Precise UWB-Based Localization for Aircraft Sensor Nodes

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***Abstract*—In this work, an indoor positioning system (IPS) is introduced to overcome the tedious task of configuration of sensor nodes in an aircraft. Our positioning system is based on a ultra-wideband (UWB) commercial off-the-shelf (COTS) system, which was selected because of its fine resolution in time. In the first part of the work, time of flight (ToF) and multilateration algorithms are implemented and evaluated in two and three dimensional scenarios. Our measurement results show an accuracy below 10 cm in line-of-sight (LOS) conditions. However, when experiments are held inside a cabin mock-up under the presence of non-line-of-sight (NLOS) condition, the accuracy gets significantly worse. To overcome this issue, we introduce a artificial neural network (ANN)-based localization approach in the second part of the work to enhance the localization accuracy using raw channel impulse response (CIR) data provided by the localization system. We first illustrate that our approach is able to distinguish between LOS/NLOS conditions, with an accuracy of more than 85 %. We then demonstrate that our ANN can also be trained to directly predict the localization of an object. Our experiments show that the localization error is reduced by approximately 70 % resulting in 12.3 cm on average, in comparison with the time-based approach which has 43 cm error for the same measurement setup.**

I. Introduction

Indoor positioning has always attracted interest because of the lack of an optimal system which is independent of the environmental conditions and also the high demand for such a system in a variety of applications. Thorough reviews of the indoor positioning use cases can be found in [1, 2], where the examples are ranging from smart cities to social networking. Comprehensive research has been performed in indoor positioning using different technologies such as Bluetooth, WiFi, UWB, each with different algorithms such as trilateration, triangulation, or fingerprinting [3, 4]. Even though there are promising centimeter-level accuracy solutions if the line of sight path is 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. Such positioning techniques and methods would enable to localize 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 enable the localization of aircraft cabin sensors and equipment, we assume that a localization system needs to have an accuracy that allows to distinguish between individual cabin seats, i.e. approximately 30 cm in 2D. Although various active indoor localization systems based on radio frequency (RF) are available on the market, most solutions are not suitable for the use-cases previously described. This is due to their poor accuracy in the challenging environment of an aircraft cabin, mainly due to the presence of obstacles.

In this work, we propose to use the Decawave DW1000-based active localization COTS system as a basis for our evaluation. This solution, based on IEEE802.15.4 UWB, enables the localization of objects in real-time. Our main contributions in this paper are a measurement study of this UWB-based localization system in an aircraft cabin mock-up, as well as advanced algorithms for improving its accuracy in such a demanding environment. We show via measurements and a numerical evaluation that this system is able to reach decimeter-level accuracy in LOS and NLOS conditions, fulfilling the accuracy requirements in harsh NLOS conditions. Our localization method is based on ToF distance measurements combined with multilateration techniques and a neural network for correcting the ToF in NLOS conditions.

While our LOS results using uncorrected ToF values are promising, an initial evaluation in an aircraft cabin showed poor accuracy, failing our industrial requirements. Due to the presence of objects such as seats, the aircraft cabin can be seen as a mixed indoor environment, with LOS and NLOS conditions depending on nodal density and placement within the cabin. To improve the NLOS performance, we propose in this work to use additional information provided by the Decawave positioning system, namely the CIR. Various analytical methods and heuristics exist to evaluate the CIR data, but require to be manually calibrated according to the measurement environment. To avoid this manual calibration, we propose to use an ANN to enhance the localization accuracy in NLOS operation. To this end, the CIR data is used

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as input for the ANN among with the corresponding ToF data. The position of the object to be localized is then estimated through the ANN. Our experiments show that the localization error is 12.3 cm in average, reducing by approximately 70 % in average compared with the time-based approach for the same measurement setup. This improved accuracy fulfills the initial requirements, enabling us to use such localization for the automatic configuration of sensors in a cabin environment.

This paper is organized as follows: Section II reviews related literature. Then Section III presents the applicable use cases for an aircraft. The time-based and the neural network-based algorithms are introduced in Section IV by explaining the required measurement parameter for a particular algorithm. Section V benchmarks our approach in a cabin environment before Section VI draws conclusions.

II. Related Work

In this section, we review various related works on active and passive indoor localization, from both the perspective of the methodologies and the technologies which were used.

