Track Initialization in a Multistatic DAB/DVB-T Network

Martina Daun
Dept. Sensor Data and Information Fusion
FGAN-FKIE
Wachtberg, Germany
Email: daun@fgan.de

Christian R. Berger
Dept. of Electrical and Computer Engineering
University of Connecticut
Connecticut, USA
Email: crberger@engr.uconn.edu

Abstract—Digital Audio/Video Broadcasting (DAB/DVB-T) is already available in a large area of Europe. The advantage of using these signals for passive air surveillance is the disposability of a large range of illuminators sending an easily decodeable digital broadcast signal. In the considered multistatic scenario, one observer provides bistatic Time Difference of Arrival (TDoA) and Doppler measurements. The main task for target tracking is to handle ghosts that arise due to problems of association between illuminators, targets and measurements. In this paper, an approach for track initialization in a single frequency network (SFN) is discussed, which is based on clustering. Special attention will be paid to the 2D estimation performance, related to fusing TDoA measurements of two distinct illuminators. Numerical results will include performance analysis via Monte-Carlo simulations for 2D Cartesian estimation performance and an analysis of the number of reasonable estimates in a real configuration of DAB illuminators.

Keywords: DAB/DVB-T, Multistatic Radar, Deghosting, MHT, Passive Radar.

I. INTRODUCTION

In bistatic scenarios illuminators of opportunity like radio or television [1], [2] can be used. Since the illuminators are dislocated from the receiver, instead of measuring the round trip time (RTT), we measure the Time Difference of Arrival (TDoA) between the signal received directly from the sender and delayed copies reflected off potential targets. In our application, Doppler shift, i.e. range-rate, is measured as well, which gives us information about the velocity. We consider a network of television or radio stations, broadcasting digital signals (DAB/DVB-T) [3] at the same frequency, a so-called single frequency network (SFN). So, even if we consider only one receiver, we usually obtain multiple copies, depending on the number of illuminators within range. Advantages in comparison to active systems are (i) a saving of costs, since no additional illuminators are needed; and (ii) the possibility of covert air surveillance. Besides all these perspectives, using non-cooperative illuminators for air surveillance still holds challenges in the fields of signal processing [4] and target tracking.

In this work, we point out difficulties concerning target tracking and present an approach that is adapted to the special requirements of DAB and DVB-T networks. The main difficulty is that the association between illuminators and measurement is principally unknown. This leads to challenging association problems. We base our tracking algorithm on Multi Hypothesis Tracking (MHT), see [5]. To decrease computational complexity, we divide it into several tracking stages. The first tracking stage works directly on the incoming measurements in bistatic range and range-rate. In the second stage we generate possible 2D estimates by combining information of two illuminators and solve the association problem (Deghosting). Lastly, the third stage delivers a 3D Cartesian state estimate. For more details about the tracking algorithm and numerical results regarding tracking performance, see [6].

In this paper, we focus on 2D Cartesian state estimation as initial point for 2D Cartesian tracking. Finding a probable initial target estimate is based on clustering and depends on an appropriate description of the probability density. Estimation performance is affected by the unknown height of the object. To reflect the additional error caused by the unknown height in the covariance matrix, we model the height by a statistical assumption (normal distributed, with known expectation and deviation) and model the corresponding “error-propagation” statistically. The full derivation is provided in [7].

We will give numerical results analyzing the 2D Cartesian estimation performance in terms of the root mean squared error, consistency and comparison to the Cramer Rao Lower Bounds. The number of appropriate estimates using all possible combinations in a scenario with DAB illuminators will be also discussed.

This work has the following structure: In section II, we will describe the scenario and give an overview about the challenges concerning target tracking. The multi-stage MHT algorithm will be briefly explained in section III, and we describe the 2D estimator in section IV. Numerical results will be discussed in section V, and section VI summarizes the results.

