Precise Onboard Aircraft Cabin Localization using UWB and ML

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Abstract—Precise indoor positioning systems are key to perform a set of tasks more efficiently during aircraft production, operation and maintenance. For instance, indoor positioning systems can overcome the tedious task of configuring (wireless) sensor nodes in an aircraft cabin. Although various solutions based on technologies of established consumer goods, e.g., Bluetooth or WiFi, have been proposed and tested, the published accuracy results fail to make these technologies relevant for practical use cases. This stems from the challenging environments for positioning, especially in aircraft cabins, which is mainly due to the geometries, many obstacles, and highly reflective materials. To address these issues, we propose to evaluate in this work an Ultra-Wideband (UWB)-based indoor positioning system via a measurement campaign performed in a real aircraft cabin. We first illustrate the difficulties that an indoor positioning system faces in an aircraft cabin, by studying the signal propagation effects which were measured. We then investigate the ranging and localization accuracies of our indoor positioning system. Finally, we also introduce various methods based on machine learning for correcting the ranging measurements and demonstrate that we are able to localize a node with respect to an aircraft seat with a measured likelihood of 97 %.

I. INTRODUCTION

Indoor positioning systems (IPSs) are a necessary step towards automation across various industries. Comprehensive research has been performed in indoor positioning using different technologies such as Bluetooth, WiFi, Ultra-Wideband (UWB), each with different algorithms such as trilateration, triangulation, or fingerprinting [1, 2]. While promising centimeter-level accuracy solutions are available when line-of-sight paths are available, it is hard to maintain that accuracy in harsh indoor conditions with human blockage, obstacles or reflective materials. One of the challenging closed areas is the cabin of an aircraft, where various obstacles are present such as seats, humans, or luggage, making it significantly different from the residential, office, outdoor or industrial environments [3, 4]. As shown later in Section V, this leads to an environment with mostly non-line-of-sight conditions and with a high number of multipaths, making it generally difficult for accurate localization.

A precise indoor positioning system would enable automatic localizing of not only wireless sensors that measure, e.g., temperature or cabin air pressure once aircraft operations started, but also other tagged items such as life vests. In this way, cost and time savings are possible by avoiding largely manual configuration of sensors in assembly lines and by supporting cabin crew operations, such as item checks, before and after flights.

In order to be of practical use in an aircraft cabin scenario, the indoor positioning system should be able to distinguish between cabin seats, i.e. provide an absolute localization error of approximately 20 cm in 2D. UWB was already shown to be a promising candidate technology for cabin wireless communication and for such localization requirements [5, 6, 7]. For our evaluation, we selected the Qorvo DW1000-based active localization commercial off-the-shelf system, based on IEEE 802.15.4 UWB. This solution enables both communication and localization of objects in real-time with centimeter-level accuracy.

While these previous works were limited to small mockups of aircraft cabins, we extend here our evaluation of UWB to a larger scale measurement campaign performed in a cabin of a real Airbus A321. Two different scenarios are evaluated, where the object to be localized is either placed near the seat or near the seat’s headrest. We perform a comparison between traditional multilateration techniques and improved methods based on neural networks (NNs). We also contribute additional methods based on NN, and show how an end-to-end training approach achieves the best localization accuracy. Finally, we also investigate how the number of anchors and the ranging accuracy influences the localization accuracy via Monte Carlo simulations.

Overall, our measurements illustrate the challenge that an aircraft cabin constitutes with respect to received signal strength indication (RSSI)-based and UWB-based indoor positioning systems. We show the influence that the cabin has on the physical properties of the radio frequency signals compared with outdoor and office environments free of obstacles. We then evaluate the ranging accuracy of the system using various correction methods and show an average error of 4.4 cm. Finally, we demonstrate that our indoor positioning system is able to achieve an average localization error of 16.7 cm and a seat assignment error of 97 %, almost fulfilling our industrial requirements for all the seats in the aircraft.

