# Robust Indoor Localization with ADS-B

Alexander Canals
canalsa@ethz.ch
ETH Zurich
Switzerland

Pascal Josephy
pjosephy@ethz.ch
ETH Zurich
Switzerland

Simon Tanner
simtanner@ethz.ch
ETH Zurich
Switzerland

Roger Wattenhofer
wattenhofer@ethz.ch
ETH Zurich
Switzerland

## ABSTRACT

Similar to satellite-based localization systems, messages sent by aircraft with the ADS-B protocol can be used to estimate the location of a mobile receiver. However, for a robust localization using a least-squares approach, ADS-B messages have to be collected over a long time. We propose a localization method based on matching the received signal with known ADS-B messages from distributed receivers. Our proposed method only requires three seconds of recording. Compared to satellite-based localization methods, this approach also works indoors as the signals sent by aircraft are much stronger.

## CCS CONCEPTS

• **Information systems → Global positioning systems**; **Mobile information processing systems**.

## KEYWORDS

ADS-B, air traffic control, indoor localization, multilateration, software-defined radio

**ACM Reference Format:**
Alexander Canals, Pascal Josephy, Simon Tanner, and Roger Wattenhofer. 2022. Robust Indoor Localization with ADS-B. In *The 27th Annual International Conference on Mobile Computing and Networking (ACM MobiCom '21), January 31-February 4, 2022, New Orleans, LA, USA.* ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/3447993.3483257

## 1 INTRODUCTION

Many applications rely on accurate indoor and outdoor localization. Satellite-based localization methods such as GPS are great for outdoor localization. These methods are based on determining the exact arrival times of signals from the navigation satellites and solving a system of equations to determine the local time and position.

In difficult reception conditions however, such as in buildings or in urban environments, the satellites are not visible or the signals are heavily affected by multipath propagation. This makes the estimation of the arrival times and therefore also localization inaccurate or even impossible in some situations.

In urban environments other already existing radio signals can be used as addition or replacement of satellite-based localization. Previously signals transmitted by aircraft in the ADS-B protocol have been proposed [9]. Since they are transmitted by aircraft that are much closer than navigation satellites, the received signal strength is much higher. However for accurate localization, collecting sufficiently many ADS-B messages from different aircraft can take long, especially indoors. As the signal strength gets lower and the environment suffers from more multipath components, many ADS-B messages cannot be correctly decoded indoors.

We present a novel localization method based on these ADS-B signals. We can accurately localize a mobile receiver with only three seconds of signals from a software-defined radio (SDR). The location is determined by comparing the received signal to a reconstructed signal for different positions based on known ADS-B messages. The method then finds the location where the received signal and the reconstructed one match best. The receiver therefore does not have to be able to correctly decode the messages sent by the aircraft. This makes the localization resilient against interference and low signal strength. Additionally, the method is robust against outliers originating from multipath propagation or incorrect ADS-B messages. Our evaluation shows that the localization even works far inside building in rooms without windows.

In contrast to satellite navigation systems, we do not know the trajectory of the aircraft in advance and also the transmit times of messages is not known. To be able to use ADS-B messages for localization, a network of distributed reference stations based on SDRs collects the sent messages and calculates the transmit times of messages at the aircraft. We have implemented ways to deal with inaccurate positions reported by aircraft and erroneous behavior of transmitters of some aircraft.

We demonstrate the performance of our localization system using a smartphone as the mobile receiver. As smartphones do not contain a software-defined radio, we connect a cheap off-the-shelf RTL-SDR receiver to the USB port of the Android smartphone.

While the proposed method is not accurate enough for precise indoor navigation, obtaining a rough position estimate indoors is useful in many situations. For many mobile applications, reliably and quickly obtaining a position is necessary. For example when

The authors of this paper are alphabetically ordered.


*ACM MobiCom '21, January 31-February 4, 2022, New Orleans, LA, USA*

ACM ISBN 978-1-4503-8342-4/22/01…$15.00
https://doi.org/10.1145/3447993.3483257

checking the public transport timetable, when calculating the best route, or to find the nearest shop. Additionally, the method could also help in positioning of first responders in disaster situations where other rough localization methods based on infrastructure such as WiFi or cellular antennas might not be available anymore.

## 2 RELATED WORK

Positioning and indoor positioning in particular are very active research areas. The proposed methods mostly differ in the achievable accuracy, the different environments where they work, and the necessary hardware.

Proximity-based localization methods observe whether a certain signal is present. The accuracy is therefore determined by the reception area. For example, radio frequency identification (RFID) or cellular radio signals can be used [13]. To allow accurate localization, a dense grid of transmitters with known locations is necessary. Our method in contrast uses messages from aircraft that can be received over hundreds of kilometers. No hardware needs to be placed close to the device that performs the localization.

In fingerprinting, a radio signal is used to calculate a fingerprint for every possible position, e.g. everywhere in a building. Often the received signal strength indicator (RSSI) or the channel state information (CSI) is used. A mobile device then calculates the fingerprint and looks up the best matching position. Such methods have been developed using Wi-Fi [3], Bluetooth [10] or even FM-radio [7]. While fingerprinting techniques can achieve a localization accuracy of a few meters, they need much preparation effort for building the database containing the fingerprints for later lookup. Although there are approaches to crowd-source the fingerprints [23], we can consider the fingerprinting method to not be practical for large areas. For ADS-B signals fingerprinting is not possible as the aircraft are always at different locations and therefore the received signal changes significantly over time. Our proposed localization method does not need a database of data collected at each location. However, we need a system of reference stations that observe the sent messages.

Signal attenuation-based methods calculate the position based on the received signal strength. These methods try to estimate the position based on the path loss. However in indoor environments, this can be difficult [13].

Many localization systems build on measuring the arrival times of signals at the mobile receiver for time of arrival (ToA) or time difference of arrival (TDoA) localization. Multiple global navigation satellite systems (GNSS) exist, developed and operated by different countries; GPS, GLONASS, BeiDou and Galileo. The basic principle however for them is very similar. Modern GNSS receivers, such as in smartphones, are often able to receive signals from multiple GNSS. While more and more satellites are available and can be combined for a more accurate position, the signals can be hardly received in buildings.

For accurate indoor localization, often dedicated hardware is needed. Systems based on ultrawideband (UWB) radio signals are able to distinguish individual multipath components for ToA or TDoA measurements because of their wide bandwidth. Ubisense, BeSpoon and DecaWave achieve median accuracies of better than one meter [16]. While these systems achieve a higher accuracy than our localization based on ADS-B signals, they need dedicated beacons installed in the building.

Most WiFi-based localization methods use signal strength measurements. Li et al. [12] however have proposed a TDoA-based system that uses passive sniffers at known locations to observe the WiFi signals and localize a device with an accuracy of 1.5 m. The idea of having passive receivers that observe the signal is similar to our system of distributed reference stations that observe the messages sent by the aircraft. However, for our method the reference stations do not need to be placed close the the location of the mobile device.

Signals transmitted in the digital television standard DVB-T have also been proposed to be used for localization systems based on arrival times [11]. To allow localization using DVB-T, enough transmitters must be available and the transmitters need to be correctly identified [6]. While these systems seem promising, only simulation results of the achievable localization accuracy exist.

ADS-B signals have also been previously used for localization of a mobile receiver [9]. Using the message arrival times, multilateration is performed, similar to GPS. However to allow accurate localization, messages need to recorded for a long time. As we show in our results, we achieve a better localization accuracy for short recordings of three seconds with our method of matching the received signals with the known ADS-B messages. Especially indoors, our proposed method is able to compute a location more often than using multilateration with ADS-B. Additionally, our method is also more robust to multipath propagation as all paths will be considered and not only the strongest which could introduce a large offset in a least-squares estimation.

Our proposed method estimates the position of the receiver for all messages from aircraft combined, instead of estimating the arrival times of the messages independently. This idea has previously been proposed for GPS to estimate the location where the arrival times and Doppler shifts match best with the expected values [8]. Optimizations have been proposed to increase the speed of the position search. However, localization indoors is rarely possible using GPS signals [4].

