Wide Area Multilateration using ADS-B Transponder Signals

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Abstract—In this paper, a method for precise tracking of aircrafts based on Time of Arrival (TOA) determination of transponder signals is presented. Target location via multilateration based on Time Difference of Arrival (TDOA) measurements is a well known powerful method. In recent time, methods of target location using direct TOA measurement processing without the indirection of generating TDOA measurements have been derived. The key to the TOA tracking is the usage of an extended target state containing the time of transmission (TOT) and an application of nonlinear estimation methods for the estimation of the system state including TOT. Field experiments investigate the performance of the TOA localization compared to the TDOA localization where the fusion of both algorithms shows the best results. A key benefit of the TOA processing is that a system is constructed with very low communication bandwidth requirements in the sensor network.

Keywords: TOA, TDOA, multilateration, localization, tracking, Extended Kalman Filter, sensor networks.

I. INTRODUCTION

State of the art multilateration systems require high bandwidth communication lines for the correlation of signals from two dislocated sensors. Furthermore, the local clocks of the two sensors must be synchronized with a very high precision. As soon as the signal structure is known, which is the case in cooperative scenarios, Time of Arrival (TOA) based systems are possible. The advantage of TOA based systems is that there is no longer a need to transfer raw signal data for correlation purpose. It is sufficient to communicate the TOA and the information content of the signal.

For precise target state estimation, a system must be able to locate a target with a single set of TOA measurements, to track a target with a time sequence of measurements and to eliminate systematic errors using a full set of measurements. Three-dimensional target location requires at least four TOA measurements. Knowing or estimating the unknown Time of Transmission (TOT) of the signal, a single TOA measurement describes a sphere on which the emitter is located. For two-dimensional localization, circles are obtained. Fig. 1 illustrates wide area multilateration in a plane using TOA measurements. Using a fixed reference sensor, four TOA measurements can be used to calculate three Time Difference of Arrival (TDOA) measurements. TDOA measurements define hyperboloids of possible emitter positions with the two associated sensors as foci. If sensors and emitter lie in the same plane, possible emitter positions are characterized by a hyperbola. Localization can be performed by intersecting these hyperbolic curves. Therefore, TDOA localization is called hyperbolic positioning. Localization based on TOA and TDOA measurements are multilateration methods. In this paper, the TDOA localization is defined as the basic multilateration method.

An overview of passive localization systems using TDOA measurements can be found in [10] and [11]. Different aspects are considered in [4], [7], [8]. The two different multilateration algorithms are compared in [6] where an error characteristic is performed. For a cooperative scenario, it is shown that the error bounds of TDOA and TOA localization are equal while the TOA localization shows better performance. In [3], [2], for air traffic surveillance, the superiority of multilateration based on TOA is demonstrated compared to the basic multilateration method.

The contribution of this paper is to show the benefits of
TOA localization compared to TDOA localization performing field experiments in air traffic control and using experimental data. The experimental setup investigates a scenario with a distributed sensor network on the ground. The aim is to localize and track multiple air targets which send Automatic Dependent Surveillance-Broadcast (ADS-B) messages. In [1], a method was introduced that allows direct message decoding and the calculation of a TOA measurement, a timestamp, for each ADS-B message at a single sensor node. This paper is an extension to [1]. For wide area surveillance, using a network with four sensors, TOAs at single sensors are determined. In a second step, target localization is performed based on TDOA and on TOA processing. Additionally, TOA tracking is presented using an iterated extended Kalman filter (EKF) and investigated for simulated and experimental measurements.

The rest of the paper is organized as follows: in Section II, the determination of TOAs at a single sensor node using ADS-B transponder signals is presented according to [1]. Section III describes the measurement setup of field trials. Experimental results are described in detail in Section IV where a comparison of localization based on TOA and on TDOA measurements is performed. In the following Section V, tracking using TOA measurements is outlined and performed for simulated measurements and experimental data. Concluding remarks are given in Section VI.