This work is organized as follows: Section II presents the related work and Section III introduces the evaluated localization system and its use-cases for aircraft cabins. Section IV introduces the various methods for improving the accuracy of the indoor positioning system. Section V describes our measurement campaign in an Airbus A321 and localization results. Section VI gives some insights on other improvement methods via Monte Carlo simulations. Finally, Section VII concludes this work.
II. RELATED WORK

A. UWB for localization

UWB-based localization has attracted a large body of works, due to its low cost and high accuracy. Various works investigated the effects of the environment on the physical properties of the radio frequency channel. Irahhauten et al. [8] reported measurements and modeling of the UWB indoor wireless channel. They concluded that there is a limited temporal correlation between powers of multipath components and that the UWB signal is more robust against fading than conventional narrowband and wide-band systems.

Ye et al. [9] quantified the effect of line-of-sight and non-line-of-sight on ranging in real indoor and outdoor environments. They evaluated the impact of various materials and conditions on the ranging error and showed that UWB is a dependable technology for ranging. Similar studies where performed to evaluate the impact of material and conditions on ranging accuracy, such as the works from Bharadwaj et al. [10], Ngo et al. [11] and Haluza and Vesely [12].

Various works investigated how to account for the non-line-of-sight on the ranging accuracy. Ngo et al. [11] proposed a solution based on geometric modeling of the environment. Bandiera et al. [13] proposed a cognitive approach based on machine learning to identify the ranging environment and estimate its relevant propagation parameters.

Schroeer [14] used UWB-based localization in industrial scenarios with anchors based on four transceivers instead of one to increase the system robustness. They demonstrated an average accuracy of 0.13 m in situations with severe multi-path signals.

UWB was also seen as key technology for robotics and drones, as shown by the recent survey from Shule et al. [15]. Hamer and D’Andrea [16] and Tiemann et al. [17] proposed various mechanisms for automatic configuration and calibration of a UWB-based communication and localization network for robotic applications.

Lian Sang et al. [18] proposed a novel error estimation model for two way ranging and illustrate how alternative double-sided two way ranging outperforms standard two way ranging. Their model includes characteristics of the conventional clock-drift error model in two way ranging methods.

Alternate uses of UWB-based ranging were also recently investigated by using the additional channel impulse response data, which characterizes the radio frequency signal propagation. Ledergerber et al. [19] proposed to evaluate channel impulse response for angle of arrival estimation. Ledergerber and D’Andrea [20] illustrated how channel impulse response post-processing can be used for building a multi-static radar network. They demonstrated that such system can be used as passive localization by localizing a tag-free human walking in a room.

Various works also proposed a learning-based approach for correcting localization error. Kram et al. [21] also proposed to use the channel impulse response as input to a NN in order to predict information about localization. Similarly, Zhao et al. [22] also used an machine learning-based solution for ranging correction for small drones, but using only the ranges to the different anchors and attitude angles of the drone as input to the NN. Compared with these works, we propose here an end-to-end approach where the position is directly predicted, outperforming NN-based approaches just correcting the ranges.

Finally, UWB was recently adopted for precise localization by different phone manufacturers (e.g. Apple, Samsung) for localizing lost items or even serving as authentication mechanism.

B. UWB for aircraft applications

UWB has already been investigated as a solution for on-board wireless communication in aircraft cabin. Chiu et al. [3][4] characterized the UWB radio frequency propagation and channel impulse response within the passenger cabin of a Boeing 737-200 aircraft. They reported the fading statistics and correlation properties of individual multipath components. The effect of human presence was also evaluated and demonstrated how it affects the path gain as the density of occupancy increased from empty to full.

Andersen et al. [23] also investigated the impact of passengers on UWB signal absorption at the front section, upper deck of a double-decker large wide-bodied aircraft mockup. They concluded that the absorbed power due to the presence of passengers is relatively small, so the effect of passengers was considered to be marginal for the tested configuration.

Neuhold et al. [24] proposed a proof-of-concept for an UWB sensor network deployed in a mockup of a small passenger cabin of a commercial aircraft with a few passengers and report experimental results on the packet loss rate. They evaluated the loss induced by a single passenger and seat row and demonstrated packet loss rates with respect to signal attenuation.