Since ADS-B messages are not encrypted or cryptographically signed, many approaches are proposed to verify the identity of the sender and its location. This can be achieved by observing characteristics of the physical signal [14] or message patterns [18]. A different approach is to use multilateration using multiple receivers on the ground [15]. In contrast to the localization of a mobile receiver as in our work where we receive messages from multiple aircraft to calculate the location of the receiver, these systems use multiple receivers to verify the origin of a message.

Data transmitted by aircraft is also interesting to the public. Platforms such as Flightradar24 and FlightAware provide a global air traffic overview. Other platforms such as the OpenSky Network mainly focus on collecting data for research projects. These platforms collect their data using many distributed receivers operated by volunteers.

Currently, we operate our own network of distributed receivers as this allows us to modify the code running on the receivers and we have access to all the raw data and can implement our own synchronization to optimize the localization performance. In the future, a collaboration with one of these global communities would allow us to increase the range and accuracy of our positioning system.

Crowd-sourced ADS-B data has been recently used for many interesting applications. Aircraft transmissions have been used to estimate meteorological information such as temperature, air pressure, wind speed [22]. It has also been showed that such aircraft data can be used to monitor government and military aircraft movements and may leak information about meetings and relationships between countries [19].

## 3 BACKGROUND

Automatic Dependent Surveillance - Broadcast (ADS-B) is used by aircraft to automatically broadcast their position and other information for air traffic surveillance. It originates from the Mode S secondary surveillance radar technique that selectively interrogates aircraft. The messages can be received by ground stations for air traffic control, but also directly by other aircraft.

ADS-B is not a continuous signal, but rather the aircraft periodically send short messages. Depending on the ADS-B version and aircraft equipment, different message types are sent over ADS-B, such as position, velocity or identification messages. The interval between messages is varied randomly to prevent continuous message collisions of different aircraft. For example messages reporting the position of the aircraft are broadcast every 0.4 s to 0.6 s. Each message has a length of 112 bits which are encoded using Pulse Position Modulation (PPM). A symbol has a duration of 1 µs where a pulse in the first half of the symbol signals a 1-bit and a pulse in the second half a 0-bit. To help with the detection of the messages, a fixed preamble of 8 µs is sent before the message bits. This results in a total length of 120 µs per message. These short bursts are sent on 1090 MHz.

The 112 message bits consist of multiple parts. The first 5 bits are the *downlink format (DF)* which is 17 for all ADS-B messages. The following 3 bits are for *capability (CA)*. The next 24 bits are for the unique aircraft identifier called *ICAO address*. Using this identifier, messages from the same aircraft can be detected. The 56 bit data field contains the payload data, such as the position, altitude, velocity, etc. At the end of the ADS-B message 24 parity bits for a cyclic redundancy check (CRC) are included.

Since ADS-B does not support any encryption, the messages can easily be detected and decoded using a software-defined radio (SDR). For our localization system especially the messages containing the position of the aircraft are relevant. As each ADS-B message can only contain 56 bits of payload data, the position is encoded using a CPR (compact position reporting) format [20]. CPR encoding allows to transmit more accurate positions in the limited message size but requires to have two messages in order to decode a globally unambiguous position. One message per CPR format type (*even* and *odd*) is required. These two types of messages are broadcast in alternating order by the aircraft.

## 4 METHOD

We present a novel approach for localization using ADS-B signals. The idea of this method is to compare the received signal with the reconstructed signal for different positions. Essentially, we construct a matched filter for every possible position. The true receiver position should exhibit the highest correlation among all possible positions. So, for every possible position we calculate how likely it is that we see the received signal. The main advantage of our proposed method is that it works without decoding the messages on the mobile receiver. This enables localizing the mobile receiver in conditions where the received signal is too weak to decode enough messages correctly.

### 4.1 Reference stations

Our proposed localization method is based on comparing the received signal with a reconstructed signal for different locations. Therefore, we first need to know what ADS-B messages are sent by the aircraft. To achieve this, we have multiple reference stations that continuously decode ADS-B messages and send them to a central server. We can infer the send times at the aircraft based on the receive time and the distance between the station and the aircraft. Therefore, for every position in the area covered by the reference stations we can reconstruct what signal should have been received for a given period of time, given these messages.

A single reference station can detect messages up to several hundred kilometers away, depending on the location and obstructions such as tall buildings and mountains. With multiple reference stations, a larger area can be covered. Additionally, multiple receivers also increase the amount of received messages in the area. Since the ADS-B message send times are not coordinated, in areas of high aircraft traffic, messages often interfere. Receivers at different locations might however be able to decode the messages since the relative message strengths are different or the messages might not even interfere because of the different arrival times. Also messages from aircraft at low altitudes, e.g. close to airports, can not be received very far because of obstacles and even the curvature of the earth. Therefore, having multiple reference stations allows to have a more complete view of the ADS-B messages in a large area. It is not necessary for our localization system to know every message that was sent by an aircraft, but the localization gets more robust if it is based on more ADS-B messages. Receiving as many ADS-B messages as possible therefore also reduces the duration of the signal recording for a position calculation.

Since we benefit from multiple reference stations, the required hardware should be inexpensive and easily deployable. The reference stations are Raspberry Pis with SDR dongles. We use RTL-SDR dongles from FlightAware that are optimized for the reception of ADS-B signals with an on-board LNA and 1090 MHz band-pass filter. The reference stations use a slightly modified version of OpenSky's dump1090-hptoa [5], which itself is a fork of dump1090-mutability. dump1090 is an ADS-B decoder optimized for RTL-SDR receivers. Each reference station detects ADS-B messages and sends them to a central server where they are stored in a PostgreSQL database.

The message arrival timestamps provided by the stations are derived by counting the incoming samples from the SDR. Since the receivers are not started at the exact same time, their clocks have an offset. On top of that, the clock frequency of the receiver's oscillators are slightly different, resulting in the clocks drifting apart. Since we need a common reference time for the localization, the server determines this clock offset and drift for each reference

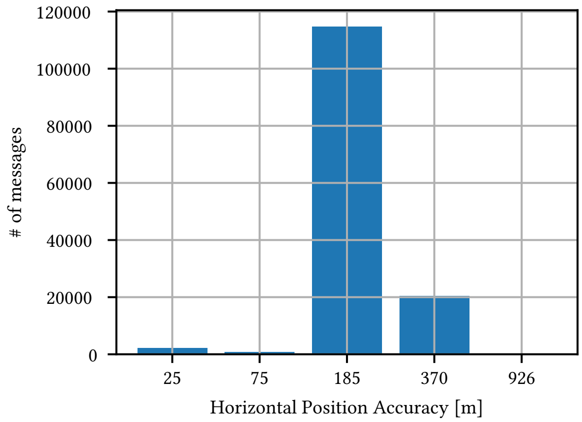



**Figure 1: Distribution of different horizontal position uncertainties as indicated by aircraft. Most aircraft show an accuracy of** 185.2 m.

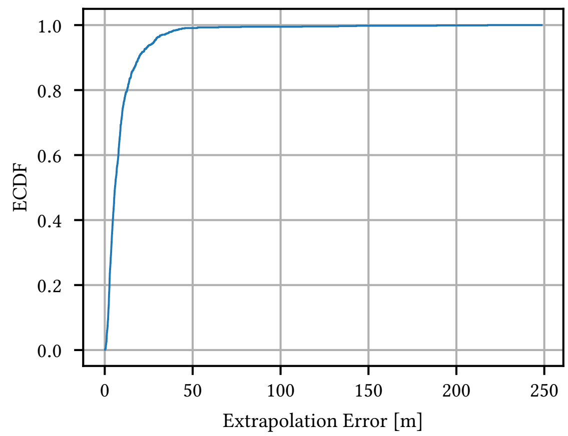



**Figure 2: Given an aircraft position and its velocity, we extrapolate the expected position at the time of the next position message. Extrapolation errors show the difference between the expected and the aircraft's transmitted position.**

station. This is done by matching the arrival times of messages that were seen by multiple reference stations.