II. MULTISTATIC SCENARIO WITH RANGE AND DOPPLER MEASUREMENTS USING DAB/DVB-T

A. Scenario Description

Without loss of generality the observer will be positioned at the origin. The positions of the i-th stationary illuminator

The work presented was done in cooperation with the Passive Sensor Systems, Electronic Countermeasures and Classification Group (FGAN-FHR, Neuenahrer Str. 20, D-53343 Wachtberg), where the signal processing issues are considered.
is given in Cartesian coordinates by $x_{s,i}$. Time Difference of Arrival (TDoA) and the bistatic Doppler shift are measured, which are directly related to the bistatic range $r_i$ and bistatic range-rate $\dot{r}_i$.

$$\text{TDoA} = \frac{r_i - ||x_{s,i}||}{c}, \quad \text{Doppler} = -\frac{\dot{r}_i}{\lambda},$$

where $c$ is the speed of light and $\lambda$ the wavelength of the signal. The measurement equations in bistatic range and range-rate are,

$$r_i = ||p|| + ||p - x_{s,i}||, \quad \dot{r}_i = \left( \frac{p}{||p||} + \frac{p - x_{s,i}}{||p - x_{s,i}||} \right)^T \cdot v,$$

where $p$ and $v$ denote the target’s position and velocity in Cartesian coordinates. The bistatic range equation describes ellipsoids in three-dimensional Cartesian space with foci at the observer and illuminator. The bistatic Doppler shift depends on the geometry and velocity of the target. With the target state $x = (p,v)^T$ and the measurement vector $z_i = (r_i, \dot{r}_i)^T$, the measurement equation is abbreviated by $z_i = h(x,x_{s,i})$. We estimate the target position and velocity from two synchronous measurements using two different illuminators ($x_{s,1}$ and $x_{s,2}$). If we project this scenario on a 2D plane, geometrically, this would be intersecting two ellipses with foci at the origin and $x_{s,i}$, c.f. Fig. 1. This basically means solving two quadratic equations successively, which can result in up to four solutions; but since in this case the two ellipses share one focal point, there will be only two solutions. This can easily be seen by examining the measurement equation:

$$r_1 = ||p|| + ||p - x_{s,1}||$$
$$r_2 = ||p|| + ||p - x_{s,2}||$$

is equivalent to solving

$$r_1 = ||p|| + ||p - x_{s,1}||$$
$$r_1 - r_2 = ||p - x_{s,1}|| - ||p - x_{s,2}||.$$ 

So the problem can be reduced to intersecting an ellipse with one part of a hyperbola. To estimate the velocity, we see that (2) is linear in $v$. After the position has been estimated, if we set the speed in $z$ to zero, two Doppler measurements give us a linear equation system. Of course if the position estimate is off, this will heavily punch through on the velocity estimate. Estimation ambiguity adds to already-existing ambiguity problems – not being able to associate measurements to senders – not to mention multi-target tracking.

### B. Problem Statement

To discuss the association problem, we consider the following example of one target, one observer and three illuminators, which involves up to three TDoA and Doppler measurements per time stage, see Fig. 2. Mis-association and ambiguity result in false estimates (ghosts) that show similar movements like a target. However, good knowledge of the target movement may help to unmask some ghosts. The approach, presented here, is based on a different criterion. We will use that target estimates lie close to each other. So, if we consider measurements of more than two illuminators, this will result in target clustering. This method avoids fostering ghost tracks and provides a quick decision criterion. But for this, target measurements of at least three illuminators are needed to extract a target track.

Without any error, the target would lie in the intersection of all the ellipses. However, in a real scenario we have to consider noisy measurements and additional error caused by the unknown height of the object, c.f. section IV, because the third dimension is neglected in this model. Furthermore, finding the true target will be impeded by missing detections. Measurements of at least three illuminators are also a prerequisite for 3D Cartesian state estimation, which is of course the final aim of target tracking. Of course, combining measurements of three illuminators also yields a better 2D estimation performance, since the influence of the unknown height of the target can be neglected. Nevertheless, considering the number of possible combinations justifies working with
combinations of two illuminators in the Deghosting stage.

