of \(A\) and \(B\), is:

\[
\begin{bmatrix} \hat{b}_R \\ \hat{b}_\theta \end{bmatrix} = A^{-1} : B \tag{10}
\]
Resolving the estimator provides a bias estimate which is used to directly cancel them from the measures coming from the sensor, so if sensor measurement model is precise enough, this bias estimation leads in mean to the real bias value, making the measures unbiased.

The corrected SMR measures (which may be assumed to be unbiased) can be used to estimate bias terms of other sensors. This assumption will be applied in the following sections. Additionally, the corrected SMR measures may be used for the multisensor tracking system.

### 2.2 Multilateration Mode-S Bias Estimation

In the multilateration mode-S sensor case, bias is aircraft dependent and represents the difference between the antenna position and the centroid of the aircraft (see the following picture).

![Figure 3. Aircraft dependent Bias](image)

For estimating this term, a method based on measurement differences has been chosen. The method consists of calculating the difference between the position provided by the multilateration sensor and the measure from the unbiased sensor, in our case a SMR. In consequence the bias terms present in the measure differences will be related exclusively with the MMS. These two positions need to be aligned in time by extrapolation (using velocity estimation of the track to which the two plots are associated with). It should be bore in mind that this action is based on the assumption that measures are associated to a certain track, to use its velocity for extrapolation.

We may then calculate the movement-aligned offset \((\Delta l_m(i))\), which is a measure of \(\Delta l\). This aligned offset measure may be calculated from MMS and SMR time aligned measures as:

\[
\Delta l_m(i) = \cos \gamma(i)(x_{MMS}(i) - x_{SMR}(i)) + \sin \gamma(i)(y_{MMS}(i) - y_{SMR}(i))
\]

where \(\gamma(i)\) is the aircraft axis orientation, \((x_{MMS}(i), y_{MMS}(i))\) is the 2D position measured by MMS, and \((x_{SMR}(i), y_{SMR}(i))\) is the 2D position measured by SMR.

Remember SMR measures would bias corrected measures.

Quite often \(\gamma(i)\) can be refined using instead the airport segment orientation \((\alpha(i))\), if the localization in an airport segment is clear. Note this assumption can be made if the aircraft is localized in only one segment. If the aircraft is localized in several segments there is no way of refining this projection matrix in order to perform a better projection. Thus, the only possibility is to trust on the estimation of the aircraft axis orientation provided by the fusion system (extract from the estimated track velocity), which in certain situation can not be reliable (i.e. in maneuvers or in intersections).

Its associated noise variance may be approximated as:

\[
v(i) = K(i)\left[ \begin{array}{cc}
\sigma^2_{x,MMS} & 0 \\
0 & \sigma^2_{y,MMS}
\end{array} \right] + G(i)\left[ \begin{array}{cc}
\sigma^2_{r,SMR} & 0 \\
0 & \sigma^2_{\theta,SMR}
\end{array} \right]G^T(i)K^T(i)
\]

where

\[
K(i) = \begin{bmatrix}
\cos \gamma(i) & \sin \gamma(i)
\end{bmatrix}
\]

and

\[
G(i) = \begin{bmatrix}
\cos \theta_{SMR}(i) & -R_{SMR}(i)\sin \theta_{SMR}(i) \\
\sin \theta_{SMR}(i) & R_{SMR}(i)\cos \theta_{SMR}(i)
\end{bmatrix}
\]

being \(R_{SMR}(i)\) the SMR range measure, \(\theta_{SMR}(i)\) the SMR azimuth measure, \(\sigma^2_{x,MMS}, \sigma^2_{y,MMS}\) the x-axis and y-axis standard deviations of the MMS measures noise, and \(\sigma^2_{r,SMR}, \sigma^2_{\theta,SMR}\) the range and azimuth standard deviations of the SMR measures noise. In this case, the chosen estimator is also a BLUE, and it has the following expression:

\[
\Delta \hat{l} = \frac{1}{N} \sum_{i} \frac{\Delta l_m(i)}{v(i)}
\]

The corrected MMS measures may be used for the multisensor tracking system.

