Automatic Adaptation of Airport Surface Surveillance to Sensor Quality

Juan Besada, Guillermo Frontera, Ana M. Bernardos, Gonzalo de Miguel
Universidad Politécnica de Madrid
besada@grpss.ssr.upm.es

ABSTRACT
This paper describes a novel method to enhance current airport surveillance systems used in Advanced Surveillance Monitoring Guidance and Control Systems (A-SMGCS). The proposed method allows for the automatic calibration of measurement models and enhanced detection of non-ideal situations, increasing surveillance products integrity. It is based on the definition of a set of observables from the surveillance processing chain and a rule based expert system aimed to change the data processing methods

Keywords
Automation, Data Fusion, Airport Surface Surveillance, Integrity assessment, Expert systems

INTRODUCTION
Multisensor multitarget tracking (MMTT) systems are the basis of modern airport surveillance systems. They rely on the coupled operation of:

- Association systems, obtaining a unique target track from data from all sensors. They contain means for track initiation, association of measures to tracks, and track deletion for tracks not receiving updates.
- Highly accurate tracking filters (such as IMM filters [1]), which exploit all available sensor measurements enabling fast manoeuvre detection and possibly airport map information.

Much effort has been devoted in the last years to the definition of bias estimation procedures for MMTT systems (among others [2][3][4]). The basic idea is estimating all bias terms in the measurements potentially causing consistency mismatch, and removing them from the raw measures, providing the tracking filters with bias corrected (therefore unbiased) measures.

In A-SMGCS, the most common sensors used for target tracking include:

- Radar data, from Surface Movement Radar (SMR)[6].
- Multilateration data from multilateration sensors, based on Mode S squitters.
- Automatic dependent surveillance (ADS-B) data [5], usually from DGPS navigation measures.

The complementarity nature of these sensor techniques allows a number of benefits (high degree of accuracy, extended coverage, enhancements to systematic errors estimation and correction, etc.) and brings new challenges for the fusion process in order to guarantee an improvement with respect to any of the sensor techniques used alone. The fusion of all measurements requires a robust process that considers detailed characteristics of all data sources and checks their consistency before being fused.

An example data processing architecture for airport surveillance is depicted in next figure. One of its main problems is the lack of automatic means to adapt to changes in sensor quality.

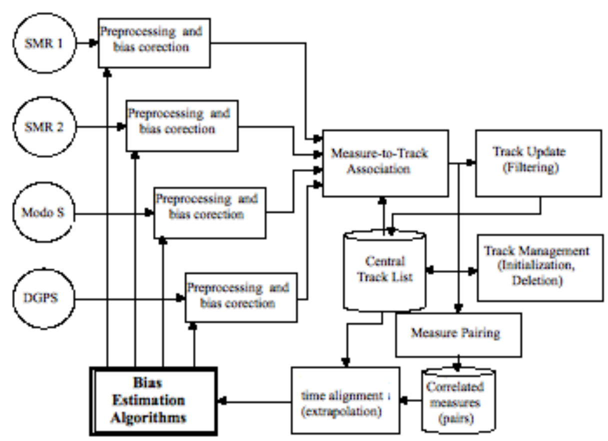

Fig. 1. Surface MMTT architecture

In this paper we define a novel approach to cover bias estimation, noise covariance estimation (present on some systems), association and detection estimation and real time adaptation to current sensor situation.

In general, in all considered measurement sources there are two types of sources of error:

- Random terms (i.e. thermal noise, quantization errors, or measurement timestamp jitter), usually modelled as white noise.
- Constant or slow-changing terms, spatially correlated, which may be modelled as bias.

In addition, not every attempt to perform detection is successful with radar sensors. Also, a certain percentage of measurements suffer errors much in excess of nominal statistics. They are usually marked as outliers, and they are due to some non-linear effect of the sensor, probably due to some kind of malfunction.

In stationary or slow changing conditions, all those problems' effect on tracking may be alleviated through manual adaptation, tuning the association and filtering processes to the current sensor situation. If there is a sudden change in detection or error behaviour of a given sensor, the system must be able to respond rapidly (and therefore automatically) in order to either adapt to the new conditions, or to even preclude the use of some sensor data.

The paper starts with the definition of all sensors of interest detection models, and then describes and justifies the overall sensor state assessment process. Then, the adaptation procedure is described, and a simulation-based example for some of the described problematic situations is included.