We therefore build a system of equations to calculate the send timestamps at the aircraft and the offsets and drifts of the reference stations as proposed in [9]. We have $N$ reference stations $i \in \{1, ..., N\}$ and $M$ ADS-B position messages $j \in \{1, ..., M\}$. $t^r_{B_i,j}$ denotes the receive time of message $j$ at reference station $i$ and $w_{B_i,j}$ the noise of this timestamp. $P_{B_i}$ is the position of the reference station, $P_j$ the position of the aircraft from where message $j$ was sent. Let $T_{B_i,j} = \frac{1}{c}||P_{B_i} - P_j||_2$ be the TOF (*time of flight*) for message $j$ to station $i$. $t^t_{B_i,j}$ is the transmit time for a message $j$ in the time system of station $i$. Let $D_{B_i}$ be the drift rate and $\Delta t_{B_i}$ the offset of station $i$ relative to the reference time.

It is not necessary to synchronize our stations to UTC as the goal is to have a common time just among our stations. We pick the station $i = 1$ to be the reference clock. Therefore we set $D_{B_1} = 0$ and $\Delta t_{B_1} = 0$.

For every received message, subtracting the TOF from the receive time gives the send time $t^t_{B_i,j}$. We are interested in the send time relative to our reference clock and the clock offsets and drifts. We can express this relation as shown in Equation 1.

$$\begin{aligned} t^r_{B_i,j} - T_{B_i,j} &= t^t_{B_i,j} + w_{B_i,j} \\ &= t^t_{B_0,j} + \Delta t_{B_i} + D_i(t^t_{B_1,j} - t^t_{B_1,1}) + w_{B_i,j} \end{aligned} \tag{1}$$

To compute the offsets and drifts for all stations, we can build a system of equations using Equation 1 for each message received by a reference station. This equation system can then be solved using a linear least-squares solver.

*Aircraft position.* The synchronization and also the localization of a mobile receiver later on rely on the accuracy of the aircraft positions contained in the ADS-B messages. The CPR message format that combines two messages to encode the position allows a position resolution of approximately 5.1 m. Depending on the ADS-B Version, position messages contain information about the integrity and uncertainty of the transmitted positions. Most aircraft transmit messages with NUCp (ADS-B version 0) or NICp (ADS-B version 1 and 2) values indicating a HPL (horizontal protection limit) of 370.4 m or 185.2 m. Figure 1 shows the distribution of reported uncertainties of aircraft during one day.

By ignoring messages with a HPL above 185.2 m, we can limit the aircraft position error without losing many messages. Since we do not have access to the GPS data of the aircraft, we cannot verify the reported uncertainty values by ourselves. However, incorrect NUC values for some airplanes have been previously observed [21].

The aircraft regularly calculates its own position using GNSS and at different instances sends the position using ADS-B. The sent position therefore does not have to correspond to the actual position when sending the message. An uncompensated latency of up to 200 ms is allowed. This error is along the track of the aircraft: the actual position at the time it sent the message is offset along its current movement direction. Using the ADS-B velocity messages, we can introduce an additional unknown to the synchronization for every received position message to estimate this offset. We observe that this factor stays rather constant per aircraft and therefore calculate the factor only on a per-aircraft basis.

To analyze the position errors perpendicular to the direction of the aircraft, we extrapolate the position using a previous position and the velocity. Evaluation of the data shows that the distance of the extrapolated position to the transmitted position is usually low, except for a few outliers, as can be seen in Figure 2.

*Duplicate messages.* Aircraft are supposed to transmit their airborne position every 0.4 - 0.6 seconds. If no recent GPS data is available, the position has to be extrapolated for up to two seconds, afterwards the aircraft is supposed to zero out the fields and send messages with type code 0. However we could observe aircraft violating these specifications by sending duplicate position messages.

This behavior seems to depend on the model and manufacturer of the aircraft. Various Airbus models such as A320, A319, A321 and A343 keep their transmission schedule but repeat a message up to three times without alternating between odd and even CPR formats. Newer Airbus models such as the A350 do not adhere to the sending rate of 0.4 s to 0.6 s between positions, but continuously repeat a message for approximately 0.5 s at a time.

Matching received messages from different reference stations or handsets depends on the uniqueness of the messages. If receivers see the same message multiple times, the messages cannot be matched accurately. Therefore, aircraft broadcasting duplicate position messages need to be detected. Once a successful synchronization between the reference stations has been established, we can leverage the calculated offsets and drifts. For messages that were seen by multiple stations, we can compare the arrival times by converting them to the different time systems. Messages that show outliers at one or multiple receivers are completely discarded. Since ADS-B messages do not include detailed information about the aircraft's ADS-B equipment, no assumptions about erroneous ADS-B transponder models or incompatible GPS receivers onboard the aircraft can be made with the given data. Similar erroneous behavior was also observed by other research [17, 21], specifically for Airbus aircraft using Thales GPS Receiver in combination with Honeywell ADS-B emitters [2]. Using crowd-sourced data from many receivers, it would be possible to build a database of aircraft identifiers that behave incorrectly and may cause problems in our system.

*Multipath and location of receivers.* Especially in urban and indoor scenarios, multipath is a common occurence. In our setup, most stations are placed next to a window in residential buildings or offices, multipath happens mostly for messages from one direction. Instead of detecting these multipath messages, we simply add an offset to the reference station position to cancel out the multipath effect. Whenever we compute a time of flight, we use the corrected reference station position to calculate the distance. This is implemented on the server by periodically excluding one reference station from the time synchronization and instead treats it as a mobile receiver. The excluded station is localized and the result is averaged over time. This can also help dealing with misconfigured reference stations with inaccurate positions.

## 4.2 Localization

With the known ADS-B messages from the reference stations, we can now build our localization method based on comparing the received signal to the known messages.

The used RTL-SDR records raw samples at a sampling rate of 2.4 MHz. Because our approach relies on correlating signals, we up-sample the signal to a sampling rate of 24 MHz in order to increase the precision of our method. The chosen up-sampling rate could be any multiple of 2 MHz which leads to the nice property that a single pulse of an ADS-B message has always a length of a whole number of samples. We denote the sampling rate by $f$. Furthermore, we use $\mathbf{y} = [y_0, y_1, \ldots, y_n]$ to refer to the samples of our up-sampled signal. Thus, the duration of our signal is $T = \frac{n}{f}$ and $T_0$ denotes the timestamp of the first sample in the system time of the receiver.

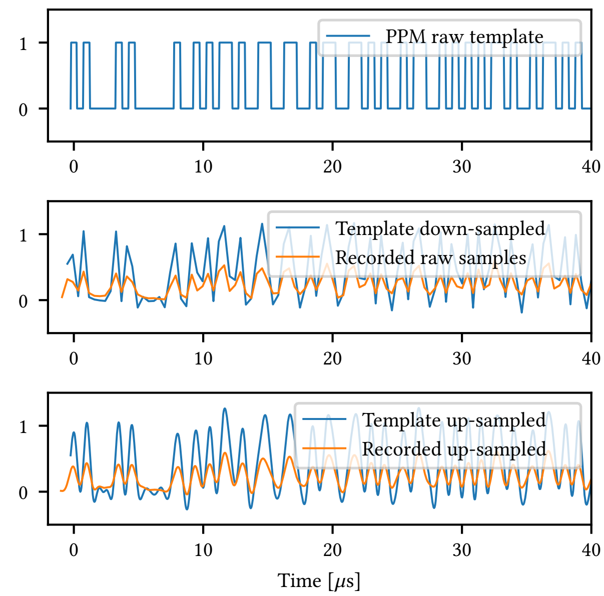



**Figure 3: In the first subplot, we see the first 40 µs of the pulse position modulated template of an ADS-B message. The second subplot shows the signal down-sampled to 2.4 MHz together with the real raw samples recorded by an RTL-SDR receiver. The last subplot shows the final template $\hat{\mathbf{z}}_j$ together with the up-sampled received samples present in y.**

*ADS-B message template.* With the previously described system of reference stations, we know the content of the decoded ADS-B messages. Given a message $j$, we can generate the signal that represents that message using the pulse position modulation scheme. In order to generate a signal that is as similar as possible to the signal present in the received and up-sampled signal, we down-sample the raw pulse position modulated template to the hardware sampling rate of 2.4 MHz. After down-sampling, we up-sample the signal as we do it with the received signal. Figure 3 illustrates the generation process of an ADS-B message template. We use $\hat{\mathbf{z}}_j$ to refer to the final message template of an ADS-B message $j$.