Schmidt et al. [6] showed how UWB is a particularly fitting technology to support intra-aircraft communications and investigated regulation aspects. Via a proof-of-concept implementation, they also highlighted the potential of UWB for intra-aircraft use and identify challenges ahead.

In our previous work [5], we already investigated the localization accuracy of a UWB-based localization system, but it was limited to a small section in a cabin mockup. We also investigated an industrial application of UWB communication and technology for aircraft communication, more specifically with the use of Wireless Avionics Intra-Communications frequency range in [7].

To the best of our knowledge, this is the first work presenting such measurement campaign of UWB-based indoor positioning system onboard a real aircraft cabin. Compared also with previous works using machine learning for UWB-based localization, we are proposing a true end-to-end approach where the localization of the tag is directly predicted by the NN based on the raw data provided during ranging.
III. LOCALIZATION SYSTEM

We introduce in this section the indoor positioning system which was used for our evaluation. An UWB-based localization system was selected as a basis for our indoor positioning system mainly because of its high accuracy, its low latency, and its strong immunity against multipath conditions compared with other solutions such as WiFi or Bluetooth-based solutions. Those characteristics were also recognized by others, making UWB a localization solution in mass market products such as smartphones.

A. Use-cases

An indoor positioning system inside an aircraft cabin is highly relevant in order to assist the optimization and automation of many industrial and operational processes, from the manufacturing phase till the end-of-life phase of an aircraft. Such system would avoid many manual and tedious tasks, leading to large time and cost savings both at aircraft manufacturing and during aircraft operation. We review in this section various use cases within the aircraft scope and the advantages that an indoor positioning system would bring.

It is expected to have hundreds to thousands of wireless sensors placed inside the aircraft monitoring the environment and devices status using sensors such as temperature, humidity, engine status, smoke detection, cabin pressure, seat, or door status. The position of each sensor is used in order to properly correlate the measured data with the corresponding area of the aircraft. This use-case is relevant in the final assembly line, but also during aircraft maintenance where sensors might be replaced.

Another possible application is to localize and identify seats. Currently, the position of each seat and their corresponding seat numbers are hard-coded in a database based on the cabin configuration, dependent on each airline preference. However, a localization system may localize seats and automatically assign seat numbers with sensors and devices placed around it. This use-case will be evaluated later in Section V.

Various tasks have to be performed by the cabin crew before each take-off and after landing. Before aircraft take-off, the presence of safety equipment such as life vests, fire extinguishers, first aid kits, or portable oxygen equipment has to be checked. An indoor positioning system could automatically identify the location of items to be checked and give a warning if a given object is missing or not at its expected place.

In case the layout of a cabin is updated, an indoor positioning system could assist with the reconfiguration of various devices and sensors, automatically assigning them to a given seat position. The new cabin layout may be automatically extracted based on localization data, and adopted for other applications by finding the new locations of sensors mounted on the seats, the floor or in the cabin luggage compartments.

Finally, regarding industrial applications and regulations, various works already demonstrated that UWB would be a compliant technology with respect to regulations for aircraft and cabin communications.

B. UWB-based ranging

Our system is based on the Qorvo EVB1000 and DWM1001 evaluation boards, a system promising centimeter-level accuracy with a measurement latency of a few milliseconds. The Qorvo platform provides an easy-to-use system for working with UWB and supports custom software running directly on the micro-controller of the evaluations boards.

Both platforms are based on the DW1000 chip, which provides the facilities for message time-stamping and precise control of message transmission times. This enables a ranging method known as two way ranging, where the time of flight between two nodes can be measured by exchanging packets and measuring their time of arrival, as illustrated in Figure 1. This use-case is relevant in the final assembly line, but also during aircraft maintenance where sensors might be replaced.

According to the DW1000’s datasheet, a ranging accuracy of 10 cm can be achieved using UWB and two way ranging, based on the DW1000 clock precision.

C. Platform

The system is composed of two types of nodes. So-called anchor nodes are placed throughout the measurement environment at known locations. So-called tag nodes with unknown prior localization can then be localized by measuring their distance with the anchors via the two way ranging process.