SENSOR MEASUREMENT PROCESS DESCRIPTION

Surface Movement Radar

SMR is a kind of radar aimed to monitor aircraft movements on airport surface [6]. It is a high-resolution radar sensor: the range of a target usually extends over several azimuth beam widths and includes a few range cells. The plot position is obtained through extraction of radar image centroid.

Due to occlusion, some parts of the aircraft may not be visible to the radar, and some others may appear disjointed. Also, measures may suffer from the presence of false alarms due to thermal noise or reflections on ground or rain (clutter). Some pre-processing is present in order to group plots belonging to the same target, and merge them into a unique measure.

ADS-B

ADS-B is based on the broadcasting of aircraft navigation information to ground through a data-link [5], using a unique identifier, known as ICAO address. Due to its cooperative nature, it does not suffer from the generation of false alarms, but sometimes outliers can appear due to coding/decoding issues.

In airport, ADS-B measures usually come from DGPS navigation systems (either of local area or of Wide areas). These high quality ADS-B measurements do not suffer measurement biases, but in the case they have integrity problems.

Multilateration Error models

Multilateration measurement performs Time Difference Of Arrival (TDOA) estimation to calculate target position, based on the emission by the aircraft of random signals and its reception by a ground-based station network.

This system can suffer from the appearance of false alarms due to presence of multipath, leading to potential duplicated data as splits, but a non-malfunctioning multilateration sensor must have a very small false alarm rate or outlier rate.

The error of multilateration is a function of several variables, such as the geometry of the receiving stations and transmitter, the timing accuracy of the receiving stations and the accuracy of the synchronization of the receiving sites. The effect on position estimation due to drift errors must be approximately cancelled through accurate synchronization.

We assume the position bias was corrected by the internal calibration system, while there can be a time offset with respect to fusion system reference clock.

SURVEILLANCE SENSORS ASSESSMENT AND ADAPTION

The proposed Multisensor Data fusion is depicted in Fig 1, where the usual Multisensor Multitarget Tracker (MMTT) has attached a parallel on-line Surveillance Sensor Assessment & Adaptation procedure. This procedure derives MMTT adaptation data from all sensor measurements and from Association data and multisensor/monosensor tracks.

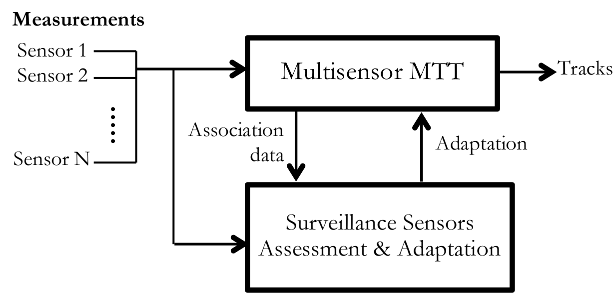

Fig. 2. Adaptive Multisensor Data Fusion Proposal

Surveillance Sensor Assessment and Adaptation is based on the observation of a set of data providing indirect information on not-modelled errors or situations, and in the update of sensor related models and algorithms within MMTT.

There are three different kinds of assessments:

- Sensor oriented, using all available data for a given sensor (with index i).
- Target oriented, using data from a given target. Those are specially important for ADS-B. We will use subindex t to indicate given aircraft.
- Grid oriented, segmenting data from a sensor in a 3D grid, to take into account variations of behaviour depending on position. Radar grids are defined in polar coordinates while multilateration grid is defined in cartesian coordinates. We will indicate given cell with index j.

<u>Sensor Detection State Analysis</u> is in charge of detecting anomalous detection or high outliers rate areas/sensors. The analysis is based on monosensor association/tracking.

To do so it performs a set of analysis:

1) Sensor/Grid estimation of track initiation rate (P_1).
2) Sensor/Grid estimation of track deletion rate (P_2).
3) Sensor/Grid estimation of track life duration statistics of deleted tracks (P_3).
4) Sensor/Grid estimation of non-associated measures rate (P_4).
5) Sensor/Grid estimation of ambiguous data association rate (P_5).
6) Target oriented number of tracks for ADS-B ICAO address (P_6).

Analysis 1) to 4) are related to high false alarm rates. 5) is related to presence of crossing targets or false alarms, splits, and possibly occlusions. In an MMTT these situations are alleviated by hardening track initiation/confirmation requirements (by tuning those algorithms' parameters), and reducing association gates around predicted tracks to reduce the probability of association of a false alarm to a track. 6) is an special case, accounting for the case of an unstable target measurement process, indication of a potentially malfunctioning ADS-B equipment.