### 2.3 SSR Bias Estimation

Considering the SSR, four bias terms can be found. Two of them are sensor based and the others are aircraft based. The ones related with the sensor, represent the range bias and the azimuth bias, as in the SMR case. The others represent the transponder induced bias (erroneously calibrated response delay), and the difference between the antenna position and the centroid of the aircraft (see Fig. 3). Consequently, the distinguished biases are:

- \(b_r\): range bias.
- \(b_{\theta}\): azimuth bias.
- \(\Delta R\): transponder induced bias, in meters, for k-th target.
the target axis orientation. We also approximate the projected in (i) x

\[ H(i) = \begin{bmatrix} \Delta x(i) \\ \Delta y(i) \end{bmatrix} = \begin{bmatrix} x_{SSR}(i) - x_{SMR}(i) \\ y_{SSR}(i) - y_{SMR}(i) \end{bmatrix} \] (16)

The biased projection on the Cartesian difference, assuming negligible noise, can be expressed as:

\[ \Delta \hat{x}(i) = H(i) \begin{bmatrix} b_h + \Delta \hat{R}_k \\ b_y \\ \Delta \hat{\theta} \end{bmatrix} = H(i) \begin{bmatrix} \hat{b}_h \\ \hat{b}_y \\ \Delta \hat{\theta} \end{bmatrix} \] (17)

Transponder induced bias could not be distinguished from range bias if there was only one target, so our aim, in the local bias estimator, will be to estimate their sum ( \( \hat{R}_k \)). H(i) is defined as:

\[ H(i) = \begin{bmatrix} \cos(\theta_{SSR}(i)) - R_{SSR}(i) \sin(\theta_{SSR}(i)) \cos(\alpha(i)) \\ \sin(\theta_{SSR}(i)) - R_{SSR}(i) \cos(\theta_{SSR}(i)) \sin(\alpha(i)) \end{bmatrix} \] (18)

being \( R_{SSR}(i) \) the SSR range measure, \( \theta_{SSR}(i) \) the SSR azimuth measure, and \( \alpha(i) \) the target axis orientation. We also approximate \( S(i) \) the covariance matrix of the noise projected in \( \Delta \hat{x}(i) \), which has the form:

\[ S(i) = G_{SSR}(i) \begin{bmatrix} \sigma_{R,SSR}^2 & 0 \\ 0 & \sigma_{\theta,SSR}^2 \end{bmatrix} + G_{SMR}(i) + G_{SMR}(\theta) \begin{bmatrix} \sigma_{R,SMR}^2 & 0 \\ 0 & \sigma_{\theta,SMR}^2 \end{bmatrix} G_{SMR}(\theta) \] (19)

where \( \sigma_{R,SMR}, \sigma_{\theta,SMR} \) are the range and azimuth standard deviations of the SMR measures noise and \( \sigma_{R,SSR}, \sigma_{\theta,SSR} \) are the range and azimuth standard deviations of the SSR measures noise. Additionally, \( G_{SSR}(i) \) and \( G_{SMR}(i) \) may be defined as:

\[ G_{SSR}(i) = \begin{bmatrix} \cos(\theta_{SSR}(i)) - R_{SSR}(i) \sin(\theta_{SSR}(i)) \\ \sin(\theta_{SSR}(i)) - R_{SSR}(i) \cos(\theta_{SSR}(i)) \end{bmatrix} \]

\[ G_{SMR}(i) = \begin{bmatrix} \cos(\theta_{SMR}(i)) - R_{SMR}(i) \sin(\theta_{SMR}(i)) \\ \sin(\theta_{SMR}(i)) - R_{SMR}(i) \cos(\theta_{SMR}(i)) \end{bmatrix} \] (20)

being \( R_{SMR}(i) \) the SMR range measure, and \( \theta_{SMR}(i) \) the SMR azimuth measure.

With these definitions in mind, we may derive a BLUE for the tree local bias terms, as in the previous cases:

\[ \phi = A_k^{-1} B_k \] (21)

where:

\[ A_k = \sum_i H^T(i) S^{-1}(i) H(i) \] (22)

\[ B_k = \sum_i H^T(i) S^{-1}(i) \Delta \hat{x}(i) \] (23)

Please note the tree terms estimated are different for each target, as they are derived only from measurements from this target. This is the reason to add a k subindex to the azimuth bias estimator. The estimator might also be defined in a recursive way [4].