For performing our ranging measurements, the tag and anchors ran a modified version of Contiki, an operating system designed for embedded sensor nodes. A simple controller/agent architecture was developed, which ensures that only a single node can send a packet at a time, preventing packet collisions. This also avoids more complex spectrum sharing mechanism.

For each ranging measurement between the tag and one of the anchors, the tag reports the resulting time of flight, the values of the various diagnostic registers from the DW1000, and the channel impulse response buffer to a central computer collecting all the data. The channel impulse response contains information about the radio frequency signal properties of the underlying propagation paths in the measurement environment.

After the ranging process with all the anchors is finished, the multilateration phase is performed in order to compute the 2D localization of the tag. The following optimization problem is solved:

\[
\min_{x_T, y_T} \sum_i \left( (x_T - x_i)^2 + (y_T - y_i)^2 + \delta^2 - r_i^2 \right)^2 \tag{1}
\]
with \((x_T, y_T)\) the coordinates of the tag which need to be computed, \((x_i, y_i)\) the known coordinates of the anchor \(i\), \(\delta_z\) the known distance along the \(z\) axis, and \(r_i\) the distance between the tag and anchor \(i\). We use a standard least square method for solving Equation (1).

IV. LOCALIZATION IMPROVEMENTS

The accuracy of the localization and multilateration approach presented earlier is highly dependent on the accuracy of the ranges and the measurement environment. A first evaluation of the raw ranging values provided by the system showed an average absolute error of 0.6 m in our aircraft cabin, which lead to a poor localization accuracy, as shown later in Section V.

Additionally, the DW1000 chip already provides mitigation techniques to overcome multipath effects in non-line-of-sight environments [30]. Despite these, our evaluation still showed non-negligible ranging error. We propose in this section different approaches for improving the overall accuracy of the system.

A. Static offset

For this first approach, we apply a static offset to each ranging measurement:

\[
\text{corrected range} = \text{range} + o_i
\]

with \(o_i\) the parameter of the model, fitted for each anchor \(i\) in the system. This is the simplest error correction model, which can compensate for static delays for the two way ranging process which were not necessarily accurately calibrated.

As shown later, this simple model is able to correct the ranging measurement in line-of-sight conditions with good results.

B. Linear regression

An improvement of the previous model is to take into account the impact of the range on the error. We model this effect using linear regression (LR):

\[
\text{corrected range} = \text{range} \cdot a_i + b_i
\]

with \(a_i\) and \(b_i\) parameters of the model, which are fitted for each anchor \(i\) in the system. This model accounts for a correlation between the measured ranges and the resulting ranging error.

C. Neural network

We propose in this section a NN-based approach to predict various aspects about the localization. We introduce here various extensions to our previous work [5], with additional output types and a fully end-to-end training and prediction.

Our NN architecture is illustrated in Figure 2. As input, a vector concatenating the measured ranges and channel impulse response data of one or all the anchors is used. This vector is then processed by three fully-connected NN layers with ReLU activation. As output, the NN predicts either the ranges, the coordinates of the tag, or the seat label associated to the tag’s position as presented in Table I.

In total, we trained four different versions of the NN, presented in Table I. The first two versions (NN 1A and NN range pred.) still require the multilateration step presented in Section III-C and Equation (1) in order to compute the 2D localization of the tag. The last two versions follow an end-to-end approach and directly predict the tag’s position, either as 2D coordinates or as label. This means that the optimization step from Equation (1) is not required for these versions in order to compute the 2D localization of the tag.

Fig. 2: Architecture of the NN and the size of the different layers. The size of the last layer depends on the type of output required.

### TABLE I: Variants of the neural network used in our evaluation

| Label          | Inputs            | Outputs                  | Problem  |
|----------------|-------------------|--------------------------|----------|
| NN 1A          | 1 anchor          | 1 range                  | Regression|
| NN range pred. | All anchors       | All ranges               | Regression|
| NN coord. pred.| All anchors       | Coord. of the tag        | Regression|
| NN seat pred.  | All anchors       | Seat label               | Classif.  |

The NNs were implemented and trained using PyTorch [31]. Hyper-parameter optimization was performed in order to fine-tune the parameters of the training process of the NNs.