Only a few works investigated positioning on board an aircraft in the literature. In [5], the identification of the corresponding seat numbers was investigated using support vector machine (SVM) for classification based on received signal strength indicator (RSSI) fingerprints in a static environment. A 99 % accuracy was achieved. It was also shown that trilateration worked better for moving objects in a cabin. To the authors' best knowledge, this is the first work evaluating the performance of an UWB and ANN-based localization system inside the cabin of an aircraft.

A. UWB localization

Various works proposed to use UWB for localizing objects, since it has proved to have better performance thanks to its very large bandwidth resulting in precise time of arrival (ToA) calculations. In [6], an IPS based on UWB was proposed resulting in a ranging error below 4 cm under LOS conditions.

On the other hand, [7] showed that such centimeter-level accuracy could be significantly degraded in the presence of LOS blockage. Experimental results revealed that the range estimator error could reach 1.21 m in some NLOS cases. Multiple mitigation methods dealing with NLOS conditions in UWB were reviewed in [8]. The review mainly focused on mathematical modeling of the signal propagation as-well-as hybrid systems using additional information such as signal strength.

In [9], a method combining ToF and time difference of arrivals (TDoA) measurements in UWB was proposed in order to exploit the advantages of both methods and reduce tag-side power consumption. Experiments showed that even though the accuracy remained the same in comparison to results of ToF or TDoA alone, tag-side power consumption could be reduced by 75 % compared to the ToF method due to the reduced number of messages which are required to calculate a position.

Finally, an UWB-based single-anchor indoor localization system was proposed in [10] by exploiting multipath components. Combined with a floor plan, reflected signal paths were used in order to map them to virtual anchors. Experimental results showed a position error of 22 cm for 90 % of the estimates.

B. Model-based indoor localization

If we consider model-based approaches, many IPS have been proposed in the literature. In [11], Bluetooth Low Energy (BLE) was used to retrieve the highest three RSSI values from the anchors around a given tag and trilateration was then applied. To find out the corresponding distance for a particular RSSI value, multiple RSSI samples were collected at different distances and the relationship between RSSI and the distance was then mathematically modeled. Similarly, [12] also used RSSI measurements for localization, but exploited frequency diversity to reduce the fluctuation in values. RSSI was measured for different frequencies and the highest value among them is used for the distance calculation.

In [13], an IPS based on WiFi was proposed using the multiple-input and multiple-output (MIMO) principle. For estimating the position, the angle of arrival (AoA) was computed at each antenna array and filtering of the multipaths was performed at the() anchors. In order to improve accuracy, RSSI values were also taken into consideration. Results showed that similar positioning accuracy than in [14] or [15] with a median accuracy of 40 cm but without the addition of hardware. A similar approach was proposed in [16], where burst messages were sent to reconstruct the signal at a higher resolution as in UWB scenarios and aims to calculate the time of arrival more precisely. The AoA is then computed based on the message having the closest ToF to the calculated one.

C. Fingerprint-based localization

Recently, IPS based on learning approaches have also gained in popularity by making use of CIR or channel state information (CSI) data.

Detection and classification of LOS versus NLOS situations were already investigated in various works. *LiFi* was proposed in [17] as an approach to classify LOS/NLOS scenarios using a model-based approach. The authors used the CSI of WiFi with signal processing to build a mathematical model. Experimental results showed that a correct classification of LOS was achieved with an accuracy of 90.4 %. Similarly, [18] proposed a real-time LOS/NLOS classification by exploiting phase and amplitude features of the physical layer and leveraged spatial diversity provided by MIMO. Variations of the amplitude and phase were used as an identification criterion and an accuracy higher than 80 % was achieved in mobile situations. In [19], an algorithm based on SVM classified was developed using on CIR data fingerprinting to identify LOS/NLOS conditions. This classification was then used to mitigate NLOS effects using a SVM for regression. A similar approach was proposed in [20], where an ANN model processing CIR data was used. Results showed that it outperforms SVM with respect to accuracy.

In [21], *DeepFi* was introduced, a passive IPS based on CSI provided by WiFi access points equipped with multiple

Table I: Positioning use cases on board aircraft and assumed requirements (LV = Life Vest, FE = Fire Extinguisher).