In the following, we define $M$ to be the number of measurements and $I$ the number of illuminators. Then we focus on the association problem, that arises if two or three measurements are combined. The number of true target estimates per detected target is $\binom{I}{2}$ or $\binom{I}{3}$ respectively, see table I. For clustering to work well, the number of true target estimates should be as large as possible. Combining three measurements is only favorable if data of six illuminators is available. Moreover, we would need at least four illuminators to solve the association problem. Besides, we have to consider the number of total possibilities, given by $2 \left( \binom{I}{2} M(M - 1) \right)$ in the 2D-case and $\binom{I}{3} M(M - 1)(M - 2)$ in the 3D case, table II.

Since the number of measurements is usually larger than the number of illuminators (multiple targets and false alarms), the 3D case would blow up complexity.

### III. Tracking Algorithm

#### A. Primary Tracking of the Measured Data

To be able to distinguish between ghosts and targets, we need the target to be detected by several illuminators. So the SNR threshold set on considered measurements is chosen to be quite low. Otherwise an increasing number of measurements will lead to increasing computational complexity. We use a primary tracking stage, which can handle clutter and missed detections, by forming tracks directly in the range/range-rate domain. Tracking is done by Multihypothesis Tracking (MHT) [5], where we assume a third-order motion model. The state vector is given by $\mathbf{z} = (r, \dot{r}, \ddot{r})^T$, where $r$ and $\dot{r}$ are measured and $\ddot{r}$ is initialized with zero mean. With this assumption, we restrict the movements of potential tracks to reasonable behavior of range and corresponding range-rate.

If a track is validated in the primary tracking stage after several measurement cycles, they are passed on to be fused to Cartesian estimates in the next stage. This reduces computational complexity, since each illuminator/target combination can generate at most one track, compared to all possible combination of any two measurements including clutter.

### B. Track Initialization in Cartesian Coordinates

During the course of the algorithm, we need to determine Cartesian target state estimates. Tracking will be done again by MHT starting from a probable target state estimate. Since 3D Cartesian estimates would make association more difficult, we transform measurements of two illuminators into 2D Cartesian estimates with a fixed height. At the moment we have no knowledge about association and need to consider all possibilities. Enumerating all these possibilities in future stages would lead into memory overload fast. We therefore want to decide quickly if an estimate belongs to a true target and to get rid of ghosts. Likelihood Ratio (LR) testing supplies a quick appraisal to find the true association possibilities.

For a given region $G$ in 2D-Cartesian coordinates and volume $|G|$, we model the background distribution according to a Poisson distribution. The probability to observe $n$ false estimates in the region $G$ is given by

$$p_F(n) = \frac{1}{n!} |G|^n e^{-|G| \rho_F},$$

with spatial false return density $\rho_F$. Of course, this assumption does only hold for one fixed time stage, since any false returns, ghosts, after conversion to Cartesian coordinates will be systematic; so the localization of a ghost at time $t_{k+1}$ does strongly depend on the localization at time $t_k$. Moreover, we will be able to calculate the spatial false estimate density, $p_F$, from the observation of the number of illuminators and volume of observed measurements and number of considered illuminators.

1. **Finding probable target estimates:** Every estimate $\hat{x} = (\hat{p}, \hat{v})$ is currently given by a position and velocity vector and a corresponding covariance matrix $\hat{P}$, i.e. $x \sim \mathcal{N}(\hat{x}, \hat{P})$. So, the true target state is supposed to lie inside the $3\sigma$ gate given by the covariance matrix with probability 0.937 [8].

For every state estimate $\hat{x}_i$, we will count the number of estimates $\hat{x}_i$ lying in its $\sigma$ gate, i.e.

$$n = \{ \hat{x}_i : (\hat{x}_i - \hat{x}_j)^T\hat{P}^{-1}(\hat{x}_i - \hat{x}_j) < k^2 \}$$

We calculate a Likelihood Ratio considering the hypotheses $h_0$ that the true target state estimates lie inside this region and $h_1$ that there are only false estimates. Since the setup parameters (probability of detection, $P_d$, and number of illuminators $I$) are given in terms of measurements and not in 2D-Cartesian, we need to reconstruct the number of associated measurements $m$ from the number of observed estimates $n$ using the relationship $n = \binom{m}{2}$. Solving for $m$ yields a functional relationship dependent on $n$: $m = \left\{ \begin{array}{ll} 0 & \text{if } n = 0 \\ \frac{1}{2} + \sqrt{\frac{1}{4} + 2n} & \text{otherwise} \end{array} \right.$