II. TOA DETERMINATION

The structure of the ADS-B messages is used to determine an exact TOA measurement for each received ADS-B message at a single sensor node. Messages from ADS-B transponders are transmitted at 1090 MHz using pulse position modulation (PPM). Each message starts with a preamble consisting of four pulses at well defined times, see Fig. 2. Over the interval $[0; 8 \mu s]$ the ideal preamble can be described \(^1\) by

$$p(t) = 2 \left[ \text{rect} \left( \frac{t - T_0}{M} \right) + \text{rect} \left( \frac{t - T_1}{M} \right) + \text{rect} \left( \frac{t - T_2}{M} \right) + \text{rect} \left( \frac{t - T_3}{M} \right) \right] - 1 \quad (1)$$

with $M = 0.5 \mu s$, $T_0 = 0.25 \mu s$, $T_1 = 1.25 \mu s$, $T_2 = 3.75 \mu s$, $T_3 = 4.75 \mu s$, where $M$ is the pulse duration and the $T_i$, $i = 0, \ldots, 3$, are the displacements of the pulse in $t$-direction.

By correlating the simulated preamble with the signal, the time of the start of the preamble can be found. The discrete correlation function $r(n)$ for the correlation of the signal with the preamble is defined as

$$r(n) = \sum_{m=-\infty}^{\infty} s(m)p(n + m). \quad (2)$$

The maximum of the correlation function yields the sample number where the preamble begins. The time $T$ of the first edge of the message is then given by

$$T = \frac{\arg \max_n r(n)}{f_s} + 8 \mu s. \quad (3)$$

This time $T$ gives an approximate value of the TOA estimate. The next subsection II-B describes the synchronization of the ADS-B message using a simulated clock to obtain more precise TOA measurements.

B. Timestamp generation

Alignment of a synchronization clock with the beginning of the message is essential to get an accurate TOA measurement and to decode the message. Therefore, the message is shifted samplewise over a simulated 1 Mbit/s synchronization clock. The signal only needs to be shifted by a small number of

\(^{1}\)For the definition of the rect function see [5].
samples to identify the exact start of the message (much less than a bit). After each shift, the absolute values of the
derivative of the signal power during positive clock cycles are
summed up. The maximum of these sums gives the
optimal envelope of falling and rising edges in positive clock
cycles. It characterizes the best alignment of message and
clock and yields the sample shift for synchronization.
The synchronization procedure is illustrated in Fig. 3 where the
clock is represented by a black line, the recorded signal power
is shown in blue and its derivative in red. Let $n_{\text{shift}}$ denote
the sample shift. The TOA of the message is then defined by

$$\text{TOA} = T + \frac{n_{\text{shift}}}{f_s}. \quad (4)$$

Using the decoded message content and the included ICAO ad-
dress of the aircraft, TOA measurements of the same message
at different sensors can be identified. Therefore, no association
problem occurs and associated TOA measurements can be
determined.

### III. Field Experiments

A distributed sensor network consisting of four station-
ary sensor nodes was deployed in the south west of Bonn,
Germany. Each sensor node is equipped with one broadband
receiving antenna (20 MHz - 3 GHz), one Agilent N6841A
RF sensor, a GPS antenna and a laptop for data processing.
The position determination of the sensor node and the time
synchronization is done by the sensor using GPS.

ADS-B messages are received at 1090 MHz center fre-
quency at a sample rate of 10 MHz, thus giving a time of
100 ns between two consecutive samples. Using the methods
described in Section II, at each sensor node, the messages are
decoded and corresponding TOAs are determined with high
accuracy (see [1] for details). The included ICAO address
is used for identification and association. Due to hardware
restrictions, only 1 second of data is recorded every 20
seconds.

The decoded messages (112 bit per message) and their
TOAs are transmitted to a fusion center for localization and
tracking. For the transmission of this small amount of data, a
broadband communication channel is not required.