Variance Assessment is another interest test. Performing differences of consecutive measures from a given sensor and target we may obtain an observation related to sensor noise, assuming constant velocity dynamics. From a collection of such measures sensor based variances may be derived. Note ADS-B and multilateration sensors provide covariances of measures, so a consistency analysis between sensor provided variances and observed variances may be performed.

In this case we also have a set of analysis:

1) Sensor/Grid estimation of covariance for radar (S_1).
2) Sensor/Grid Consistency between sensor provided covariance and measured covariance for multilateration (S_2).
3) Target oriented consistency analysis between measured covariance and ADS-B provided covariance (S_3).

Each of previous analysis can provide better-adapted covariance data (enabling improved statistical data fusion) or serve as the basis for the detection of malfunctioning sensors.

Bias Assessment, in parallel to bias Estimation and correction is a key element for alignment of sensor data. It is based on the analysis of the mismatch between different sensor measures, taking into account the previous characterization of this mismatch. It obtains the lists of sensor and target biases (to be denoted as b_0 and b_1).

In addition, after performing tracking, the offset between bias-corrected measures and predicted tracks is averaged in a grid, in order to localize areas with additional bias terms not corrected, potentially due to malfunctioning sensors. Let's call these values b_2.

Monosensor/Multisensor Compatibility Assessment provides additional integrity to our proposal. Multisensor tracks are based on data from all sensors, while monosensor tracks have only one sensor measures. A statistical compatibility assessment of all monosensor tracks and multisensor tracks may be used to detect uncorrected bias terms, or, by analyzing the presence of missed detections, malfunctioning sensor.

The main observations here are:

1) Sensor/Grid/Target Monosensor/Multisensor track offset compatibility assessments (C_1)
2) Sensor/Grid/Target missed measure analysis for radar (C_2)

ADAPTATION EXPERT SYSTEM DESIGN

An expert system has been designed to take decisions that make the whole system perform better when some sensor or target's measures stop behaving as expected. The adaptation decisions the expert system is able to take for each sensor, grid or target include changing the track initialization method, changing the size of the association windows, updating the measurement models used for filtering or completely removing measurements under certain conditions.

The knowledge used in the system is structured as a set of rules. These rules are used to inference the conclusions (in this work, conclusions are the need to take any of the adaptation decisions described above) using the sensor detection state, variance assessment, bias assessment and monosensor/multisensor compatibility assessment data.

Our system has more than 50 different rules, most of which can be inferred from previous discussion. Due to lack of space here we are just providing some of them:

- For each sensor i, and grid cell j (all actions are for sensor-cell i,j).

if $P_1(i,j)>u_{1,1}$ **and** $P_3(i,j)<u_{3,1}$ **and** $P_4(i,j)>u_{4,1}$ **then** harden initialization

if $P_1(i,j)>u_{1,2}$ **and** $P_2(i,j)>u_{2,2}$ **and** $P_3(i,j)<u_{3,2}$ **and** $P_4(i,j)>u_{4,2}$ **then** disable initialization

if $S_1(i,j)>nominal\_S_1(i)$ **or** $C_1(i,j)>u_{9,1}$ **then** increase radar measure covariance matrix

if $S_2(i,j)=inconsistent$ **or** $C_1(i,j)>u_{9,2}$ **then** increase multilateration measure covariance matrix

if $P_1(i,j)>u_{1,3}$ **or** $P_2(i,j)>u_{2,3}$ **or** $P_3(i,j)<u_{3,3}$ **or** $P_4(i,j)>u_{4,3}$ **or** $P_5(i,j)>u_{5,3}$ **or** $S_1(i,j)>> nominal\_S_1(i,j)$ **or** $S_2(i,j)=$ very inconsistent **or** $b_0(i,j)>u_6$ **or** $b_2(i,j)>u_8$ **or** $C_1(i,j)>u_{9,3}$ **then** disable use of measures for association and tracking

- For each sensor i (all actions are performed for measures from i-th sensor).