Theoretically, it would be possible to get a more accurate message template by recording the raw samples of each ADS-B message at the reference stations. These samples would contain the exact characteristics of each transmitter. However, this would result in a huge amount of data that the reference stations continuously have to send to the server instead of only the decoded message bits. Additionally, the message could be strongly affected by multipath and noise on the channel between the aircraft and the reference station.

*The likelihood function.* The main idea behind our proposed method is that we compare the received signal to the theoretical signal for a given position. In order to reconstruct the received signal, we have the following three parameters:

- $P_H$, the position of the mobile receiver,

- $\Delta t_H$, the time offset between the system time of the mobile receiver and the system time of the reference stations and
- $D_H$, the clock drift between the two system times.

For a specific message $j$ we denote by $t_j^t$ the synchronized time of transmission in the system time of the reference stations and by $P_j$ the position of the aircraft at the time of transmission.

From satellite based localization and least-squares based localization for ADS-B messages, we know that the geometric distance should be equal to the measured range:

$$\underbrace{||P_H - P_j||_2}_{\text{geometric distance}} \stackrel{!}{=} \underbrace{c(\overbrace{t_{H,j}^r - t_j^t}^{\text{time of flight}} + \overbrace{\Delta t_H + D_H(t_{H,j}^r - t_{H,1}^r)}^{\text{clock offset and drift}})}_{\text{range measurement}} \tag{2}$$

Given the parameters enumerated above, we are able to calculate the theoretical time of arrival $t_{H,j}^r$ by reformulating Equation 2:

$$t_{H,j}^r = \frac{t_j^t - \Delta t_H + D_H t_{H,1}^r + \frac{||P_H - P_j||_2}{c}}{D_H + 1} \tag{3}$$

Once we know the theoretical time of arrival $t_{H,j}^r$, we can infer the index of the sample within our received raw signal $\mathbf{y}$ that corresponds to this time:

$$\delta_j = \lfloor (t_{H,j}^r - T_0) \cdot f \rfloor \tag{4}$$

An ADS-B message has a duration of 120 µs, which corresponds to 2880 samples at our sampling rate of 24 MHz. The sub-sequence of samples in our received signal $\mathbf{y}$ where message $j$ should be present is therefore given by

$$\mathbf{z}_j = [y_{\delta_j}, y_{\delta_j+1}, \dots, y_{\delta_j+2879}] \tag{5}$$

The idea of our proposed method is to correlate the samples $\mathbf{z}_j$ where the message should be present with the message template $\hat{\mathbf{z}}_j$.

Given that not all ADS-B messages will be present in our signal, we often correlate the message template with random noise. We therefore shift the range of the samples of $\hat{\mathbf{z}}_j$ from [0, 1] to [-0.5, 0.5]. As a result of the pulse position modulation scheme, the mean of the samples is now close to zero. This ensures that the correlation with random noise is also close to zero in expectation.

As the received ADS-B messages are from different airplanes which have different distances to the mobile receiver, we expect different amplitudes of the messages present in $\mathbf{y}$. We therefore divide the correlation by the norm of $\mathbf{z}_j$. This ensures that the correlation of different messages have comparable values.

The final likelihood function $\mathcal{L}$ is the sum of these normalized correlation values of all $k$ messages:

$$\mathcal{L}(P_H, \Delta t_H, D_H|\mathbf{y}) = \sum_{j=1}^{k} \frac{\mathbf{z}_j \cdot (\hat{\mathbf{z}}_j - 0.5)}{\|\mathbf{z}_j\|} \tag{6}$$

*Efficient evaluation.* We have seen how we can assign a likelihood to all tuples $(P_H, \Delta t_H, D_H)$. However, the function is not convex (because even the correlation between two ADS-B message templates is not convex). As a consequence, there is no efficient method to find the tuple and therefore also the desired $P_H$ that maximizes the likelihood. Here we propose an evaluation strategy that finds the best position with a very high probability.

The clock drift of the used RTL-SDR sticks is below 0.5 ppm. Assuming extreme clock drifts of both, the reference stations and the mobile receiver, this implies that over a period of one second the first and the last sample drift no further than 1 µs in time. The search space of possible drift values $D_H$ is therefore bounded and only depends on the length of the recorded signal.

Also, we assume that we have an initial guess $\tilde{P}_H$ of the approximate mobile receiver position. Given that in urban areas there are cell towers every few hundred meters, we can simply map our position to the position of the cell tower we are connected to to get an accurate reference position. Therefore, the search space of the position $P_H$ is also bounded. Furthermore, we can remove one spatial dimension and only optimize $P_H$ in two dimensions, assuming that the mobile receiver is placed on the ground. We use the elevation model "ALOS World 3D – 30m (AW3D30) Version 2.2" with a resolution of 1 arcsecond which corresponds to a mesh of approximately 30 meters at the equator, with increasing accuracy towards the poles. The elevation model gives the height of any

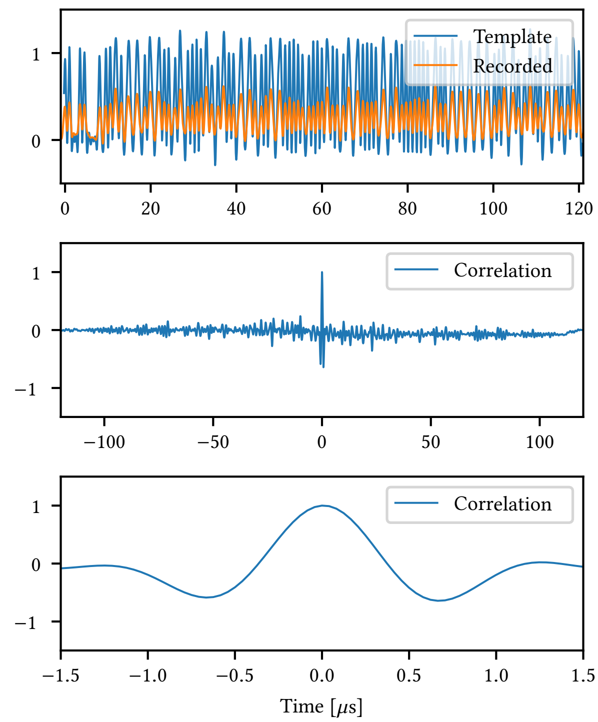



**Figure 4: In the first subplot we see a recorded message $\mathbf{z}_j$ together with the corresponding message template $\hat{\mathbf{z}}_j$. The second and third plot show the correlation of the recorded message with its template. While the second subplot shows the whole correlation, the third subplot only shows the region of interest around the time offset zero. For correlation we used the shifted message template $\hat{\mathbf{z}}_j - 0.5$.**

point on earth, given its two-dimensional coordinates (longitude and latitude).

As aircraft signals are strong enough to penetrate walls, we can generally assume that the received signal $\mathbf{y}$ contains at least one ADS-B message $j$ that we are able to fully decode. By using the time of arrival of this message, we can obtain an initial guess for the clock offset. As the impact of the clock drift $D_H$ is bounded, we can assume a clock drift of zero for simplicity and reformulate Equation 2:

$$\Delta\tilde{t}_H = \frac{||\tilde{P}_H - P_j||_2}{c} - (t^r_{H,j} - t^t_j) \quad (7)$$

Hence, the search space of possible clock offsets $\Delta t_H$ is also bounded and only depends on the accuracy of the reference position.

We have shown that the search space of all unknowns can be bounded. However, we still require too many evaluations of the likelihood function to localize the mobile receiver with meter-lever accuracy, even if the reference position is known to a few hundred meters. We propose an iterative approach to tackle this problem. Initially, we evaluate the search space with only a coarse grid and refine the resolution iteratively.