### IV. Localization

In multilateration scenarios, nonlinear measurements are
taken. Therefore, nonlinear estimation methods must be ap-
plied to estimate the emitter state. Suitable are nonlinear meth-
ods like the Maximum Likelihood (ML) estimator, nonlinear
forms of the Kalman Filter or closed form formulations. For
TOA localization, additionally the time of transmission has to
be estimated.

#### A. TOA Localization

Let $p = (x, y, z)^T \in \mathbb{R}^3$ be the emitter position, $p_i =
(x^{(i)}, y^{(i)}, z^{(i)})^T \in \mathbb{R}^3$, $i = 1, \ldots, 4$, the sensor positions, $\tau$
the unknown time of transmission (TOT) and $c$ the speed of
light, then the TOA measurements are defined by:

$$t_i = \tau + \frac{||p - p_i||}{c}, \quad i = 1, \ldots, 4, \quad (5)$$

where $||*||$ denotes the Euclidean distance. $r_i = ||p - p_i||$, $i = 1, \ldots, 4$ are the distances between emitter and sensor $i$, $h_i = t_i$ describes the measurement function for gaining TOA
measurements. The measurement function does not depend
on the emitter velocity. Therefore, the velocity vector $v =
(\dot{x}, \dot{y}, \dot{z})^T \in \mathbb{R}^3$ only influences the measurement function via
the dynamic model.

Fig. 1 shows a typical TOA scenario for wide area surveil-
lance. For better visibility, a two-dimensional scenario is
illustrated, where sensors and emitter lie in the same plane.
A single TOA measurement describes a spheric curve of possible
emitter positions, circles in two, spheres in three dimensions.
Circles intersect in the area of the true emitter position.

Under the assumption of additionally white Gaussian measure-
ment noise uncorrelated from each other and from time
step to time step, the measurement equation is modeled by:

$$z_i = t_i + v_i, \quad v_i \sim \mathcal{N}(0, \sigma_i^2), \quad i = 1, \ldots, 4, \quad (6)$$

$v_i$ is the measurement noise at a single sensor with standard
deivation $\sigma_i$. $z = (z_1, z_2, z_3, z_4)$ is the TOA measurement
vector of a single emitter at one time step.

Now the Likelihood function can be formulated. The ML
estimate for the extended target state $p^+ = (\tau, x, y, z)^T \in \mathbb{R}^4$
follows as:

$$\hat{p}^+ = \arg \min_{p^+} \sum_{i=1}^4 \frac{(z_i - t_i)^2}{\sigma_i^2}. \quad (7)$$

The ML estimator is implemented according to the simplex
method due to Nelder and Mead, [12]. This optimization
algorithm requires a starting point for initialization. The result
of a closed form algorithm for TDOA localization, see subsection
IV-B, gives the initialization point $p_{\text{init}}$ for the simplex
method. Additionally, the initial time of transmission $\tau_{\text{init}}$ is
computed using the TOA of sensor 1:

$$\tau_{\text{init}} = t_1 - \frac{||p_{\text{init}} - p_1||}{c}. \quad (8)$$

#### B. TDOA Localization

Calculating the difference between two TOAs eliminates the
unknown time of emission and yields the TDOA measure-
ments. The full measurement set is defined by:

$$t_{ij} = t_i - t_j = \frac{||p - p_i||}{c} - \frac{||p - p_j||}{c}, \quad (9)$$

where $h_{ij} = t_{ij}$ is the measurement equation.

The measurement equation is modeled under the assumption
of white Gaussian measurement noise:

$$z_{ij} = t_{ij} + v_{ij}, \quad v_{ij} \sim \mathcal{N}(0, \sigma_i^2 + \sigma_j^2), \quad (10)$$
the measurement noise \( v_{ij} = v_i + v_j \) is composed of the noises at the two associated sensors and has the covariance \( \sigma_i^2 + \sigma_j^2 \), due to the fact that sensors are uncorrelated from each other.

A TDOA scenario for wide area surveillance using the full measurement set is depicted in Fig. 4. TDOA measurements localize the emitter on hyperbolic curves with the two associated sensors as foci. If emitter and sensors lie in the same plane, the emitter location is found by intersecting hyperbolae.