V. NUMERICAL EVALUATION

We describe in this section our measurement campaign made in real aircraft cabin, and the ranging and localization results which were measured.

A. Measurement environments

Our measurements were performed in a real Airbus A321 fully furnished with 161 seats, specifically used for tests and measurements located at the Airbus manufacturing plant in Finkenwerder, Germany. The interior cabin of this aircraft is illustrated in Figure 3a. In total, 11 anchors were placed throughout the cabin according to Figure 4 using Qorvo’s MDEK1001 development module. In order to assess a potential industrial installation, the anchors were placed inside the luggage compartments as close to the cabin’s hull as possible.

For our ranging measurements, Qorvo’s EVK1000 evaluation kit was used as the tag to be localized. All 161 seats in the cabin were measured, with two different positions: directly
on the seat as illustrated on Figure 3(b) or on the headrest as illustrated on Figure 3(c). For each position, 10 different ranging measurements were performed, 7 of them used for training the various NNs presented in Section IV-C and 3 for the evaluation presented here.

As a comparison, we also performed measurements in two additional environments: outside and in an indoor office environment, both where no obstacle between the tag and anchors was present. These additional environments will serve as references to estimate the impact of the cabin on the measurements.

The UWB channel, communications, and ranging parameters used for our measurements are summarized in Table II.

### TABLE II: UWB channel parameters used for the measurement campaign

| Parameter        | Value                  |
|------------------|------------------------|
| UWB channel      | 4                      |
| Center frequency | 3993.6 MHz             |
| Bandwidth        | 1331.2 MHz             |
| Preamble length  | 128 symbols            |
| Preamble code    | 17                     |
| Data rate        | 6.8 Mbps               |
| Ranging method   | Single sided two way ranging |

B. Impact of the environment on the properties of the physical signal

We first review the impact of the different measurement environments on the properties of the physical radio frequency signal.

Two samples of the channel impulse response data are presented in Figure 5, one in the aircraft cabin, and the other in the indoor office environment, both for a distance between the nodes of approximately 10 m. While both environments exhibit multipath effects, the magnitude of this effect is much larger in the aircraft environment. We also notice a stronger fading of the radio frequency signal in the aircraft environment.

To numerically assess the fading of the radio frequency signal, we use the first path power level as our metric. Based on Qorvo’s documentation, we use the following estimation formula for computing this power level:

$$10 \cdot \log_{10} \left( \frac{F_i^2 + F_2^2 + F_3^2}{N^2} \right) - A$$

where $F_i$ corresponds to the first path amplitude point $i$ registers, and $A$ a constant dependent on the radio configuration.

The impact of the ranging distance on the first path power levels are presented in Figure 6. Compared with the outdoor and indoor environments, there is a much stronger attenuation on the received signal power in the aircraft, mainly due to the higher number of obstacles.

This strong attenuation had an impact on the connectivity, since ranging between the extreme front and back of the cabin was difficult due to the power levels below the DW1000 sensitivity margin.
Fig. 6: Impact of distance on estimated first path power level. Areas correspond to the 25% and 75% percentiles.

We note also in Figure 6 a correlation between the estimated first path power and the distance to anchor. This relationship is often used in well-known localization methods such as Bluetooth-based or WiFi-based systems, which use RSSI information for distance estimation. To understand how such a system would have performed in our measurement environment, we fitted a polynomial of degree 3 to the data and computed the resulting absolute ranging error of such a RSSI-based system. Results are presented in Figure 7. Compared to the non-corrected values provided by the UWB ranging system, the RSSI-based estimator provides worst results, with an average absolute error of 2.52 m. This demonstrates why RSSI-based systems are not sufficient for our use-cases and motivates our choice of a UWB-based system.