	Final Assembly Line	**Aircraft operation**			**Maintenance**	
Use-case	Auto-configuration	Checks (LV and FE)	Check left items	Localize crew dev.	Self removing	Auto-conf.
Required accuracy	< 10 cm	< 30 cm	< 50 cm	< 10 cm	< 10 cm	< 10 cm
Required resolution	< 30 cm	< 50 cm (LV), < 3 m (FE)	< 10 cm	< 10 cm	< 50 cm	< 30 cm
Localization time	< 5 min	< 1 min	< 1 min	Real time	< 5 min	< 5 min
Presence of people	Few	Few	Many	Many	Few	Few
Base stations	Partially installed	Installed	Installed	Installed	Installed	Installed
Sensor nodes	Partially installed	Installed	Installed	Installed	Installed	Installed
Additional nodes	FAL nodes	Crew devices	Crew devices	Crew devices	Maintenance devices	
Localized item	Sensors	Passive and sensor tags	Passive	Sensors	Sensors	Sensors

antennas. An ANN was trained in different measurement environments and an average localization accuracy of 0.95 m and 1.8 m was achieved. The influence of other parameters on the performance of the system was investigated such as the number of antennas, the presence of obstacles in the environment or human blockage between devices for a short period.

In [22], detection of the presence of humans was investigated by detecting changes in CIR values. Experimental measurements showed that an accuracy of 97 % was achieved for detecting the presence of humans, and a localization accuracy of 1.22 m and 1.39 m was achieved in two different environments. Similarly, [23] proposed to use WiFi CSI data in combination with the acoustic signal from a scene in order to identify a given person from a group of 2 to 8 persons. Using a SVM-based classifier, an accuracy higher than 80 % was achieved depending on the group size.

In addition to localization of nodes and objects, [24] proposed *SignFi*, a system for sign language recognition based on the use of WiFi CSI data. Classification of human gestures was performed using convolutional neural networks, and an accuracy of 94.8 % for classifying 276 signs was achieved.

III. Indoor Localization for Aircraft

An IPS inside an aircraft 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 IPS would bring. Table I summarizes those use cases and their corresponding requirements for the IPS.

A. Final assembly line

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 [25]. The position of each sensor must be known in order to properly correlate the measured data with the corresponding area of the aircraft. While this position may be manually defined at installation, a localization system automatically identifying the positions of sensors can avoid this tedious task, also avoiding human errors. Another possible application is to identify the seats. In the current scenario, the position of each seat and their corresponding seat numbers are hard-coded based in 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.

B. Cabin crew operations

An important use case for automation and localization is cabin crew operations. 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 (LV), fire extinguishers (FE), first aid kits, or portable oxygen equipment has to be checked. Those tasks are currently manually performed and may be easily automated using an IPS. The system can 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. Finally, crew devices and objects such as smartphones or trolleys may also be automatically located in order to assist cabin operations.

C. Aircraft maintenance

During aircraft maintenance, sensors are checked and inspected, and defective ones are repaired or replaced. During this process, an IPS would provides similar benefits than in the final assembly line (FAL) use-case. The location of defective sensors may be easily found since it can already be measured during the lifetime of the aircraft. After a device or sensor replacement, the new location may be automatically updated using an IPS.

Finally, while the cabin configuration and layout is determined based on the airlines specifications during manufacturing, changes to this layout may occur during the lifetime of the aircraft to accommodate for changes of business or passenger needs. In case the layout of a cabin is updated, an IPS 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 the other applications by finding the new locations of sensors mounted on the seats, the floor or in the cabin compartment.

IV. Localization Using Ultra-Wide Band

We introduce in this section the IPS which was used for our evaluation. An UWB-based localization system was selected as a basis for our IPS mainly because of its high accuracy, its low latency, and its strong immunity against multipath conditions compared to 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.

Our system is based on the Decawave EVB1000 evaluation boards, a system promising centimer-level accuracy with a latency of a few milliseconds, which would fulfill the requirements illustrated in Table I. The Decawave platform provides an easy-to-use system for working with UWB and supports custom software running directly on the nodes.

We consider a typical aircraft environment where *Anchors* refers the pre-deployed nodes and *Tags* indicates the nodes to be localized. In the scope of this work, anchors are located at well-known predefined positions as reference points, and tags refer to sensors or items such as seat or temperature sensor. In the rest of the paper, we mainly considering the FAL requirements and boundary conditions mentioned in Section III and Table I.