Figure 4 shows the correlation of a recorded ADS-B message with its message template. Each pulse in the received ADS-B messages is at least 0.5 µs long. As the likelihood function is the sum of such individual correlations, its peak shape will be similar. We see that it suffices to evaluate the correlation every 0.5 µs to find its peak. In the space domain, this corresponds to a distance of approximately 150 m in terms of speed of light. For that reason, we will also find the peak of the likelihood function using a coarse resolution of 0.5 µs in the time and 150 m in the space domain. Only in few cases this will result in an incorrect position.

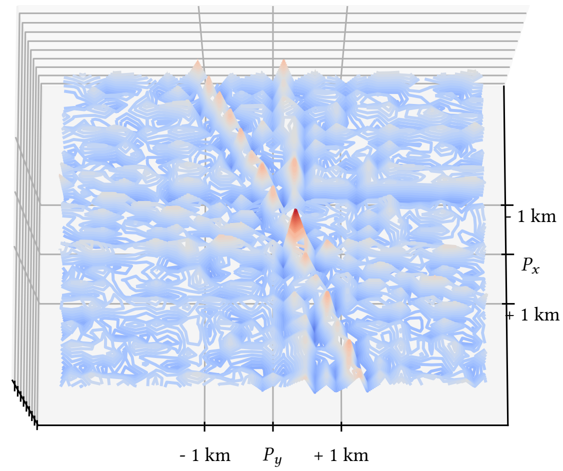
Once the tuple that maximizes the likelihood is found, all parameters can be refined. For that reason, we can put tighter bounds on the parameters and increase the resolution.

Figure 5 illustrates the evaluated likelihood function of the iterations for four recorded ADS-B messages. Three of the messages contain more than 2 bit errors and could not have been used for localization with the traditional approach. For this illustration we use a simplified two dimensional model, assuming no drift and offset and that the mobile receiver and the airplanes are placed on the ground. While the mobile receiver position $P_H$ is placed at the origin, the airplanes are placed at four random positions $P_j$.

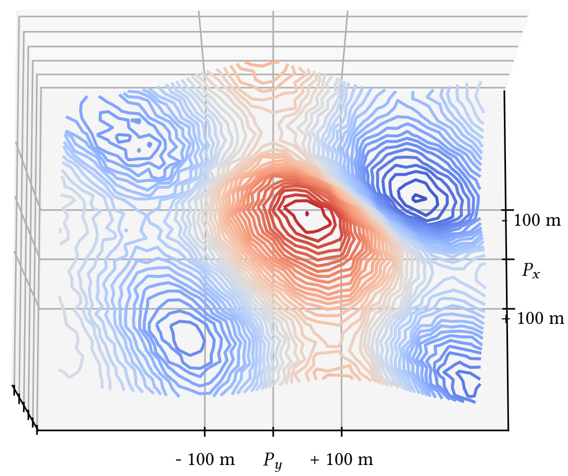
*Remaining sources of error.* Even though we can find the position where our message templates match best, this will not always be exactly the location of the mobile receiver. Besides random noise and the multipath channel between the aircraft and the mobile receiver, multiple sources of error can affect the estimation.

As stated in Equation 3, the calculation of the time of arrival $t^r_{H,j}$ depends on the time of transmission $t^t_j$. The accuracy of synchronization and calculation of the transmission times directly affects the localization performance. Therefore the previously described steps to ensure a precise synchronization are very important.

Also, our proposed method works by correlating the known templates of the messages with the received signal. This relies on the assumption that we can reconstruct the source signal given the decoded message bits. However, this is not perfectly possible in the case of real-world ADS-B messages. Both the position and the duration of the individual pulses of the bits can vary by up to 50 ns [5]. While this is absolutely fine for the decoding of ADS-B messages, in our case this can have an impact on the correlation.




**(a) Resolution of** 150 m**.**




**(b) Resolution of** 15 m**.**

**Figure 5: The likelihood of different values for $P_H$ given a fixed offset and drift. The reference point $P$ in the first subplot corresponds to the reference position $\tilde{P}_H$. The reference point in the second subplot is given by the position maximizing the likelihood in the first subplot. We clearly see that already the first iteration shows a clear peak. The exact peak position is then refined in the second iteration with a finer resolution.**

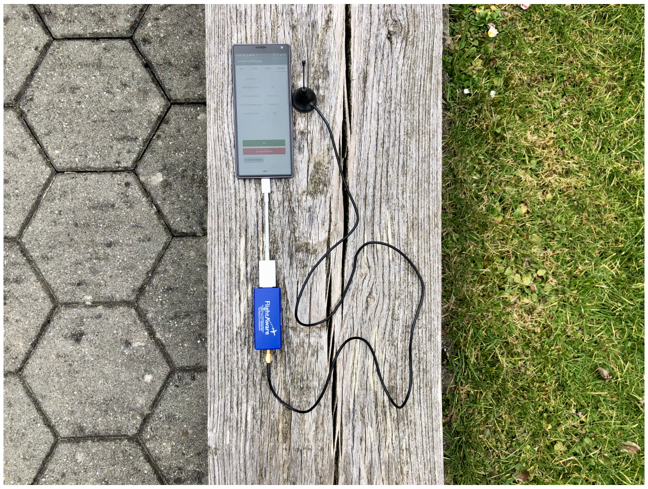


**Figure 6: The evaluation setup consists of an Android smartphone with an RTL-SDR receiver attached to it.**

## 5 EVALUATION

We have presented a new localization method based on ADS-B messages from aircraft based on finding the location that best matches the received raw signal. We now evaluate the accuracy and reliability in different conditions, such as outdoors and in buildings and compare it to classical multilateration with ADS-B messages and multilateration using GNSS.

### 5.1 Data collection

We evaluate the system using a Sony Xperia 10 smartphone running Android 9 with an RTL-SDR receiver attached to it over USB. The setup can be seen in Figure 6. On the smartphone a ported version of dump1090-hptoa is running to access the raw signal from the SDR and also decode ADS-B messages and an auxiliary app records the data directly to JSON files. The app also records raw GNSS measurements reported by the GNSS sub-system of the smartphone for GPS and GLONASS.

Each recording consists of three seconds of raw signal samples and additionally the decoded ADS-B messages and all raw GNSS measurements during this time. This allows us to collect all data necessary to compare our method to classical multilateration with ADS-B messages and multilateration using GNSS.

As ADS-B messages are short bursts that are sent only periodically, the recording duration directly influences the number of messages that are received and can be used for localization. A longer recording yields more ADS-B messages and a higher localization accuracy. The mobile receiver should however not move far during the recording for a single localization. The recording duration should be therefore chosen as a compromise.

The app was used to record data sets consisting of many individual recordings at different locations and at different times of the day. The collected recordings were then transferred to a computer for offline processing. For deploying the localization system, the recordings could be processed directly on the smartphone or sent to a server for the position calculations.

For each recording of three seconds we calculate the following position estimates:

- **ADS-B multilateration** For this estimate, we only use the decoded ADS-B messages of each recording to calculate the position using a least-squares approach. This method also uses the same elevation model as our newly proposed method to remove one spatial dimension and allow a fair comparison to our new method.
- **GNSS** This position estimate is based on the GPS and GLONASS satellite range measurements recorded by the GNSS receiver on the smartphone. We use the open-source framework `laika` [1] to calculate a position for every set of range measurements. As we have three independent sets of range measurements in a recording, one per second, the final position estimate is obtained by averaging the three positions.
- **ADS-B likelihood** This position estimate is calculated using our novel likelihood localization method based on the recorded raw ADS-B signal from the RTL-SDR.

For our novel approach, we use a position estimation strategy with three iterations of increasing resolution. Our initial search space spans an area of 2.4 km by 2.4 km, which always contains the actual receiver position, with a resolution of 150 m. The second iteration uses a smaller search space of 600 m by 600 m and a resolution of 15 m. The search space of the last iteration is 30 m by 30 m with a resolution of 1.5 m. For the drift values we evaluate nine values in the first iteration and refine the best drift trying three values in the second and third iteration.

Each position estimate of the compared methods is based solely on the data from a three second recording. No filtering over multiple recordings from the same location has been performed. In an actual application the position accuracy could be improved by using for example a Kalman filter over multiple position estimates to remove noise in the position estimation.