So the probability of finding $n$ estimates, including the available true target estimates, can be approximated by a binomial sum depending on the probability of detection and the number of illuminators:

$$p(n|h_0) = \sum_{i=0}^{n} \binom{I}{m_i} P_d^m (1 - P_d)^{I-m_i} p_F(n - i),$$

Table I

<table>
<thead>
<tr>
<th>$I$</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\binom{I}{2}$</td>
<td>1</td>
<td>3</td>
<td>6</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>$\binom{I}{3}$</td>
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<td>1</td>
<td>4</td>
<td>10</td>
<td>20</td>
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</table>

Table II

<table>
<thead>
<tr>
<th>$I = 5, M$</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>2D</td>
<td>400</td>
<td>600</td>
<td>840</td>
<td>1120</td>
<td>1140</td>
<td>1800</td>
</tr>
<tr>
<td>3D</td>
<td>600</td>
<td>1200</td>
<td>2100</td>
<td>3360</td>
<td>5040</td>
<td>7200</td>
</tr>
</tbody>
</table>

1Combining three measurements gives usually only one solution (non-ambiguous), since the second solution can be neglected by only considering heights greater than zero.
where \( n \) is rounded down. The LR will be calculated by dividing the probability that no measurement belongs to a target using the background distribution:

\[
L(n) = \frac{p(n|h_0)}{p_F(n)}. \tag{9}
\]

In the four dimensional (2D position and 2D velocity) case the volume of the \( k \sigma \) area \( |G| \) can be calculated by [8]

\[
|G| = \frac{k^4 \pi^2}{2} \sqrt{\text{det}(\hat{P})}. \tag{10}
\]

In the following we call estimates probable, if \( L(n) > \lambda \), for some threshold \( \lambda \). This approach is in some points heuristic, but has been shown to work quite well. To be more precise, we could replace (6) by,

\[
n = \# \{ \hat{x}_i | (\hat{x} - \hat{x}_i)^T (\hat{P} + \hat{P}_i)^{-1} (\hat{x} - \hat{x}_i) < k^2 \}. \tag{11}
\]

However, computational complexity increases enormously by inverting matrices in each single step.

An alternative approach is to look back at the measurements space. For each estimate and each possible illuminator \( x_{s,j} \) we need to determine an expectation \( \hat{z} \) and covariance \( \hat{R}^{i} \) according to the relationship in the measurement equation \( h \). An advantage is that the measurement covariance matrix \( R \) is fixed, so (6) can be replaced by

\[
n = \# \{ \hat{z}_i | (\hat{z} - \hat{z}_i)^T (\hat{R}^{i} + R)^{-1} (\hat{z} - \hat{z}_i) < k^2 \}. \tag{12}
\]

Both approaches ensure that we take care of the actual uncertainty for geometrical reasons given by the covariance matrix. With to estimates with significant uncertainties, we will need to search in a bigger region for similar estimates, and simultaneously the probability of finding some estimates by chance increases. So, it will be important to describe the error in the covariance matrix well. Since generally the height of the object is not known in advance, we pick up uncertainties, resulting from the unknown height, in the covariance matrix.

IV. ESTIMATION ERROR WITH UNKNOWN TARGET

Assume the height \( z \) to be a Gaussian random variable with density \( \mathcal{N}(z; \mu(z), \sigma^2_z) \). Applying the approach derived in [7] we only need to find a function \( g \) to intersect two ellipsoids for a given height \( z \). In

\[
g(r_1, r_2, z) = (x, y, z), \tag{13}
\]

\( r_1 \) and \( r_2 \) denote the range information from two illuminators. The function \( g \) transforms measurements into the Cartesian space and characterizes the dependencies of the position estimate on the height of the object. We note that the mapping \( z \) to \( z \) does not intuitively make sense, but it is necessary to get an estimate of the whole state vector including the cross terms of the corresponding covariance. In the following, we will neglect the ambiguity and discuss the estimation error only for the true point of intersection. The solutions can be determined analytically, but are too lengthy to be displayed here (we used MATHEMATICA [9] to solve the equations). In [7] two different schemes are presented, one of which is based on linearization and the other one on the Unscented Transform (UT). Here we will show results for the linearization, so we need to determine the derivatives of \( g \) with respect to \( r_1, r_2 \) and \( z \) (derivatives are again calculated with MATHEMATICA).