if $P_1(i)>w_{1,1}$ **and** $P_3(i)<w_{3,1}$ **and** $P_4(i)>w_{4,1}$ **then** harden initialization

if $P_1(i)>w_{1,2}$ **and** $P_2(i)>w_{2,2}$ **and** $P_3(i)<w_{3,2}$ **and** $P_4(i)>w_{4,2}$ **then** disable initialization

if $S_1(i)>nominal\_S_1(i)$ **or** $C_1(i)>w_{9,1}$ **then** increase radar measure covariance matrix

if $S_2(i)=inconsistent$ **or** $C_1(i)>w_{9,2}$ **then** increase multilateration measure covariance matrix

if $P_1(i)>w_{1,3}$ **or** $P_2(i)>w_{2,3}$ **or** $P_3(i)<w_{3,3}$ **or** $P_4(i)>w_{4,3}$ **or** $P_5(i)>w_{5,3}$ **or** $S_1(i)>> nominal\_S_1(i)$ **or** $S_2(i)=$ very inconsistent **or** $b_0(i)>w_6$ **or** $b_2(i)>w_8$ **or** $C_1(i)>u_{9,3}$ **then** disable use of measures for association and tracking

- For each target t (all actions performed for measures from t-th target)

if $P_6(i,t)>z_6$ **then** disable initialization from ADS-B

if $S_3(t)<z_3$ **or** $C_1(t)>z_{9,1}$ **then** increase ADS-B measure covariance matrix

if $b_1(t)<z_7$ **or** $C_1(t)>z_{9,2}$ **then** disable use of measures for association and tracking

Some other rules are aimed to restore the default behaviour of the MMTT when the conditions of the sensors return back to the expected ones. For instance, when measured covariances return to nominal values the increased covariance matrix is not used anymore.

SIMULATION RESULTS

We have conducted a set of simulations and worked with real data in order to be able to tune the different thresholds in the expert system rules, to increase overall system integrity. Due to lack of space and confidentiality requirements over real data, only one simulated scenario will be described next. In this simple scenario we have three sensors with overlapping coverage, two of them are SMR, and the others is a Multilateration sensor. After bias correction, there is a remaining uncorrected bias leading to a mismatch of around 50 meters in Multilateration. Due to that, $b_2(i,j)$ and $C_1(i,j)$ exceed their corresponding thresholds and therefore, for this cell, which leads to precluding the use of this sensor measure to perform tracking. The results, interpolated for different times, for a given trajectory, are summarized in next figure. Axes are expressed in Km, and the scenario is related to two aircraft crossing in two taxiways. One of them does not broadcast Mode S squitters and therefore is not visible by Multilateration sensor.

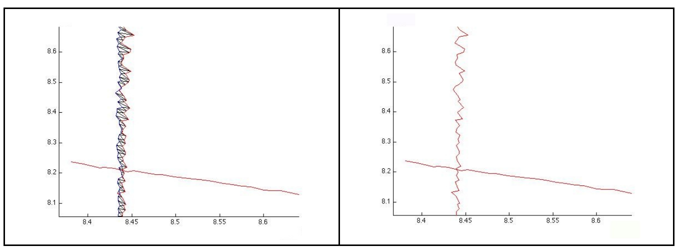

Fig. 3. Adaptive Multisensor Data Fusion Results

In the left part of the figure the monosensor tracks from the radar feeding the track in red, and the Multilateration measures blue, and the multisensor track in black (with extremely problematic velocity vector). Meanwhile, in the right, after removal of the problematic sensor by our automatic procedure, only one of the monosensor track is available which becomes equivalent to the multisensor track, with increased stability in velocity.

CONCLUSION

In this paper we are proposing the use of a set of figures of merit, coupled with an expert system, to provide a Multisensor Multitarget Tracker oriented to airport surveillance, with automatic sensor context adaptation capabilities. Such tests are performed using the information provided by the surveillance sensors and the MMTT, and the output of the tests is defined by a rule based expert system which takes decisions and makes changes in the MMTT by changing parameters or disabling sensors in order to obtain better results.

Some Air Traffic Control surveillance systems already include simple adaptation mechanisms. However, such mechanisms are usually tightly bounded to the MMTT itself, which makes them more difficult to maintain or improve. This work aims to extract these mechanisms and place them in a separate procedure, which allows expressing the adaptation knowledge in a more formal way. Also, having a Surveillance Assessment & Adaptation process eases future enhancements of the context adaptation mechanisms, as all the rules are centralized.

Future enhancements of this approach include automatic optimal threshold search and applying machine learning techniques to the context adaptation process.

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