The covariance associated to these local estimates, after the i-th measure difference, is:

\[ P_k = A_k^{-1} \] (24)

The global estimator is fed with the information accumulated in the local bias estimators. After deleting the track, its information is delivered to the global bias estimator, in order to update its estimators. The interest information (estimators and associated covariance) is taken from local estimators following next graph:

**Figure 4. Information extraction at track deletion**

\( \hat{R}_k \) can be considered an estimator of \( b_R \), but taking into account it is biased due to the presence of the
transponder induced bias ($\Delta R_t$). Then, the selected terms would be estimates of the sensor related biases. This bias can be modeled as a uniform random variable between -75 meters and 75 meters, different for each target, the covariance matrix associated with the information provided should be modified to consider this issue, and so we define $M_k$, the covariance of the selected estimates if we assume they are estimates of the global biases:

$$M_k = C_k + \begin{bmatrix} \sigma_{\text{Trans}} & 0 \\ 0 & 0 \end{bmatrix}$$ \hspace{1cm} (25)

where:

$$\sigma_{\text{Trans}} = \frac{75}{\sqrt{3}} m$$ \hspace{1cm} (26)

The global estimator is then obtained through an optimal weighted average of the (independent) estimates from each target, extracted only at track deletion time.

$$\hat{e}_R = \sum_k M_k^{-1} \left( \sum_k M_k^{-1} \hat{\theta}_k \right)$$ \hspace{1cm} (27)

Note these estimators are independent of $k$, as they are global. The global estimator covariance matrix will have the following form:

$$M = \begin{bmatrix} m_{11} & m_{12} \\ m_{21} & m_{22} \end{bmatrix} = \sum_k M_k^{-1}$$ \hspace{1cm} (28)

Both the global estimate and its covariance could be implemented in a recursive way [4].

Thus, for every aircraft there will be two bias estimators, one concerning all biases and another one concerning the global ones. Consequently, we could information from both estimators to correct the measure.

Note the central estimate is not only an estimate of the sensor global bias terms, but it can also be assumed to be a probably biased estimate of two bias terms coincident with those in the local bias estimator: sum of radial biases, local to target and central ($\hat{\theta}_k = \hat{\theta}_k + \Delta \theta_t$); and global azimuth bias. Additionally, we may assume we have prior information regarding $\Delta \theta_t$, which may be assumed a sample of a uniform distribution, independent for each target. This distribution would have zero mean and, assuming an aircraft length of $L$ (~80 meters), its variance will be:

$$\sigma^2_{\Delta \theta} = \frac{L^2}{12}$$ \hspace{1cm} (29)

Therefore, we could define a new “local” estimator, available when the track is initiated. We will call it “a-priori local bias estimator”. This information extraction process is depicted in Figure 5, where we define not only the estimator, but also its covariance when we assume the estimated terms are the same in the local bias estimate.

$$\begin{pmatrix} \hat{b}_R \\ \hat{\theta}_k \end{pmatrix} \xrightarrow{M} \begin{pmatrix} m_{11} + \sigma^2_{\text{Trans}} & m_{12} \\ m_{21} & m_{22} \end{pmatrix} \begin{pmatrix} \hat{b}_R \\ \hat{\theta}_k \end{pmatrix}$$

In conclusion, the local estimator is updated after every received measure and the global one is updated after every track deletion. Then, the a-priori local estimator is synthesized from the global estimator during track initiation. The correction estimate should then be derived or modified after every received measured is integrated.

### 3 Bias Estimation implementation and integration in Data Fusion System

After describing the bias estimation methods, the integration with the fusion system is going to be addressed. The scheme of the bias estimator is based on the assumption that there are two kinds of biases, the aircraft based (local) and the sensor based (global) ones. The general software scheme is depicted in Figure 6. It is composed of several cooperating estimation objects, as depicted in Figure 7.

In general, each of the estimation objects performs three different tasks:

- It selects those measures to be inserted in the appropriate estimation equation, checking some validation tests to be defined.
- It integrates the valid measures in the estimators, according to the methods described in section 2.
- It cancels the bias terms in raw measurements, when necessary in the data fusion system (association hypothesis testing, tracking, ...). The corrections cannot be used in all circumstances, in order not to compromise tracking stability.
In next sections we will describe the implementation of these three functions for the different estimators in our system. Before including the measures in the appropriate estimators, a function receives the transformed measures and selects the sensor it comes from (and, in the case of MMS and SSR, it also selects the associated track).