A. Positioning using multilateration approach

When there is LOS between anchor and tag, it is possible to perform ToF measurements accurately thanks to Decawave's picosecond-precise timestamps at transmission and reception of messages. In order to avoid the clock synchronization challenge between nodes, a two-way ranging (TWR) approach is selected. To measure the signal propagation time between two nodes, messages are exchanged between the nodes in one or double-sided ways [26]. After measuring the ToF, the distance can be easily estimated by multiplying ToF with the speed of light.

Based on the ranges between the tag and the different anchors, the coordinates of the tag (x_T, y_T, z_T) can be computed using multilateration. While a closed-form solution can be obtained for 2D and 3D positioning based on circles or spheres intersections, we selected an optimization-based approach which proved to be more robust to ranging errors in our numerical evaluation. Given the n anchors coordinates $(x_1, y_1, z_1), \ldots, (x_n, y_n, z_n)$ and the measured ranges between the anchors and the tag $r_1, \ldots, r_n$, the coordinates of the tag are computed by minimizing the following equation:

$$\sum_{i=1}^{n} \left(\sqrt{(x_i - x_T)^2 + (y_i - y_T)^2 + (z_i - z_T)^2} - r_i \right)^2 \quad (1)$$

The aim of this equation is to minimize the difference between the measured ranges and the Euclidean distances computed based on the coordinates. The iterative Gauss-Newton algorithm can be used for solving this minimization problem.

This method is labeled *time-based approach* in the remaining of this work.

B. Artificial neural-network approach

As illustrated with our measurements later in Section V, the multilateration approach previously introduced has poor accuracy in NLOS conditions, i.e. when there are obstacles between nodes. To overcome this issue and fulfill our requirements, we chose to use a fingerprint-based approach, one of the most common techniques in indoor localization. An offline phase is first performed where data acquisition is done at difference locations of the target environment. During this phase, CIR and ToF values are recorded in order to gather more information about a specific location. Then in an online phase, the estimation is done by considering the best match between offline data and current retrieved data. We selected to use an ANN to perform this task and estimate the tag position.

The CIR data contains the information about the measured environment. It provides additional information about the propagation of the RF signal such as reflections, allowing to distinguish the different paths between the sender and receiver. After each ranging measurement, the Decawave chip stores the CIR in an internal accumulator with 1016 complex values, which can easily be programmatically retrieved.

The ANN takes the CIR and ToF values of the anchor-tag pairs as input, and hence can be viewed as the following function:

$$f\left(CIR_1 \,||\, ToF_1 \,||\, \ldots \,||\, CIR_n \,||\, ToF_n\right) \quad (2)$$

with $\cdot||\cdot$ corresponding to the concatenation operator. Apart from a linear normalization step to the interval $[0, 1]$, the ANN uses raw CIR and ToF values provided by the Decawave chip.

We define two tasks for the neural network: *(i)* a classification task predicting LOS or NLOS conditions, *(ii)* and a regression task predicting the tag coordinates. Although the main goal of our work is to determine the position of an object, we defined the preliminary simpler task of LOS/NLOS classification in order to assess if a ANN may indeed be trained for the more complex task of regression.

1) LOS/NLOS Classification: The first task for the ANN is to determine if there is either LOS or NLOS between two ranging nodes, which is a binary classification problem. In this case, we only use the CIR data of the anchor with which the ranging is performed. We use a standard fully-connected neural network (FCNN) with two hidden layers as illustrated Table II.

Table II: Size of the different layers for the classification task. Indexes represent the weights (w) and biases (b) matrices.

Layer	**Size**
Linear with ReLU6 activ.	$(1016, 989)_w + (989)_b$
Linear with ReLU6 activ.	$(989, 989)_w + (989)_b$
Linear	$(989, 1)_w + (1)_b$
	Total: 1 985 913 parameters

In order to train this FCNN, the Adam optimization algorithm is used [27] with the binary cross-entropy loss:

$$loss = \frac{1}{N}\sum_{i=1}^{N}(y_i \cdot \log \widetilde{y_i} + (1-y_i)\cdot \log(1-\widetilde{y_i})) \quad (3)$$

with $y_i = 0$ if there is LOS at measurement position i, and $y_i = 1$ for NLOS, and $\widetilde{y_i}$ the prediction of the neural network. The layer sizes presented in Table II and other hyper-parameters such as learning rate or dropout parameter were automatically found using hyper-parameter optimization.

2) Neural Network based Localization: The second task aims at predicting the 2D coordinates of the tag, which is a regression task. Our experiments mainly focused on 2D localization with 3 anchors, but it may easily be extended to a 3D localization problem with more anchors.