Fig. 7: Absolute ranging error of an RSSI-based distance estimator

Finally, we also numerically quantify the multipath effects visible on Figure 5 with the following metric:

\[
multipath_{\text{metric}} = \frac{1}{N-1} \sum_{i=1}^{N} \left( 1 - \frac{CIR_i}{\max_k CIR_k} \right)
\]  

A value close to 0 indicates a strong single path in the channel impulse response data, while a value close to 1 indicates the presence of multiple peaks with similar energy levels. This is illustrated in Figure 5 where the channel impulse response measured indoor would have a value close to 0 due to its strong peak, while the one measured in the cabin would have a larger value, closer to 1 due to the presence of multipaths.

Results with respect to the ranging distance are presented in Figure 8. As expected, there is a strong correlation between the ranging distance and the multipath metric in the aircraft cabin. In the outdoor and indoor environments, the multipath metric remains close to constant.

Overall, Figures 5, 6 and 8 illustrate the different challenges that an aircraft cabin poses and its impact on the properties of the radio frequency signals. This will be illustrated in the next sections, where these effects result in large ranging errors.

C. Ranging accuracy

We evaluate in this section the ranging accuracy, i.e. the accuracy of the individual distance measurements between tag and anchors. We use the absolute difference between measured and true range as our metric:

\[
ranging error = |\text{range} - \text{range}_{\text{true}}|
\]  

Table III provides a summary of the impact of the different correction methods presented in Section IV on the absolute ranging error in the both the outdoor and the cabin environment. In the outdoor environment, we achieve decimeter level accuracy with the offset and LR corrections, with an average of 4 cm which matches the advertised accuracy of the DW1000 system.

In the aircraft environment, we notice a larger ranging error of 30 cm in average even after offset and LR correction. This is especially visible at the tail of the statistical distribution as shown by the 95% quantile and later in Figures 9a and 9b.

The NN-based error correction brings a large benefit, almost matching the accuracy measured in the outdoor environment. Despite larger errors, the variant of the NN only using the
TABLE III: Summary of the absolute ranging error before and after correction methods in the aircraft and outdoor environments

| Env.     | Method          | Mean    | Median   | Q-95 %    |
|----------|-----------------|---------|----------|-----------|
| Outdoor  | Raw data        | 0.389 m | 0.430 m  | 0.499 m   |
|          | Corr. w/ Offset | 0.077 m | 0.045 m  | 0.275 m   |
|          | Corr. w/ LR     | 0.040 m | 0.033 m  | 0.103 m   |
| Aircraft | RSSI estimator  | 2.520 m | 1.944 m  | 6.835 m   |
|          | Raw data        | 0.604 m | 0.411 m  | 1.728 m   |
|          | Corr. w/ Offset | 0.335 m | 0.223 m  | 0.968 m   |
|          | Corr. w/ LR     | 0.307 m | 0.211 m  | 0.892 m   |
|          | NN 1A           | 0.160 m | 0.113 m  | 0.486 m   |
|          | NN range pred.  | 0.044 m | 0.020 m  | 0.169 m   |

input of one anchor (labeled NN 1A in Table III) still brings a benefit compared with the LR correction.

Figures 9a and 9b present additional details about the impact of the LR and NN corrections on the ranging accuracy. As expected from the conclusions from Section V-B the ranging error when the tag is placed on the seat is larger compared to the headrest.

D. Localization accuracy

We evaluate in this section the localization accuracy, i.e. the accuracy of the computed 2D coordinates based on the ranging measurements. We use the Euclidean distance to the true coordinates as our metric:

$$\text{localization error} = \sqrt{(x_T - x_{\text{true}})^2 + (y_T - y_{\text{true}})^2}$$

with \((x_T, y_T)\) the computed coordinates of the tag after multilateration or the predicted coordinates from the NN.

Table IV provides a summary of the impact of the corrections from Section V-B on the localization error. As for the previous results, the larger ranging errors also lead to larger localization errors when the tag is placed on the seat compared with when it is placed on the headrest. Figures 10a and 10b present additional details about the impact of the LR and NN corrections on the localization accuracy.