According to [9], closed form formulations for TDOA localization with a minimum of four sensors exist. Using the algorithm described in [9], a common reference sensor must be used. Without loss of generality, let sensor 1 be the reference sensor to obtain the TDOA measurement set \( (z_{12}, z_{13}, z_{14}) \). The closed form algorithm additionally has to estimate \( r_1 = ct_1 \), the distance of the emitter to the reference sensor, sensor 1. Therefore, only a two-dimensional position estimate can be obtained with a set of four sensors resulting in three TDOA measurements. This is a characteristic feature of the closed form algorithm, where an extended parameter vector, in this case \( (x, y, r_1)^T \), is to be calculated. The obtained position estimate is processed in a ML estimator to receive two- and three-dimensional position results. For three-dimensional computation, the two-dimensional closed form result is extended by a height coordinate. Prior knowledge on the emitters, which are aircrafts, can be used to find the three-dimensional initialization point \( p_{\text{init}} \) by setting the initial z coordinate to 10 km.

For the sake of simplicity and due to the fact that the full covariance matrix is not invertible, the ML estimate for the full TDOA measurement vector \( z_{\text{TDOA}} = (z_{12}, z_{13}, z_{14}, z_{23}, z_{24}, z_{34}) \) is implemented as least squares algorithm where the covariance is neglected:

\[
\hat{p} = \arg \min_p \sum_{i=1}^3 \sum_{j=i+1}^4 (z_{ij} - t_{ij})^2.
\] (11)

As in TOA localization, the simplex method gives the localization result.

C. Results

In field trials, TOA measurements are gained using the stationary network of four sensors with distances of 8 km to 13 km. In an area of about 100 km to 80 km, aircrafts are localized by exploiting ADS-B transponder signals. The signals of different aircrafts are obtained, a total of 1375 measurement vectors are determined. For these measurement vectors TOA and TDOA localization is performed as described in subsections IV-A and IV-B. Sensor positions are given in WGS-84 coordinates. For localization, sensor positions are transformed into an ENU coordinate system with sensor 1 in the origin. In this Cartesian coordinate system, the localization process is performed, reverse transformation into GPS coordinates gives the localization results.

ADS-B messages can contain position information in the message field: two-dimensional position and height information as altitude in feet, but it does not contain information about the TOT. If the message contains position and height information, this information is taken as ground truth. Not every message contains position information, therefore not every location result can be verified. About half of the decoded messages (608 messages) contain position information. Position errors are computed in two and three dimensions for single emitters. Errors are averaged over the number of measurements and computed as 2D-error (xy), 3D-error (xyz) and for single coordinate in z direction, the altitude. For

<table>
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<td>2.497</td>
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<td>xyz mean error [km]</td>
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<td>2.728</td>
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<td>z mean error [km]</td>
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TABLE I
Comparison of TDOA and TOA localization error
evaluation of TOA localization, the estimate of $\tau$ is neglected. The TOT is not available as part of the ADS-B message. Therefore, no true TOT for verifying the estimated results is known. Outliers of computation are discarded using knowledge on the coverage of sensors. The maximal coverage of receiving ADS-B signals is at about 250 to 400 km. Position results in larger distances to the sensors are deleted. The percentage of outliers is only in the range of 0.3 % to 1.3 % dependent on the choice of estimation algorithm. Fig. 5 shows the three-dimensional results for TOA processing. Sensor positions are marked with orange circles. For several airplanes, ground truth positions are illustrated as white circles. Estimated position results are indicated as colored crosses. Different airplanes are marked using different colors. The results for the whole scenario are given in Table I. Mean errors of localization are presented for TDOA and TOA localization and a fusion of TDOA and TOA localization.

Using the result of the closed-form algorithm as initialization point, the TDOA localization shows slightly better results as the TOA localization. Both results are comparable, the fusion of the TDOA and TOA ML gives the best results. Here, the two-dimensional result of the TDOA ML estimator is used as initialization point for the TOA ML estimate. The result of the fused ML estimator is superior to the single methods.