We are interested in evaluating our localization method in indoor and outdoor settings. The reliability of the localization outdoors depends on different factors such as nearby obstacles, the satellite constellation for GNSS measurements and the number of aircraft nearby for localization based on ADS-B messages. Indoors however, many additional parameters affect the quality of the localization, such as the distance to windows, size of windows, building material of walls, etc. We therefore recorded ten data sets at eight different locations. Table 1 shows the different data sets and the achieved performance. Two data sets were recorded outdoors while the other eight were recorded indoors in different rooms of different buildings. Most rooms had windows on one side and the receiver was not placed close to the windows. Data set *3* set was recorded in a bathroom with no windows in the middle of an apartment. This recording shows the performance of the localization with extremely difficult signal reception. Data sets *5*, *6*, and *7* were recorded in the same building on different days. In total the data sets contain 926 individual recordings of three seconds length.

### 5.2 Computational effort

Before we evaluate the localization accuracy, let us consider the computational effort and memory utilization necessary to calculate the position estimates.

| # | Date | recordings | ADS-B multilateration [m] | GNSS [m] | ADS-B likelihood [m] (our work) |
|---|---|---|---|---|---|
| 1 | 2020-03-14 | 89 | 51.7 | **13.5** | 21.3 |
| 2 | 2020-03-15 | 90 | 81.9 | 173.1 | **70.7** |
| 3 | 2020-02-24 | 50 | - | - | **75.0** |
| 4 | 2020-03-15 | 80 | 40.5 | **21.6** | 36.3 |
| 5 | 2020-02-21 | 164 | 20.0 | 90.5 | **14.9** |
| 6 | 2020-02-24 | 93 | 30.8 | 33.2 | **22.9** |
| 7 | 2020-03-10 | 90 | 55.1 | 192.1 | **31.28** |
| 8 | 2020-03-18 | 90 | - | - | **97.5** |
| **all indoor sets** | | 746 | 46.8 | 77.8 | **29.9** |
| 9 | 2020-03-14 | 90 | 46.6 | **8.7** | 23.7 |
| 10 | 2020-03-15 | 90 | 23.0 | **9.7** | 18.0 |
| **all outdoor sets** | | 180 | 31.6 | **9.0** | 20.4 |

**Table 1: Median position error for all data sets and all position estimates. The data sets are additionally also separated into indoor and outdoor data. In total ten different data sets recorded on different days are evaluated for the three localization methods.**

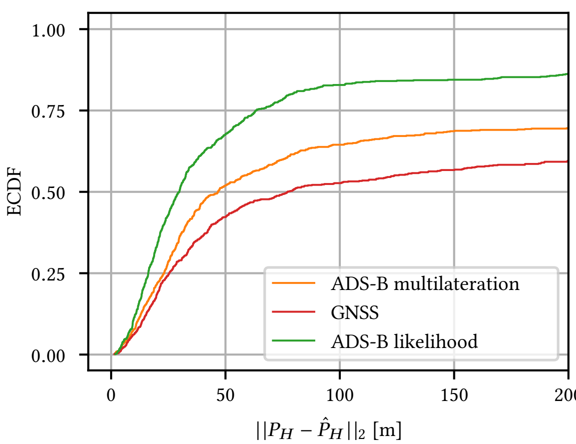



**Figure 7: The empirical cumulative distribution function of the position error for the 746 indoor recordings. The *ADS-B likelihood* estimate is more often successful and more accurate than the *ADS-B multilateration* and *GNSS* estimates.**

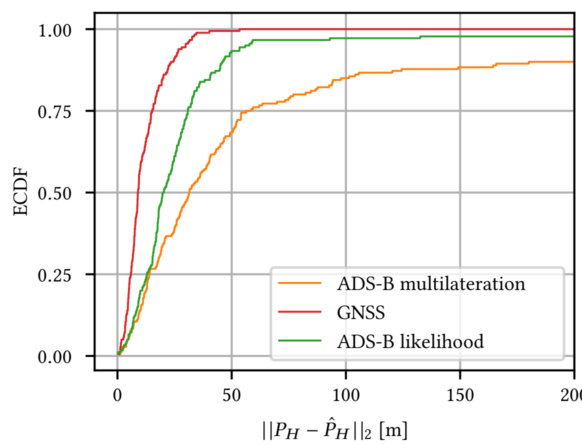



**Figure 8: The empirical cumulative distribution function of the position error for the 180 outdoor recordings. The *GNSS* estimate is the most accurate, but also the *ADS-B likelihood* achieves a median accuracy of 20.4 m and is more accurate than the *ADS-B multilateration* estimate.**

As our proposed localization method requires the raw ADS-B signal, much disk space is needed. Specifically, each sample consists of an I and Q component, both requiring 8 bits of memory. Given the hardware sampling rate of 2.4 MHz and the recording duration of three seconds, the overall space requirement per recording is 14.4 MB. In contrast, the decoded ADS-B messages and the satellite range measurements only use a couple of kilobytes. For our offline evaluation this amounts to a large amount of data for all recordings combined. If the position was computed directly on the phone, the memory could be freed after each localization.

Let us now analyze the processing time of the different tasks involved. There is no efficient way of finding the parameters that maximize the likelihood function. However, using our iterative evaluation strategy, we are able to significantly reduce the computational effort to get a precise position. As we described before, the first iteration spans a search space of 2.4 km with a resolution of 150 m. The offset search space is 8 µs with a resolution of 0.5 µs. Therefore, the search space consists of 17 values in those three dimensions and 9 drift values. This leads to 44 217 evaluations of the likelihood function in the first iteration. Analogously, in the second and third iteration we perform 45 387 respectively 6615 evaluations of the likelihood function. Each evaluation of the likelihood function itself consists of correlating the message templates of all ADS-B messages with the corresponding samples of the received signal.

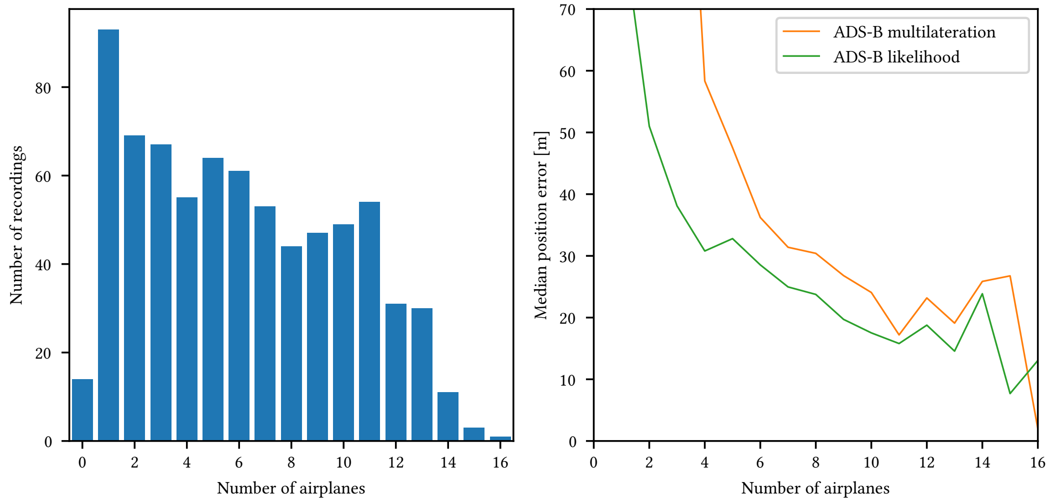



**Figure 9: Indoor localization accuracy in relation to the number of airplanes decodable at the mobile receiver. The figure on the left shows the distribution of the number of aircraft in the recordings and the figure on the right shows the localization accuracy. The accuracy is expressed as the median error for the respective number of airplanes decodable at the mobile receiver. The *ADS-B likelihood* method is more accurate, especially for low numbers of visible aircraft where a localization using *ADS-B multilateration* is not possible anymore because of the low number of directly decodable messages.**

In contrast, for the GNSS and the classical ADS-B localization, a system of non-linear equations has to be solved. For the evaluation we used an iterative solver that numerically differentiates the residual function.