With

\[
R = \text{diag} \left( \sigma^2_{r_1}, \sigma^2_{r_2}, \sigma^2_z \right) \quad \text{and} \quad G = \begin{pmatrix} \frac{\partial g}{\partial r_1} & \frac{\partial g}{\partial r_2} & \frac{\partial g}{\partial z} \end{pmatrix}, \tag{14}
\]

where \( G \) denotes the \( 3 \times 3 \) Jacobian of the function \( g \), the approach can be shortened to calculating the expectation \( \hat{x} \) and covariance matrix \( \hat{P} \) of the desired estimate by

\[
\hat{x} = g(\hat{r}_1, \hat{r}_2, \mu(z))
\quad \hat{P} = \text{GRG}^T
\]

with \( \hat{r}_i = r_i + w_i \) and measurement noise \( w_i \). Sometimes the function \( g \) will not provide a valid solution. This means the two ellipses do not intersect due to measurements errors. This can happen in two geometric cases. Firstly, one of the ellipses might not exist, which means that the measured range is smaller then the distance between the observer and the sensor. Secondly, the ellipses might not intersect, since one ellipse lies inside the other (one shared focal point).

Our formulas will have imaginary square roots in these cases. Disregarding a solution implementationwise would mean waiting for the next measurements. If this is not an option, setting the square roots to zero will render an estimate. In [7] the implementation using the unscented transform sets imaginary square roots to zero, whereas the implementation using linearization sets the covariance to infinity, signaling that the estimate has to be excluded. Of course, UT uses an additional approximation that could cause inconsistency, so waiting for the next measurements seems to be the appropriate strategy here.

V. NUMERICAL RESULTS

A. Simulation Setup

This section will give detailed results for the methods derived previously. We will present Monte Carlo simulation results and evaluate the performance based on the average estimation error. More importantly, we will check the consistency of the estimates with the derived covariance matrices and see how well they can be used to determine the optimal measurement subset.

1) Average Estimation Error: The root-mean-square error of the position estimate (RMSPOS), is an absolute error measure and direct performance criteria. It is averaged over all simulation runs. The RMS error from \( N \) Monte Carlo runs for the position estimates \( \hat{x} \) and for truth \( x \) is

\[
\text{RMS}(x) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} |\hat{x}_i - x|^2} \tag{16}
\]
2) Crämer-Rao Lower Bound: Since we consider non-linear measurements and additive white Gaussian noise, \( w \), the Crämer-Rao lower bound (CRLB) can be derived in a standard way. The general calculation of the Fisher information matrix, can be replaced by a more specialized formula,
\[
    J_0 = E \{ \nabla_x \log \Lambda(x) [\nabla_x \log \Lambda(x)'] \nabla_x \log \Lambda(x) \}
\]
\[
    = \frac{\partial h}{\partial x} \text{Cov}(w)^{-1} \frac{\partial h'}{\partial x},
\]
(17)
where \( \Lambda(x) = p(z|x) \) is the likelihood function. Unfortunately, for two measurements, the matrix \( J_0 \) will usually not be invertible. This shows that we cannot estimate the full state vector \( x \) without additional assumptions. As information is additive, these additional assumptions, usually in the form of a prior distribution on \( v \), can be added to the Fisher information matrix [10],
\[
    J = J_0 + J_P
\]
where \( J_P \) is the Fisher information of the prior. Assuming a Gaussian prior on \( v \), the following form will be taken,
\[
    J_P = \begin{bmatrix}
        0 & 0 \\
        0 & P^{-1}
    \end{bmatrix}
\]
(19)
3) Consistency: Filter consistency is usually measured using the normalized (state) estimation error squared (NEES), defined as
\[
    \epsilon = \tilde{x}^T P^{-1} \tilde{x},
\]
(20)
which should be chi-square distributed with \( \eta_x \) degrees of freedom, if the filter is consistent. In Monte Carlo simulations that provide \( N \) independent samples \( \epsilon_i \), \( i = 1, \ldots, N \), the average NEES is
\[
    \bar{\epsilon} = \frac{1}{N} \sum_{i=1}^{N} \epsilon_i
\]
(21)
where now it must be tested whether \( N \bar{\epsilon} \) is chi-square distributed with \( N \eta_x \) degrees of freedom. This hypothesis is accepted, if \( N \bar{\epsilon} \) is in the appropriate acceptance region.