V. TRACKING USING TOA MEASUREMENTS

A method is presented which directly tracks targets based on TOA measurements from distributed sensors. Like in TOA localization, an extended target state additionally comprising the time of signal transmission is used. The estimation of the unpredictable time of transmission is accomplished iteratively using an EKF. In Subsection V-A, the tracking algorithm is described in detail, the tracking results are analyzed in Subsection V-B.

A. Description of the tracking method

Tracking comprises track initiation and track continuation. Target location based on TOA sensor data is used for track initiation.

The quality of an estimated target location vector $\hat{p}$ is given by the deviation sum $D$ (which is the variance of the TOT):

$$D = \sum_{i=1}^{n} \frac{(\tau(\hat{p}) - \tau_i)^2}{n}.$$  \hspace{1cm} (12)

It is computed from the transmission times $\tau_i$ according to the observed TOA measurements $t_i$ at each sensor $i$:

$$\tau_i = t_i - \frac{||\hat{p} - p_i||}{c}$$  \hspace{1cm} (13)

and from the mean TOT $\tau(\hat{p})$ resulting from all $n$ sensors:

$$\tau(\hat{p}) = \frac{\sum_{i=1}^{n} \tau_i}{n}.$$  \hspace{1cm} (14)

The analytical solution of equation

$$||p - p_i||^2 = c^2(\tau - t_i)^2$$  \hspace{1cm} (15)

described in [3] is used to derive a first solution $p^{(1)}$ for the target location. The analytical method comprises the solution of a quadratic equation and therefore two solutions may be possible. Plausibility criteria like expected target height or distance from the sensor can be applied to select the most appropriate solution [3]. An additional way to a solution is nonlinear optimization according to Nelder and Mead minimizing the deviation sum $D$. The optimization result is an alternative solution $p^{(2)}$. Finally, the solution with the smallest deviation sum is selected.

A very positive aspect is that the numerical properties of the analytical- and the optimization method seem to be kind of complementary. In geometrical regions, where the analytical method tends to instability, the optimization method often is more stable and vice versa. For the wide area sensor configuration displayed in Fig. 6 (a) using orange circles, the accuracy of the analytical (Fig. 6 (a)), the numerical (Fig. 6 (b)), and the combined target location method (Fig. 6 (c)) are compared. The color bar indicates the transition from green high accuracy areas to violet or dark gray areas of low accuracy in the vicinity of sensors.

Compared to the numerical method, the analytical method, displayed in the second square, shows larger weak areas as the numerical method. The combined method presented in the right square clearly shows smaller weak areas as both single methods. But even the combined method is not free from artifacts, small weak areas within areas of high accuracies. These artifacts occur in regions with low observability, where the solutions are very sensitive to the random noise in the TOA measurements.

The Kalman Filter equations comprising models for target movement, for the measurement geometry, the sensor noise and the system noise are quite straightforward. Because Kalman Filter technology is well known, the focus is on the specialities without repeating the Kalman Filter equations here.

The target state comprises the position $p$, the velocity $v$, and the transmission time $\tau$. The Jacobian $H$ with the derivatives of the measured values with respect to the variables of the extended position state $p^+ = (\tau, x, y, z)^T$ has the following structure (the velocity entries of the full $H$ matrix are zero):