To evaluate the computational effort, we timed the processing of one data set. For processing, we used a MacBook Pro (16-inch, 2019) with a 2.3 GHz 8-Core Intel Core i9 processor. Currently, the evaluation script is only single threaded. On average the processing time to calculate a *ADS-B likelihood* position estimate is 118.2 s. For *ADS-B multilateration* the estimation takes 2.47 s and for *GNSS* 0.24 s.

The computation could be accelerated by a native implementation, currently the evaluation is performed by a python script. Especially the likelihood method would be suitable to parallelization as each position guess can be evaluated independently. This could be achieve using multiple CPU cores or even a GPU. Calculations could also be implemented directly in hardware.

For this evaluation, each position estimation of the *ADS-B likelihood* estimate is computed independently. While tracking a device, the search space could be reduced significantly as we already know a previous position. Depending on the time between measurements and the expected maximum velocity of the device, even the first or second iteration could be omitted. As long as the correct position lies within the search space, the accuracy of the algorithm is not affected by reducing the search space or removing the earlier iterations. The computation time of the position is proportional to the number of evaluations of the likelihood function. For the three iterations with the search space as described before, 96 219 evaluations of the likelihood function need to be performed. Using the result of a previous localization, we can not only reduce the area in which we search the receiver, but also the search space for the offset is reduced as we have a closer initial position guess. Also the search space for the drift is smaller, as we can assume that the drift does not change significantly in a short time. Therefore, if we assume a search area of 150 m by 150 m, we can directly start at the second iteration with a smaller search space. This will result in a total of only 7704 evaluations of the likelihood function for the second and third iteration together, reducing the computation time by a factor of 12.5.

## 5.3 Localization accuracy

Of course, we are most interested in the position accuracy of our proposed localization method. For this purpose, we calculate all position estimates for our method, classical ADS-B localization and GNSS for every recording. The position error is defined as the horizontal distance between the calculated position estimate and the actual receiver position. The median position errors of all data sets and all position estimates are presented in Table 1.

Indoors, we have a total of 746 recordings from eight data sets. The empirical cumulative distribution function of the position error of these recordings is shown in Figure 7. The median error of the *ADS-B likelihood* estimate is 29.9 m. The two baseline estimates *ADS-B multilateration* and *GNSS* result in a median error of 46.8 m and 77.8 m. The data set *5* is the best in the indoor setting with a median error of 14.9 m for the *ADS-B likelihood* estimate.

In the outdoor setting, we recorded two data sets with 180 recordings. The corresponding empirical cumulative distribution function of the position error is shown in Figure 8. A receiver under open sky is best suited for satellite-based localization systems. As we expect, the *GNSS* estimates are very accurate with a median position error of only 9.0 m. The median position errors for the *ADS-B multilateration* and *ADS-B likelihood* estimates are 31.6 m and 20.4 m.

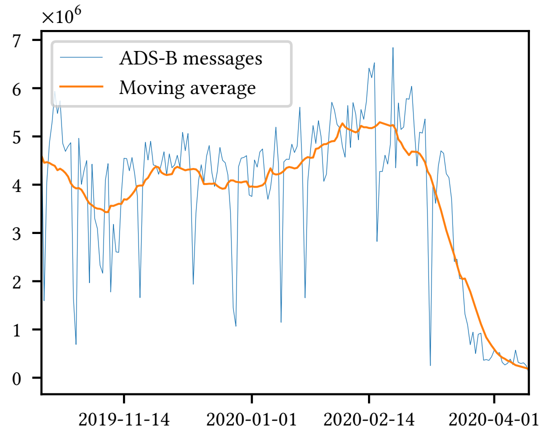



**Figure 10: The number of ADS-B messages received by the reference stations over time. We observe that the number of received messages drastically decreased in March of 2020. The outliers (days with very few ADS-B messages) are due to some server outages.**

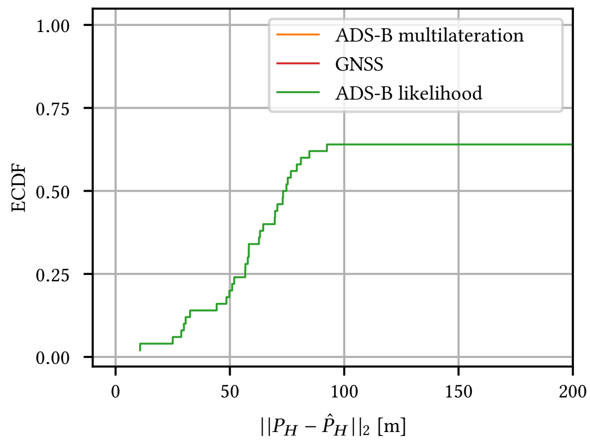



**Figure 11: The empirical cumulative distribution function of the position error for data set *3*. This data set was recorded in a room with no windows. Only our proposed *ADS-B likelihood* could successfully estimate the position.**

Our novel likelihood method uses only three seconds of recording and is better in both the indoor and outdoor scenario with a median position error of under 29.9 m.

*Indoor localization accuracy.* If we look at the results of the indoor data sets, we note that the accuracy of the *ADS-B multilateration* estimate is very low with a median position error of 46.8 m. As we see in Figure 7, in many cases it could not calculate the location. There were just too few ADS-B messages from different aircraft in order to solve the system of equations. By using our proposed *ADS-B likelihood* method, the accuracy can be improved to a median position error of 29.9 m. The method is also able to find compute a location in more cases as the weak message indoors do not have to be decoded correctly.

The median position error for the *GNSS* estimate is higher than for the methods based on ADS-B messages. This is expected as only a fraction of the available satellites are visible in an indoor setting. Also, as often most satellite signals are received through the same window, the system of equation is very ill-posed and the resulting errors are large.

*Impact of the number of aircraft.* We want to take a closer look at the impact of the number of visible aircraft on the localization accuracy for the indoor data sets. Figure 9 compares the localization accuracy of our proposed *ADS-B likelihood* estimate and the *ADS-B multilateration* in relation to the number of aircraft for which we were able to decode messages at the mobile receiver. Note that we consider the number of distinct aircraft, which is usually lower than the number of ADS-B messages, as there are normally multiple messages from the same aircraft. Clearly, the more aircraft present in a recording the more accurate the position estimates become. We note that our novel *ADS-B likelihood* method is more accurate than *ADS-B multilateration*. The difference is especially large for low numbers of visible aircraft. Our method can even find a position when the mobile receiver sees too few messages for a successful multilateration, as we can compare the signal to messages that were very weak and not decodable locally.

Although the overall median position error for our proposed *ADS-B likelihood* is better than the classical multilateration using ADS-B, the method still needs sufficient aircraft that send messages. Weaker ADS-B messages are still usable but towards the end of March 2020 the amount of aircraft dropped drastically. The reason is the worldwide coronavirus pandemic that lead to travel restrictions and forced most airlines to ground a substantial part of their fleet. Figure 10 shows the moving average of the daily number of ADS-B messages received by our network of reference stations. The number significantly decreased in March. Our data sets were collected at the end of February and in March as indicated in Table 1. The performance of some of our data sets may already be affected by sparse air traffic and, as a result, a lower number of ADS-B messages. As the global air traffic has not yet recovered, we are restricted to these data sets.

*Very low signal strength.* Data set *3* was recorded in extreme conditions in a building with concrete walls in a room with no windows. The empirical cumulative distribution of the position error of this data set is depicted Figure 11. Only very few ADS-B messages were decoded on the receiver and there were no satellites in view. Not surprisingly, the *ADS-B multilateration* estimate never results in a successful localization. However, by using our proposed *ADS-B likelihood* estimate, we can successfully calculate a position estimate in most recordings.

## 6 CONCLUSION

We have proposed a new method for localization of a mobile receiver based on ADS-B messages. It compares the received signal to the expected ADS-B messages and finds the most probable location. Our novel likelihood method uses only three seconds of recording and works reliably in many different settings. It achieves a median accuracy of 20.4 m outdoors and 29.9 m in buildings. As the mobile receiver does not need to be able to decode the ADS-B messages, also very weak messages help in the localization. To achieve an accurate localization, we have implemented a robust synchronization between distributed reference receivers.