The integration process was performed in three steps. The first one was the insertion of a bias estimator in a scenario where there were only SMR sensors. The next step was to introduce a MMS. Finally, the SSR was introduced. The integration tips described below come from this integration steps.

3.1 SMR bias estimator implementation

There is a global bias estimator for each SMR in the airport. A prerequisite for its implementation is the availability of a database containing the airport layout in the form of airport segments.

Regarding measure insertion, the first task is to localize the target position, as accurate as possible, in order to know the number of airport segments in which the target can be located, using a preliminary bias correction based on prior bias. The received measure will only be inserted in the sensor bias estimator if the target is located in just one segment, because that is the only way of calculating the separation distance in Fig. 2, without ambiguity. Once the distance is obtained, the matrices (A,B) can be updated.

Regarding bias correction, the first thing to do is to check if the bias estimation is available (considering the estimator convergence, which can be assessed taking into account estimator variance $A^{-1}$). Finally, if estimator has converged, biases can then be cancelled from the delivered measure, using the following equation, where $(R_{\text{unbiased}}, \theta_{\text{unbiased}})$ are the range-azimuth measures to be used in the rest of the target tracking system:

$$
\begin{bmatrix}
R_{\text{unbiased}} \\
\theta_{\text{unbiased}} \\
\end{bmatrix} = 
\begin{bmatrix}
R_{\text{measure}} \\
\theta_{\text{measure}} \\
\end{bmatrix} - 
\begin{bmatrix}
\hat{b}_R \\
\hat{b}_\theta \\
\end{bmatrix}
$$

(31)

If there is not bias correction available, the delivered measure is the original one, and the measure variance is increased to roughly take into account the bias terms.

3.2 MMS bias estimator implementation

A local MMS estimator is associated to each track, so the estimator functions are called after data association, in order to insert the measures into the appropriate local estimator and also cancel estimated biases from measures whenever is possible and desired. Two measures must be inserted: the MMS measure, and an SMR reference measure. They also must be aligned in time. Consequently, the estimators will be provided with an up-to-date reference and MMS measures.
Once a new pair of measures is available, it may be injected in the MMS bias estimator. Our preliminary integration results showed that there could be a problem with axis orientation extraction from velocity on airport segment axis. This problem appeared in places where the target could be located in several segment, and in maneuvering areas. The consequent errors impacted both bias estimation and bias correction. So, only these pairs of measures of the same target obtained in areas with non-ambiguous airport segment localization are injected into the local MMS bias estimator. This injection leads to a modification of $D\hat{t}$ coherent with Eq. 15.

Bias correction is performed over Cartesian coordinates, obtaining $(x_{MMS,\text{unbiased}}(i), y_{MMS,\text{unbiased}}(i))$, measures to be used in the rest of the tracking system:

$$x_{MMS,\text{unbiased}}(i) = x_{MMS}(i) - \Delta l_m(i) \cos \gamma(i)$$
$$y_{MMS,\text{unbiased}}(i) = y_{MMS}(i) - \Delta l_m(i) \sin \gamma(i)$$ (32)

This correction is not performed when there is ambiguity in airport segment localization (aircraft heading would be too unpredictable), or while $D\hat{t}$ has not converged. When the correction is not applied, to reduce the impact of these measures, we increase their covariance matrix, mainly in the longitudinal direction, to take into account the lack of information regarding antenna location.

### 3.3 SSR bias estimator implementation

SSR is the most complex bias estimator due to the presence of both sensors based and target based error terms. It demands the exchange of information between the global bias estimators and the local estimators, in order to obtain a correction bias estimate. This exchange is performed at track initiation and also at track deletion, as described in section 2.3.

The same kind of errors regarding local bias initialization and maneuvering areas as in the case of MMS appear. So, only these pairs of measures with non-ambiguous airport segment localization are injected into the local SSR bias estimator. This injection leads to a modification of $A_k$ and $B_k$ according to Eq. (22) and (23).