As illustrated in Equation (2), the ANN takes the concatenation of the CIR data and ToF measurements of the different anchors as input and predicts the x_T and y_T coordinates. As for the previous task, we use a standard FCNN with two hidden layers as illustrated Table III.

Table III: Size of the different layers for the regression task. Indexes represent the weights (w) and biases (b) matrices.

Layer	**Size**
Linear with ReLU6 activ.	$(3051, 1764)_w + (1764)_b$
Linear with ReLU6 activ.	$(1764, 1764)_w + (1764)_b$
Linear	$(1764, 2)_w + (2)_b$
	Total: 8 500 718 parameters

In order to train this FCNN, the Adam optimization algorithm is also used with the L1 loss:

$$loss = \frac{1}{N}\sum_{i=1}^{N}(|x_{T_i} - \widetilde{x_{T_i}}| + |y_{T_i} - \widetilde{y_{T_i}}|) \quad (4)$$

with (x_{T_i}, y_{T_i}) the correct 2D coordinates at measurement i, and $(\widetilde{x_{T_i}}, \widetilde{y_{T_i}})$ the predicted coordinates from the ANN. As previously, the layer sizes presented in Table III and other hyper-parameters were also automatically found using hyper-parameter optimization.

V. Numerical Evaluation

We numerically evaluate in this section both localization approaches presented in Section III. We present our measurement environments and illustrate the results obtained from the implemented time-based localization and the neural network-based localization respectively.

In order to numerically compare the performance of our system and the two numerical approaches, we focus here on the Euclidean distance between the actual coordinates and estimated ones.

A. Measurement environment and dataset

We performed our measurements in two environments. First, LOS experiments are conducted in an indoor area where there is nothing in between the devices as shown in Figure 1 in case of 2D localization. A similar setup than the one illustrated in Figure 1 is also used for 3D localization using 4 different anchors placed at different heights. NLOS experiments are conducted inside an Airbus A330 aircraft cabin mock-up which can be seen in Figure 2.

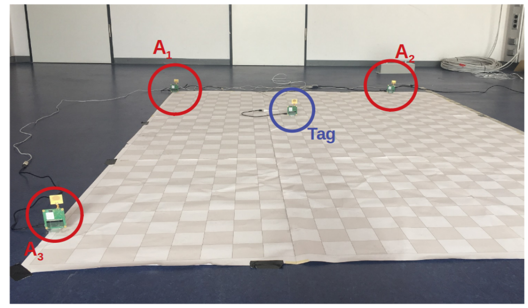

Figure 1: Overview of the LOS measurement setup.

Figure 2: Overview of the cabin mock-up where the measurements were performed.

The training dataset of the classification task is collected at random positions inside our measurement environment with corresponding labels, i.e., LOS or NLOS. Similarly, test data is also collected in different positions to measure the performance of the network.

For the regression task, CIR and ToF are recorded every 20 cm in a 2 m by 3 m grid inside the mock up with their x and y positions as training data. Test data is obtained by placing the tag in different random positions than the training data set.

B. Time-based localization results

1) Results in LOS conditions: The time-based localization algorithm introduced in Section IV-A is applied at 31 different positions in total and the location of the tag is estimated 20 times in each position. 2D and 3D measurements are performed with respectively 3 and 4 anchors. Results are presented in Figure 3.

Our measurements show that a maximum localization error of 6.5 cm for 2D and 13 cm for 3D respectively was achieved for 80 % of the measurements, which satisfies most of the system requirements given in Table I.

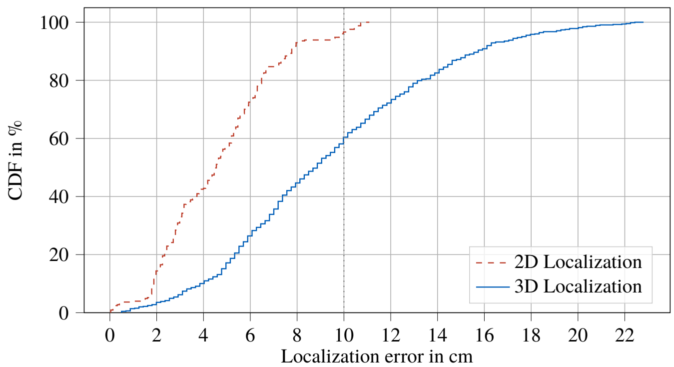

Figure 3: 2D/3D LOS error CDF of the time-based approach.