B. 2D Initialization from Two Measurements

We will run Monte-Carlo simulations with \( N = 10^2 \) and measurement errors of \( \sigma_r = 85 \text{m} \) and \( \sigma_v = 10 \text{m/s} \), in a plane of 40km by 40km. The observer will be at the origin, arranged with two illuminators in an equi-lateral triangle of side length \( d = 20 \text{km} \), i.e. \( x_{1,1} = (-d/2; \sqrt{3}d/2; 0)' \) and \( x_{1,2} = (d/2; \sqrt{3}d/2; 0)' \). For every considered target position the velocity is sampled according to a Gaussian distribution with zero mean and deviation \( \sigma_{x/v} = 100 \text{m/s} \) and \( \sigma_z = 10 \text{m/s} \). The target height is either fixed or modeled according to the Gaussian distribution \( \mathcal{N}(z; \mu_z, \sigma_z^2) \).

In this section we will give numerical results for 3D estimation while modeling the height via statistical assumptions. First we will look at two illuminators and calculate the Cramer Rao Lower bounds (CRLB) for a given target height of 5km, see Fig. 3(a). We notice that estimation is difficult in the regions where ellipses are likely to not intersect, due to measurement errors. For once, on the lines between illuminators and the observer the Doppler shift is zero, which is equivalent to the range-rate. Since the derivative of the observations gives no information in the Fisher sense. Second, if the illuminators and the target align, the target not in-between the illuminators, the derivatives become collinear and the Fisher matrix will not be invertible.

1) Estimation with Known Height of the Target: If the height of the target is known, estimation via the intersection of two ellipses (see Section IV) is straightforward and the CRLB is achieved. It is largely consistent, except for the regions in which the CRLB diverges, see Fig. 3(b). This is because the covariance would also have to become infinitely large.

2) 2D Estimation with Unknown Height of the Target: Let the height \( z \) now vary around its expectation according to a given Gaussian distribution \( \mathcal{N}(z; \mu_z, \sigma_z^2) \). We consider the case of \( \mu_z = 5 \text{km} \) and \( \sigma_z = 500 \text{m} \). Generally this will lead to decreased estimation accuracy, which is obvious if we consider the CRLB with \( \sigma_z = 500 \text{m} \), see Fig. 4(a). The impacts on the RMS position error will now be considered for only the \( xy \)-plane (RMSPOSXY) alone, since the error in \( z \) direction is controlled by \( \sigma_z \) only. The results can be seen in Fig. 4(b).
First, if we neglect the variation in $z$, i.e., we still assume the height to be constant at $z = 5$ km in our calculations and do not incorporate this added uncertainty in the covariance. This way the solution becomes heavily inconsistent in our simulated plane, peaking at the difficult regions, see Fig. 5(a). Accordingly we show that for non-negligible height variation, standard 2D assumptions lead to strong inconsistencies even in the $x, y$ estimates.

Now, if we employ the approach of incorporating the added uncertainty into the covariance, the estimation error does not improve, but it leads to largely consistent areas. Of course the inconsistencies around the difficult regions persist, similar to the known height case, see Fig. 5(b) and 3(b).