$$H_{p^+}(k|k-1) = \begin{bmatrix} \frac{\partial \tau_i(p^+)}{\partial p} \\ \frac{\partial \tau_i(p^+)}{\partial v} \\ \frac{\partial \tau_i(p^+)}{\partial p} \\ \frac{\partial \tau_i(p^+)}{\partial v} \end{bmatrix} \hspace{1cm} (\tau, x, y, z)^T = p^+(k|k-1)$$
\[
\begin{bmatrix}
\frac{\partial t_1(p^+)}{\partial t} & \frac{\partial t_1(p^+)}{\partial x} & \frac{\partial t_1(p^+)}{\partial y} & \frac{\partial t_1(p^+)}{\partial z} \\
\frac{\partial t_2(p^+)}{\partial t} & \frac{\partial t_2(p^+)}{\partial x} & \frac{\partial t_2(p^+)}{\partial y} & \frac{\partial t_2(p^+)}{\partial z} \\
\frac{\partial t_3(p^+)}{\partial t} & \frac{\partial t_3(p^+)}{\partial x} & \frac{\partial t_3(p^+)}{\partial y} & \frac{\partial t_3(p^+)}{\partial z} \\
\frac{\partial t_4(p^+)}{\partial t} & \frac{\partial t_4(p^+)}{\partial x} & \frac{\partial t_4(p^+)}{\partial y} & \frac{\partial t_4(p^+)}{\partial z}
\end{bmatrix}
\]

\[p^+ = p(k|k-1)\]

t_a, i = 1,\ldots,4, is the distance between the predicted or estimated position and the sensor i. The value 1 of the first component of the Jacobian does not play any role for track update. But for the covariance update it is essential.

The special problem with the transmission time \(\tau\) is that it cannot be predicted. As soon as at least four TOA measurements are available the transmission time can be calculated. In terms of filter techniques, this means that the transmission time cannot be derived by an estimation process with a specified gain. Instead the problem is solved by an iterative target state update, see Fig. 7, with re-estimation of the transmission time.

As shown in the EKF diagram the transmission time \(\tau\) is the mean time value resulting from the predicted or estimated target position and the TOAs at each sensor position.

The iteration for the position update \(p(++)\) together with the time of transmission update starts using the first Jacobian (16) to calculate the Kalman gain \(K(+)\) resulting from the predicted position \(p(k|k-1)\). The estimated position is used to recalculate the Jacobian, the TOT and the expected TOA measurement vector \(h(p(\cdot))\). The iteration converges rather quickly, but it is only applicable to the position. For a complete update of the state vector and the covariance, only one update cycle is used. In this update cycle, the gain matrix \(K(+)\) and the predicted TOA times \(h(p(\cdot)) = (h_1(p(\cdot)), h_2(p(\cdot)), h_3(p(\cdot)), h_4(p(\cdot)))^T\) derived in the iteration are applied. This step is based on the original predicted state \(x(k|k-1)\) and the covariance \(P(k|k-1)\).

As a summary, the differences of the TOA Kalman Filter and a normal EKF approach comprise an additional first component equal to 1 in the Jacobian (16) corresponding to the transmission time \(\tau\) and an iterative calculation of the position estimate, see Fig. 7. The additional component in the Jacobian only has an effect on the covariance update. A covariance update without this component leads to a significantly modified track covariance and to a reduced tracking performance.

B. Tracking results

Tracking results using the method described in Subsection V-A are obtained based on simulated and real measurements from a network of four sensors. Simulation results are based on one Monte Carlo run. Fig. 8 shows the result of a tracking accuracy analysis for wide area multiaturation with simulated TOA data. The sensor positions of the four sensors are illustrated with orange circles. The scenario comprises a regular horizontal pattern and analyzes a vertical maneuver. Simulations are realized to demonstrate the possibility of tracking vertical maneuvers of targets in the whole observation area. In the xy plane, 40 targets move in parallel at a constant horizontal speed of 540 knots (278 m/s). They perform maneuvers in the direction of the altitude. The flight paths begin with a level flight, then climb or descend with a constant rate, and continue with a level flight again. During the level flights, the vertical speed is zero, the vertical speed of climbing and descending flights is 10 m/s. TOA measurements are generated by adding white Gaussian noise with standard deviation of 25 ns. The true trajectories of targets are displayed as blue diamonds. Estimated target trajectories are illustrated in different colors. For the whole scenario, a horizontal mean error of 43 m is achieved.

