Centralized Sensor Data Fusion is really more powerful than Track Fusion

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Abstract

Systematic sensor errors complicate centralized data fusion. [1] sensor model specific alignment procedures, which allow the compensation of essential bias values like azimuth deviation and range offset, do not remove systematic errors completely. The residual errors, like time differences between different sources and varying spatial deviations, lead to a reduction of the tracking performance in the centralized architecture. A detailed statistic of deviations between predicted track states and observations, evaluated for each track and each sensor, provides additional model independent bias information. It turns out, that this information is sufficient for a further decisive reduction of the residual errors. A feedback control mechanism can be established, which allows a continuous compensation of sensor and track specific bias values down to a level appropriate for the application of advanced recursive tracking methods.

The centralized tracking, supported by bias control, finally gains its superiority over track fusion mainly from the following capabilities:

- Maneuver recognition based on bias controlled, multiple source measurements
- Recursive filter selection according to the maneuver condition
- Performance enhancement in group tracking, 2D data processing, track initiation and correlation gate determination

The processing of the complete set of aligned data, recursively adapted to the target maneuver, allows an optimal use of information from all contributing sensors.

1 Introduction

A classical example for a Multiple Sensor System collecting mutually complementary aspects of a dynamically evolving scenario is the tracking subsystem operating in the Control Reporting Center GIADS, with the capability to track 3000 targets in an area of

2000*2000 km^2 with data from 20 radar sensors. During the long way developing appropriate data fusion algorithms for this system, the key question of data fusion, the usage of a centralized or a decentralized architecture, has always been present.

In the decentralized architecture the data from single sensors are fused to source tracks, which are combined to system tracks in a second data fusion step. In the centralized architecture, system tracks are asynchronously updated by sensor data from different sensors. In the latter method, systematic sensor errors (bias errors) usually lead to a reduction of the tracking performance. In the decentralized method, bias errors have no influence in the first fusion step. In the second fusion step, an impact of the bias errors on heading and speed can be avoided. The main disadvantages with the decentralized architecture are a reduced update rate and resulting deficiencies in the maneuver recognition.

As recommended in [2], we always favored the centralized architecture but the remaining key problem was the tracking performance reduction, caused by residual bias errors which could not be removed by the automatic sensor alignment.

In this paper the bias control method, which allows a further reduction of the residual sensor bias errors, is presented. The operational results, which have been achieved, are discussed in respect of the comparison of the centralized and decentralized data fusion architecture.

2 Bias Control

The bias control method discussed in this paper implies that the contributing sensors already have been optimally aligned in terms of azimuth-, range offset-, range scale- and position bias. But even the optimal alignment of the above mentioned parameters is not perfect and leaves residual errors. The key to improve the the tracking performance is therefore a further reduction of these residual errors.

The method presented comprises three processes, the data collection gathering statistical information, the bias calculation evaluating possible data correction values and the bias correction, which actually compensates bias errors.

2.1 Data Collection

It is the aim of the data collection to get stable data as quick as possible. This is achieved using a low pass filter with filter variable α, which takes into account a weight Γ derived from the number of already collected samples and a decay time τ for the already collected information. The according relations used to update (+) an estimation value x with a measurement z are expressed in (1).

(1) $x(+) = (1-\alpha)x+\alpha z, \qquad \alpha = e^{-dt/\tau}/(1+ \Gamma), \qquad \Gamma= 1+\Gamma e^{-dt/\tau}.$

The collected data comprises sensor specific horizontal deviations and co variances. For normalization purpose, the mean values concerning all sensors are evaluated as well.

The weight definition in equation (1) is not applicable to the collection of time difference δt data. The δt-weight additionally has to take into account the specific covariance in the flight direction, evaluated using the speed vector $\underline{v}$ of the track and the spatial covariance matrix $\underline{\underline{cov}}_i$ of the contributions of the sensor considered. The additional weight factor G linearly depends on the track speed and the measurement covariance. The complete δt data comprises a matrix of all possible pairs of sensors i and j and the specific weight G_{ij} of the information related to the pair and the according time differences δt_{ij}. The matrix values ij are updated with spatial deviation vectors $\underline{\delta x}_i$, the difference between the predicted track position and the position measured by sensor i. A time difference Δt_i and a weight G_i is related to a deviation vector $\underline{\delta x}_i$ and a speed vector $\underline{v}$:

(2) $\Delta t_i = \underline{\delta x}_i \underline{v} / \underline{v}^2$, $G_i = \underline{v}\ \underline{\underline{cov}}_i\ \underline{v} / |\underline{v}| \Gamma_i$, $\Gamma_i (+) = 1 + \Gamma_i\, e^{-dti/\tau}$.

In accordance with (1) the matrix elements δt_{ij} and G_{ij} derived at time t_1 with time difference Δt_i for sensor i are updated with a time difference Δt_j derived a time t_2 with sensor j as follows ($dtij = t_2 - t_1$).

(3) $\delta t_{ij} (+) = (1-\alpha)\delta t_{ij} + \alpha(\Delta t_j - \Delta t_i)$, $\alpha = G_{ij}/(G_{ij} + G_i)$, $G_{ij} = G_{ij}\, e^{-dtij/\tau} + G_j$

2.1 Bias Calculation

The aim of the bias calculation is to compensate the sensor specific systematic error in the measurement data. Due to target maneuvers all sensor values can contain common bias values, which are not helpful in the compensation of sensor specific errors. Therefore the difference between a sensor specific bias value $\underline{\delta \hat{\imath}}$ and the mean value of all sensor bias values $\underline{\delta}°$ is used to derive the compensation $\underline{\delta}_i$, using a control factor β and a coordinate transformation φ_i. The coordinate transformation φ_i converts the Cartesian tracking coordinates, oriented to local north at the track position considered, to polar coordinates, measured by sensor i.