TABLE IV: Summary of localization accuracy in the aircraft cabin

| Method             | Tag on seat | Tag on headrest |
|--------------------|-------------|-----------------|
|                    | Mean Q-90 % | Mean Q-90 %     |
| Raw data           | 0.923 m     | 0.354 m         |
| Corrected w/ LR    | 0.379 m     | 0.199 m         |
| NN range pred.     | 0.208 m     | 0.161 m         |
| NN coord. pred.    | 0.167 m     | 0.142 m         |

Regarding the NN variants, the NN directly predicting the coordinates appears to result in a better accuracy compared with the NN predicting the only ranges. This is explained by the additional multilateration process required for the range variant, since small errors on the ranging can propagate in the multilateration computation, leading to larger errors. This illustrates that an end-to-end training approach is more effective for the localization process.

E. Seat assignment

Finally, we evaluate in this section the use-case where the tag has to be assigned to a seat based on its localization. This is performed by assigning it to the closest known seat position given the computed coordinates. This is formalized as:

$$\text{assigned seat} = \arg \min_{\text{seat}} \sqrt{(x_T - x_{\text{seat}})^2 + (y_T - y_{\text{seat}})^2}$$

with \((x_{\text{seat}}, y_{\text{seat}})\) the known locations of the different seats in the aircraft.

According to the cabin geometry presented in Figure 4 a seat assignment accuracy of 100 % would require a localization system with a maximum error of 0.226 m. Following the results from Table IV our localization system is close to reaching this required accuracy.

Accuracy results of the different methods are presented in Table V. Since seat labels represent 2D coordinates (eg. seat 5A implies row 5 and column A), we split the accuracy in Table V according to the \(x\) axis (i.e. seat row axis) and the \(y\) axis (i.e. seat letter axis) illustrated in Figure 4.
For most methods, we notice a large difference between the two axes, where the accuracy along the $x$ axis is better than on the $y$ axis. This is explained by the geometry of the aircraft cabin and the anchor placements within the cabin, making it more sensitive to small errors along the $y$ axis.

The results from Table V match the ones from Section V-D and the requirement of 0.226 m localization error. As previously, the NN directly predicting the seat label also achieves the best results, with an accuracy better than 97% in both use-cases. This illustrates again the impact of an end-to-end approach for training a NN.

**F. Localization speed**

We detail in this section the time required for the localization process. As illustrated in Figure 11 our system requires the exchange of two messages with each anchor, which require less than 1 ms per anchor. The collected ranges and channel impulse response data are then processed, either by the multilateration process by solving Equation (1) or by executing the NN.

Table VI illustrates the processing time required for the NN on three different platforms: a server with an Intel CPU and a Nvidia GPU representative of servers used in datacenters, and the last two generations of the Raspberry Pi. Two different implementations of the NN are presented here: PyTorch v1.10 and Genann v1.0. While PyTorch is designed for performance and can also take advantage of GPU acceleration, we also selected Genann as a reference worst-case implementation since it does not rely on any hardware acceleration such as GPU, CPU extensions such as Single Instruction, Multiple Data instructions, or parallelization.

**TABLE VI: Execution time of the NN inference on different hardware platforms and NN frameworks**

| Hardware platform | Implem. | Avg. time |
|-------------------|---------|-----------|
| Xeon 5120 at 2.20 GHz + RTX 2080 GPU | PyTorch | 0.2 ms |
| Xeon 5120 at 2.20 GHz | Genann | 2.6 ms |
| Raspberry Pi 4 Model B+ Rev 1.4 | Genann | 5.4 ms |
| Raspberry Pi 3 Model B+ Rev 1.3 | Genann | 31.9 ms |

Overall, the NN is fast even on low-cost hardware platforms, mainly due to the small sizes of the layers and a single hidden layer. These values illustrate that the NN inference is not a bottleneck in the localization system.

**VI. IMPROVEMENT OPTIONS**

With our measurement campaign and our evaluation in Section V, we showed that our UWB-based localization system is able to achieve an accuracy sufficient for assigning about 97% of the seats in a real aircraft cabin.

We discuss in this section various ways to further improve this accuracy, especially in conditions where the end-to-end training a NN might not be possible. We use Monte Carlo simulations to evaluate alternate configurations and their impact on the localization accuracy.