Fig. 9 shows the result for the scenario from Fig. 8 in the vertical view, the results for the altitude plotted against the longitude. The blue diamonds again visualize the true trajectories which demonstrate two vertical maneuvers of targets: a level phase followed by a climbing or descending flight and finally a level phase. Tracking results are displayed in different colors. Vertically a mean error of 320 m can be
achieved.

Fig. 10 shows the tracking result for the same sensor configuration as in Fig. 8 for a maneuvering target scenario concerning the horizontal plane. The diamonds again visualize the true target trajectory. Estimated target positions are illustrated using short lines. The start points of the lines give the position results, the directions of the lines symbolize the estimated target velocities. The mean horizontal position error is 36 m. (Vertically an error of 326 m could be achieved.)

Corresponding to the field trials, two sensor configurations are analyzed based on simulated measurements to get an overview on the expected accuracies in the field experiments. For the sensor configuration in the field experiments, see Section III and Fig. 1 (sensor positions are orange circles), simulations are performed analyzing targets with uniform motion. Additionally, measurements are generated for a more widespread sensor configuration using five sensors. For this configuration, the expected information gain is very high. Per time step, one additional TOA measurement from sensor 5 is obtained. Moreover, a large part of the observation area is in the inner area of the sensor configuration, where the expected accuracy is very high. For both sensor configurations, initialization results according to the initialization procedure depicted in Subsection V-A are computed for several targets moving in parallel.

Fig. 11 (a) shows the simulation results for the sensor configuration of the field trials where areas of poorer performance occur. The lines connect the localization results for one target in one Monte Carlo run. The resulting mean error is 846 m (horizontally) and 891 m vertically (target height = 10 km). With the more widespread configuration of 5 sensors, Fig. 11 (b), significantly smaller mean error values of 11 m (horizontal) and 21 m (vertical) are achieved. The results show that the sensor locations and the number of sensors have an essential influence on the achievable system performance.

Fig. 12 shows the tracking results for the experimental measurements obtained from the field experiments described in Section III. The diamonds correspond to the ADS-B transponder reports of the targets, which have been used to determine the accuracy. Tracking results for different aircrafts are displayed in different colors corresponding to the colors of ADS-B positions. For tracking, a TOA accuracy of 50 ns has been assumed. The algorithm exploits all decoded ADS-B messages, not only messages containing position information like in Subsection IV-C. Tracking results are only performed
for targets of which at least 6 TOA measurement vectors are obtained over time. Additionally, only those targets are taken into account where results are fused over time. A total of 52 aircrafts are tracked. The evaluation result for the tracking is obtained by comparison with 354 transmitted position messages. The horizontal mean error is 925 m, which is in the expected range for this sensor configuration. Compared to the localization results in Subsection IV-C, the performance of the tracking is better. The reason is that for localization only one time step is used for each localization result. Tracking over time leads to an enhancement of performance. Furthermore, a larger number of targets is considered in localization inducing poorer localization performance.

Fig. 13 shows a vertical view (altitude view) of the tracking results. The achieved mean error is with 1084 m again in the expected range.

The life data tracking results show that the TOA tracking method is applicable to experimental data. Its performance attains the expected accuracy supported by simulated measurements.

VI. CONCLUSIONS

In field experiments, aircrafts are localized using ADS-B transponder signals. A method is presented which is appropriate to directly localize and track targets based on TOA measurements from a distributed sensor network. TOA measurements are determined at single sensor nodes which implies low communication requirements and a distributed data processing. The localization is realized based on TOA and on TDOA measurements using a ML estimator. For TOA localization, an extended target state additionally comprising the time of signal transmission is used. Furthermore, a Kalman filter based TOA tracking is performed where the estimation of the unpredictable time of transmission is accomplished iteratively. This tracking method is verified with simulated and recorded live data from four sensors.

The tracking results show that the method is appropriate to track target movement within a plane parallel to the sensor plane with very high accuracy. Movement perpendicular to the sensor plane can be tracked with limited accuracy.

The technically important aspect of this solution is that a high tracking accuracy and a high reliability can be achieved with a network of low cost sensors.

REFERENCES