(4) $\underline{\delta}_i = \varphi_i (\beta(\underline{\delta \hat{\imath}} - \underline{\delta}°))$, $\beta < 1$.

The compensation of the relative time differences between the sensors is more complicate, because a compensation vector δt_i for the correction of the time of all sensors i has to be derived from the difference matrix δt_{ij}. The following problem has to be solved:

Given a difference matrix δt_{ij} and weights G_{ij} a compensation vector δt_i shall be found in a way that $G_{ij}(\delta t_i - \delta t_i - \delta t_{ij})^2$ is minimized with the constraint that $\Sigma_i \delta t_i$ is zero. The minimization problem can be transformed to the standard problem finding the best solution for an over determined system of linear equations (The number of equations exceeds the number of variables). An additional requirement to the solution method is to be able to handle singular structures, which can occur if there are groups of sensors with small overlapping zones. The solution method therefore must be able to resolve loosely coupled sub configurations and to handle them independently.

2.2 Bias Correction

In order to be applicable for an operational system, the bias correction must be stable, even if too few information is available. If the evaluated weight of the contribution of a sensor is below a threshold value, there is no bias correction applied. Usually, this happens if a sensor starts to detect a target. The use of a reduced accuracy value for those plots, helps to reduce the impact of possible alignment errors in this case. If the overall contribution of a sensor does not sufficiently overlap contributions of other sensors, a correction of the residual bias errors is generally not possible. But just in this case, the bias errors do not have an impact on the tracking performance .

3 Presentation of the Results

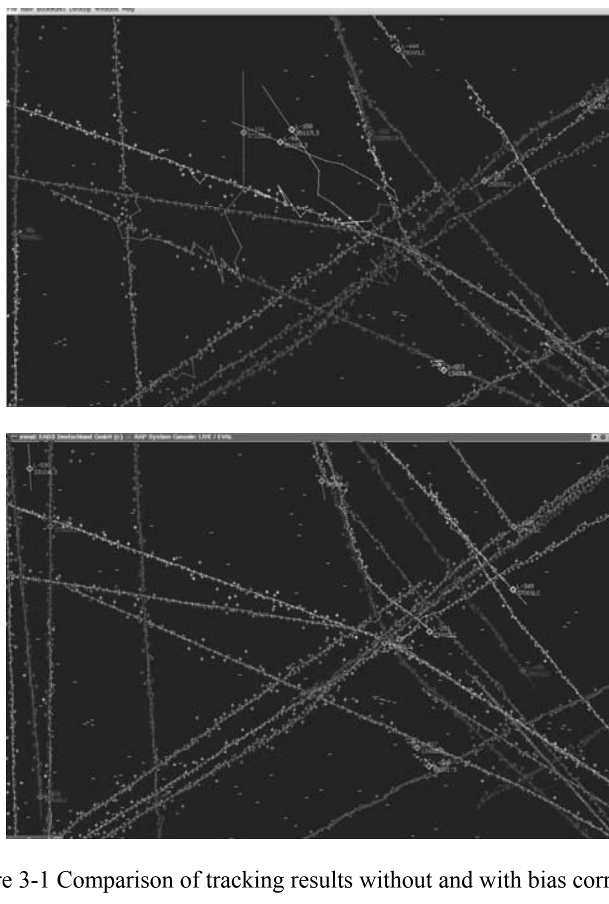

Figure 3-1 Comparison of tracking results without and with bias correction

Figure 3-1 shows two screens with tracks and correlated plots from the same live scenario. In each screen the lines represent track paths displayed using different colors for different tracks. The symbols represent plots. The plot color is chosen in accordance with the correlated track. The screen above shows track disturbances caused by residual bias errors in plots from different sources. The screen below shows that with the bias control method, these disturbances have disappeared and that the application of this method therefore is successful. The plots have not been corrected on the screen. The bias correction only has been applied in the tracking process.

3.1 More centralized data fusion algorithms

Multiple data sources are not only useful for maneuver detection, but they also help to speed up the track initiation in a cluttered environment, provide valuable information to estimate the size of a group of targets and allow to get height information based upon slant ranges. The enhanced track update rate in combination with a detailed sensor error model allows to derive optimized correlation gates. Tracks detected by more than one sensor are most likely genuine tracks. If the mean number of detections of a group per sensor scan exceeds as an example the value of 1.2, than it is very likely, that there are two targets in the group. In an isolated situation a residual detection probability of 0.2 would be considered to be definitively too low to initiate an additional target. If the number of tracks exceeds the number of plots per scan, the redundant tracks can be deleted quickly. The extended Kalman Filter automatically provide height information if the contributing 2D sensors are not too far separated.

Summary

In a multi target and multi radar environment, a track and sensor specific evaluation of differences between prediction and measurement provides data for an accurate estimation of residual bias errors. A feedback controlled correction of the sensor data with the estimated bias values, leads to a decisive reduction of the level of remaining systematic errors. The achieved low level of systematic errors allows to apply recursive tracking methods with maneuver recognition and enhances the performance of 2d data processing, group tracking and track initiation.

Due to the fact that very high processing power easily can be provided at data fusion centers, the bias controlled centralized sensor data fusion is therefore appropriate to use the information, provided by multiple radar sensors, in an optimal way.

References

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[2] David L. Hall.; Mathematical Techniques in Multisensor Data Fusion, Artech House Boston London 0-89006-558-6 ; Chapter 8