In the future it would be interesting to combine the proposed method based on ADS-B messages with a similar method for GNSS. This could allow to improve the performance outdoors to the level of GNSS multilateration while still having the benefits of the ADS-B messages in buildings.

## REFERENCES


[1] [n.d.]. *Laika.* https://github.com/commaai/laika online, accessed 2021-03-26.

[2] Busyairah Syd Ali, Wolfgang Schuster, Washington Ochieng, Arnab Majumdar, and Thiam Kian Chiew. 2014. Framework for ADS-B Performance Assessment: the London TMA Case Study. *NAVIGATION* 61, 1 (2014), 39–52.

[3] Paramvir Bahl and Venkata N. Padmanabhan. 2000. RADAR: An In-Building RF-Based User Location and Tracking System. In *Proceedings IEEE INFOCOM 2000, The Conference on Computer Communications, Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies, Reaching the Promised Land of Communications, Tel Aviv, Israel, March 26-30, 2000.* IEEE Computer Society, 775–784.

[4] Pascal Bissig, Manuel Eichelberger, and Roger Wattenhofer. 2017. Fast and robust GPS fix using one millisecond of data. In *Proceedings of the 16th ACM/IEEE International Conference on Information Processing in Sensor Networks, IPSN 2017, Pittsburgh, PA, USA, April 18-21, 2017*, Pei Zhang, Prabal Dutta, and Guoliang Xing (Eds.). ACM, 223–233.

[5] Roberto Calvo-Palomino, Fabio Ricciato, Blaz Repas, Domenico Giustiniano, and Vincent Lenders. 2018. Nanosecond-precision time-of-arrival estimation for aircraft signals with low-cost SDR receivers. In *Proceedings of the 17th ACM/IEEE International Conference on Information Processing in Sensor Networks, IPSN 2018, Porto, Portugal, April 11-13, 2018*, Luca Mottola, Jie Gao, and Pei Zhang (Eds.). IEEE / ACM, 272–277.

[6] Liang Chen, Lie-Liang Yang, Jun Yan, and Ruizhi Chen. 2017. Joint Wireless Positioning and Emitter Identification in DVB-T Single Frequency Networks. *IEEE Trans. Broadcast.* 63, 3 (2017), 577–582. https://doi.org/10.1109/TBC.2017.2704422

[7] Yin Chen, Dimitrios Lymberopoulos, Jie Liu, and Bodhi Priyantha. 2012. FM-based indoor localization. In *The 10th International Conference on Mobile Systems, Applications, and Services, MobiSys'12, Ambleside, United Kingdom - June 25 - 29, 2012*, Nigel Davies, Srinivasan Seshan, and Lin Zhong (Eds.). ACM, 169–182.

[8] Pau Closas, Carles Fernández-Prades, and Juan A. Fernández-Rubio. 2007. Maximum Likelihood Estimation of Position in GNSS. *IEEE Signal Process. Lett.* 14, 5 (2007), 359–362. https://doi.org/10.1109/LSP.2006.888360

[9] Manuel Eichelberger, Kevin Luchsinger, Simon Tanner, and Roger Wattenhofer. 2017. Indoor Localization with Aircraft Signals. In *Proceedings of the 15th ACM Conference on Embedded Network Sensor Systems, SenSys 2017, Delft, Netherlands, November 06-08, 2017*, M. Rasit Eskicioglu (Ed.). ACM, 12:1–12:14.

[10] Ramsey Faragher and Robert Harle. 2015. Location Fingerprinting With Bluetooth Low Energy Beacons. *IEEE J. Sel. Areas Commun.* 33, 11 (2015), 2418–2428.

[11] Jie Huang and Letizia Lo Presti. 2013. DVB-T positioning with a one shot receiver. In *International Conference on Localization and GNSS, ICL-GNSS 2013, Turin, Italy, June 25-27, 2013.* IEEE, 1–5.

[12] Shenghong Li, Mark Hedley, Keith Bengston, Mark Johnson, David Humphrey, Alija Kajan, and Nipun Bhaskar. 2018. TDOA-based passive localization of standard WiFi devices. In *2018 Ubiquitous Positioning, Indoor Navigation and Location-Based Services, UPINLBS 2018, Wuhan, China, March 22-23, 2018.* IEEE, 1–5. https://doi.org/10.1109/UPINLBS.2018.8559705

[13] Hui Liu, Houshang Darabi, Pat P. Banerjee, and Jing Liu. 2007. Survey of Wireless Indoor Positioning Techniques and Systems. *IEEE Trans. Syst. Man Cybern. Part C* 37, 6 (2007), 1067–1080. https://doi.org/10.1109/TSMCC.2007.905750

[14] Alessandro Nicolussi, Simon Tanner, and Roger Wattenhofer. 2020. Aircraft Fingerprinting Using Deep Learning. In *28th European Signal Processing Conference, EUSIPCO 2020, Amsterdam, Netherlands, January 18-21, 2021.* IEEE, 740–744.

[15] Yogesh Anil Nijsure, Georges Kaddoum, Ghyslain Gagnon, François Gagnon, Chau Yuen, and Rajarshi Mahapatra. 2016. Adaptive Air-to-Ground Secure Communication System Based on ADS-B and Wide-Area Multilateration. *IEEE Trans. Veh. Technol.* 65, 5 (2016), 3150–3165.

[16] Antonio Ramón Jiménez Ruiz and Fernando Seco Granja. 2017. Comparing Ubisense, BeSpoon, and DecaWave UWB Location Systems: Indoor Performance Analysis. *IEEE Trans. Instrum. Meas.* 66, 8 (2017), 2106–2117. https://doi.org/10.1109/TIM.2017.2681398

[17] Matthias Schäfer, Martin Strohmeier, Vincent Lenders, Ivan Martinovic, and Matthias Wilhelm. 2014. Bringing up OpenSky: a large-scale ADS-B sensor network for research. In *IPSN'14, Proceedings of the 13th International Symposium on Information Processing in Sensor Networks (part of CPS Week), April 15-17, 2014, Berlin, Germany*, Adam Wolisz, Jie Liu, and Lin Zhong (Eds.). IEEE/ACM, 83–94.

[18] Martin Strohmeier and Ivan Martinovic. 2015. On Passive Data Link Layer Fingerprinting of Aircraft Transponders. In *Proceedings of the First ACM Workshop on Cyber-Physical Systems-Security and/or PrivaCy, CPS-SPC 2015, Denver, Colorado, USA, October 16, 2015*, Indrajit Ray, Roshan K. Thomas, and Alvaro A. Cárdenas (Eds.). ACM, 1–9.

[19] Martin Strohmeier, Matthew Smith, Daniel Moser, Matthias Schäfer, Vincent Lenders, and Ivan Martinovic. 2018. Utilizing air traffic communications for OSINT on state and government aircraft. In *10th International Conference on Cyber Conflict, CyCon 2018, Tallinn, Estonia, May 29 - June 1, 2018*, Tomás Minárik, Raik Jakschis, and Lauri Lindström (Eds.). IEEE, 299–320.

[20] Junzi Sun. [n.d.]. *The 1090 Megahertz Riddle - Airborne position.* https://mode-s.org/decode/content/ads-b/3-airborne-position.html online, accessed 2021-03-24.

[21] Busyairah Syd Ali, Wolfgang Schuster, Washington Ochieng, and Arnab Majumdar. 2016. Analysis of anomalies in ADS-B and its GPS data. *GPS Solutions* 20, 3 (01 Jul 2016).

[22] Roman Trüb, Daniel Moser, Matthias Schäfer, Rui Pinheiro, and Vincent Lenders. 2018. Monitoring meteorological parameters with crowdsourced air traffic control data. In *Proceedings of the 17th ACM/IEEE International Conference on Information Processing in Sensor Networks, IPSN 2018, Porto, Portugal, April 11-13, 2018*, Luca Mottola, Jie Gao, and Pei Zhang (Eds.). IEEE / ACM, 25–36.

[23] Chenshu Wu, Zheng Yang, and Yunhao Liu. 2015. Smartphones Based Crowdsourcing for Indoor Localization. *IEEE Trans. Mob. Comput.* 14, 2 (2015), 444–457.