However, we are not only interested in position estimates, but also in an appropriate initial velocity estimate. Velocity is an important additional criterion when looking for similar estimates, see subsection III-B.1 In Fig. 6 the RMS error for the velocity estimate is shown; again, we only consider the RMS error for $\dot{x}/\dot{y}$. It can be seen in Fig. 6(a) that the estimation performance in velocity does mainly depend on the estimation performance in $x/y$. Imbedding the modeling assumptions in the algorithm again delivers largely consistent areas, c.f. Fig. 6(b).

3) Selecting the Best Initialization from Multiple Combinations: Now we consider a three-illuminator and one-observer geometry. The illuminators are arranged according to a triangle centered on the observer, $x_{s,1} = (-d/2; \sqrt{3}d/2; 0)'$, $x_{s,2} = (d/2; \sqrt{3}d/2; 0)'$ and $x_{s,3} = (0; -\sqrt{3}d/2; 0)'$. This gives three possible combinations of measurements to form an estimate. In this setup we will choose one of the estimates according to the smallest trace of the covariance matrix. Again we compare the results for the two different approaches. In Fig. 7(a), the estimation performance for considering the additional error in the covariance is shown, whereas the model used in Fig. 7(b) assumes height to be fixed. For both simulations, the height was varying with $\sigma_z = 2$ km. This time we notice a remarkable improvement in estimation performance by using the height modeling. This shows that the estimated covariance matrix is a reasonable measure for the true estimation error. In Fig. 7(b) the regions with bad estimation performance are enlarged, where non-consistent estimation was responsible for choosing the wrong combination.

4) Number of reliable initialization combinations: Obviously it does not make sense to consider estimates, whose...
estimation error is bigger than several kilometers. Therefore the algorithm disregards estimates, whose root trace of covariance is above a chosen threshold (for example 1.5km). To use clustering, we will need to pay attention to the number of estimates that would be available in a given region. In the following we will analyze a scenario, based on a real constellation of four DAB senders and one receiver in Rheinland-Pfalz, Germany. The DAB senders are marked by triangles and the observer is marked by a circle, see Fig. 8. For 100 Monte Carlo simulations, we calculate the mean number of estimates, whose trace of covariance is smaller than 1.5km. The results are shown in Fig. 8(a). The region near the observer is characterized by a low number of estimates and the number is also reduced at the line between observer and illuminator. However, in large areas we are able to generate 5 or 6 appropriate estimates. The mean RMS error of the considered estimates, Fig. 8(b), reflects this observation. We observe large areas with good estimation performance and increasing estimation errors at the transition regions.

Even more important than the maximal number of appropriate estimates is the number of probable estimates, which would be selected by Likelihood Ratio testing, see subsection III-B.1. In this last part of the section we will concentrate again on the association problem. In the scenario described above, we generate every possible combination, including wrong association and ambiguity. At the same time, we will need to consider up to 144 possible target estimates, c.f. section II-B. Next, we apply the approach, derived in subsection III-B.1 and count for the number of probable estimates which fulfill the criterion. Since the true combination is known, we will divide these estimates into those, for which the decision was the right one and for which it was not. Results for 100 Monte Carlo Runs are shown in Fig. 9. As expected, there exist regions near the receiver where finding a probable target estimate is difficult due to bad geometrical conditions, but we also note large areas in which the number of chosen estimates is greater than one, which is sufficient to start a 2D track; these areas coincide with the parts of the surveillance area in which new targets would be expected to appear. The mean number of estimates, which are pointed out erroneously, Fig. 9(b), should be manageable by MHT. So, using the presented track initialization technique, the number of combinations to be considered can be significantly reduced without substantially restricting the detection of the target.
VI. CONCLUSION

The key challenge in target tracking using DAB/DVB-T networks is the unknown association between illuminator and measurements. We demonstrated this aspect and developed a strategy to evaluate association possibilities by using Likelihood Ratio testing. For some geometrical configurations, the association is impeded by bad estimation performance. The influence of the height of the target on 2D Cartesian estimation has been discussed, and numerical results have shown that incorporating uncertainties of the height in the covariance matrix improves estimation consistency. The opportunities of the approach have been analyzed considering a real scenario.

REFERENCES