**A. Increased anchors count**

One obvious approach for improving the results is to add additional anchors throughout the cabin. Since the localization error is correlated with the distance between anchor and tag, having more anchors would increasing the number of anchors closer to the tag, thus reducing the overall ranging error.

To evaluate this option, we performed Monte Carlo simulations where we simulated additional (virtual) anchors. The

\[\text{CDF} = \frac{\text{tag distance}}{\text{range of tag}}\]

\[\text{Localization error} = \sqrt{\left(\frac{x}{\text{accuracy}_x}\right)^2 + \left(\frac{y}{\text{accuracy}_y}\right)^2}\]

\[\text{accuracy} = \frac{\text{number of anchors}}{\text{number of tags}}\]

The number of anchors required for a given accuracy can be estimated using these equations. In practice, this means that for a desired accuracy, we can calculate how many anchors are needed to achieve that accuracy.

\[\text{Number of Anchors} = \sqrt{\left(\frac{\text{accuracy}}{\text{Localization error}}\right)^2 + \left(\frac{\text{accuracy}}{\text{Localization error}}\right)^2}\]

\[\text{Accuracy} = \frac{\text{Number of Anchors}}{\text{Number of Tags}}\]

By increasing the number of anchors, we can significantly reduce the localization error and improve the accuracy of the system.
additional anchors were randomly placed throughout the cabin. The ranging error from the original anchors was statistically fitted to a Johnson’s $S_U$-distribution, which was then used for generating the ranging errors for the additional anchors:

\[
\text{simulated range} = \text{true range} + \text{noise} \quad \text{(9)}
\]

This specific distribution was chosen because it resulted in the best fit among a set of 50 other statistical distributions.

Based on these additional ranges, we performed the LR correction and multilateration operations to compute the coordinates of the tag. Multiple runs of this process were performed and the best localization errors were kept.

Results are presented in Figure [11]. Compared with our original measurements with 11 anchors, the additional anchors indeed result in a better localization accuracy. By doubling the number of anchors, it would be possible to match the 0.226 m requirement for the headrest position. For the seat position, the increased number of anchors is not sufficient for reaching the required localization accuracy.

\[
\text{simulated error} = \text{measured error} \cdot \alpha \quad \text{(10)}
\]

with $\alpha$ a scaling factor in the $[0, 1]$ interval. As previously, we then performed the LR correction and multilateration operations to compute the coordinates of the tag based on the ranges with scaled error.

Results are presented in Figure [12]. Scaling the errors indeed lead to a fulfilled requirement for the headrest position. For the seat position, we note that a better localization accuracy would be required.

**C. Other approaches**

We showed in Section V-E that the assignment accuracy is sensitive along the $y$ axis of the cabin. Additional anchors along this axis should help improving this accuracy. For our aircraft use-case, anchors could be placed along the wings of the aircraft, yet additional measurements would be required to validate if ranging would be possible in such conditions.

**VII. Conclusion**

We presented in this work an Ultra-Wideband (UWB) based localization system targeting use-cases in aircraft cabins. Our main contribution is a measurement campaign performed on-board a real Airbus A321 aircraft, as well as various methods for correcting ranging errors based on linear regression (LR) and neural networks (NNs).

Our measurements results confirm our previous findings from [5]. While our previous measurements were performed in a mockup of a small cabin section, the results presented here illustrate that UWB is indeed a valid candidate for an onboard aircraft localization system. With our end-to-end NN approach, we were able to localize a tag with an average localization error of about 16 cm and assign it to a seat with an accuracy of 97%. We also show that compared against a simpler system using only received signal strength indication (RSSI) – such as Bluetooth-based localization systems – UWB results in more accurate localization. Our measurements also confirm that an aircraft cabin is a challenging environment for localization, due to the presence of many obstacles and propensity for multipath effects.

Overall, we demonstrate the viability of the UWB technology for localization for an application in the aircraft industry. Via Monte Carlo simulations, we also explored various methods for increasing the accuracy when using the LR approach.

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