Bias correction is performed in Cartesian transformed coordinates, in areas with non-ambiguous localization, following:

$$\begin{bmatrix} x_{SSR,\text{unbiased}}(i) \\ y_{SSR,\text{unbiased}}(i) \end{bmatrix} = \begin{bmatrix} x_{SSR}(i) \\ y_{SSR}(i) \end{bmatrix} - H(i) \begin{bmatrix} \hat{b}_{\theta,k,\text{correction}} \\ \hat{\Delta}_{l,k,\text{correction}} \end{bmatrix}$$ (33)

where $(x_{SSR,\text{unbiased}}(i), y_{SSR,\text{unbiased}}(i))$ are the measures, assumed unbiased, to be used for tracking. In the case of ambiguous localization, the term related with antenna displacement cannot be cancelled without danger, and therefore a different cancellation method is proposed:

$$\begin{bmatrix} x_{SSR,\text{unbiased}}(i) \\ y_{SSR,\text{unbiased}}(i) \end{bmatrix} = \begin{bmatrix} x_{SSR}(i) \\ y_{SSR}(i) \end{bmatrix} - H(i) \begin{bmatrix} \hat{b}_{\theta,k,\text{correction}} \\ \hat{\Delta}_{l,k,\text{correction}} \end{bmatrix}$$ (34)

This correction has a related increase of measures variance, higher in the longitudinal direction, to desensitize the tracking against these biased measures. During initialization of the local biases, the same correction in Eq. 34 is performed, and the variance should not only be increased in the longitudinal direction, but also in the radial direction, as $\hat{\Delta}_{l,\text{correction}}$ had not been accurately estimated.

### 4 Simulation results and conclusion

Through theoretical analysis and simulation, we proved the convergence of the estimators. In this paper, we include some convergence results of a scenario consisting of five aircraft moving around the airport. In Fig. 8 and 9 the convergence of the SMR range bias and MMS antenna displacement estimators are presented. It can be seen that after a short transient, the estimators converge in mean to the real value. Convergence is shown drawing both the estimated value and a 95% confidence interval for each estimator. The real parameter values, to be estimated, are presented in table 1.

<table>
<thead>
<tr>
<th>Biases</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b_R$</td>
<td>-50m</td>
</tr>
<tr>
<td>$b_\theta$</td>
<td>-0.1º</td>
</tr>
<tr>
<td>$\Delta l$</td>
<td>20m</td>
</tr>
</tbody>
</table>

Table 1. Real parameter values

Figure 8. Convergence of SMR range bias ($b_R$) estimator

Figure 9. Convergence of MMS $\Delta l$ estimator

The remaining estimators share a similar behaviour. Note the convergence of SSR estimators will be slower, due
to the higher number of estimated parameters, the reduced
number of measures (since the SSR has a larger scan
period), and the higher SSR measurement noise variance.

The simulated scenario in Fig. 10 to 12 shows one-run
bias effects over target tracking. In this simulation, there
were four sensors (two SMR, a MMS and a SSR). It can be
seen that, using the described bias estimation methods, the
overall tracking quality is similar to that attained if biases
were not present, while not correcting bias terms severely
degrades tracking performance.

Finally, RMS statistics evolution in time for along-
trajectory position error (longitudinal error) and speed
module error are presented, in Fig. 13 and 14, for the
previous case, from a Monte Carlo simulation with 500
iterations. In blue you can see the results for uncorrected
biases and in red the results with corrected measures are
presented. The results show a clear improvement in tracking
quality. Similar results could be shown for transversal
position error and for heading. The attained velocity
stability is especially important for conflict detection,
planning and routing.

Summarizing, the proposed bias estimation and
correction system shows quite an important improvement
over raw measurement processing. In this paper we did not
only presented the bias estimation systems, but also its
integration in the complete tracking system, and the effects
induced (potential track instability during initialization or in
maneuver areas), and techniques to mitigate these problems.
The system was implemented and integrated in Madrid-
Barajas prototype simulator, and is part of a proposal for
modernization of this airport surveillance function.

References

Sensor Calibration for Airport Data Fusion, IEEE 2004

surveillance radar, Digital Avionics Systems Conference,

[3] J A. Besada, J. García, G. de Miguel, A New
Approach to On-line Optimal Estimation of Multisensor
Biases, IEE Proceedings Radar, Sonar and Navigation,
(October) 2003.