In order to better understand if some specific locations are better than other regarding accuracy, Figure 4 illustrates the error at different points of the setup for the 2D measurements. It is clearly visible that there is a correlation between the tag location and the measurement error. For instance, the middle area has the lowest error. The only reason for getting poor accuracy is because of the wrong measurement of the ToF.

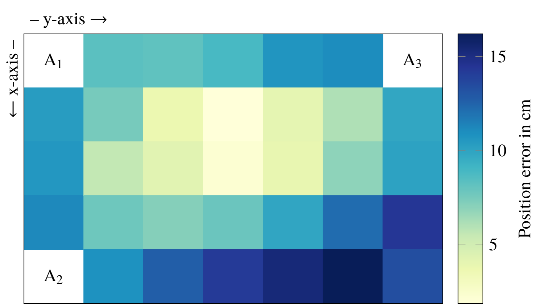

Figure 4: 2D LOS error heat map of the time-based approach.

In order to better understand this correlation, Figure 5 illustrates the correlation between the measured range and the actual range, namely:

$$abs.\ error = |actual\ range - measured\ range| \tag{5}$$

Figure 5 indicates that measurements where anchors and tags are separated by 1.5 m to 2 m result in a lower ranging error. For distances larger than 2 m, there is a linear relationship between error and true range as the tag is further away from the anchor. Since this relationship can be seen for all anchors in our measurements, we conclude that antenna orientation and antenna delay configuration affect the calculation of the ToF process. Since the antennas used for measurements are not perfectly omni-directional, the received signal cannot have the same power in every direction. This influences the signal-to-noise ratio and impact the accuracy of the leading-edge detection used by the Decawave chip for the TWR process. Therefore, it is possible that the signal is detected later or before than it should be at the receiver side, which causes measurement errors.

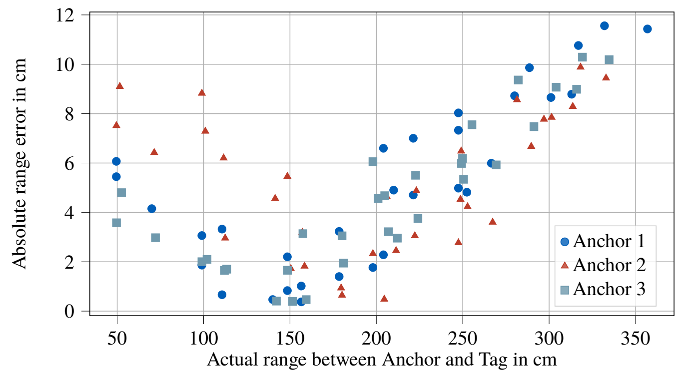

Figure 5: Anchor absolute range errors.

2) Results in NLOS conditions: While previous results confirm that the Decawave nodes are localizable with decimeter-level accuracy in LOS conditions, we investigate now the performance of our system under NLOS condition. The measurements are performed inside an aircraft cabin mock-up as illustrated in Figure 2.

The results of the time-based approach are illustrated in Figure 7. In those NLOS conditions, there is a notable degradation in the performance of the system, with an average of 43.2 cm in average, and an error below 60 cm for 80 % of the measurements. This value makes such a localization system miss our target requirements presented earlier. The obstacles between the anchors and the tag cause wrong measurement of the ToF mainly due to the attenuation of the first path. In that case, the system may assume a longer multipath as the first path, also resulting in the wrong estimation.

Figure 6 illustrates the ranging errors of Decawave's TWR measurements, namely:

$$error = actual\ range - measured\ range \tag{6}$$

We note from Figure 6 that 58 % of the ranges are overestimated, while the rest is underestimated. While overestimated ranges may be explained and corrected by looking for another local maximum corresponding to the first path in the CIR data, such heuristic is inapplicable for underestimated ranges. Those findings and overall poor accuracy in NLOS conditions motive us to improve those measurements using another approach, as introduced in Section IV-B.

C. Neural network-based localization results

We evaluate in this section the performance of the ANN approach presented in Section IV-B and compare its results with the time-based approach evaluated previously.

1) LOS/NLOS classification results: In this first task, we evaluate if the ANN is able to correctly classify if there is LOS or NLOS conditions based on the CIR data at the anchor. Training and test data sets are obtained at 290 different positions inside the measurement environment depicted in

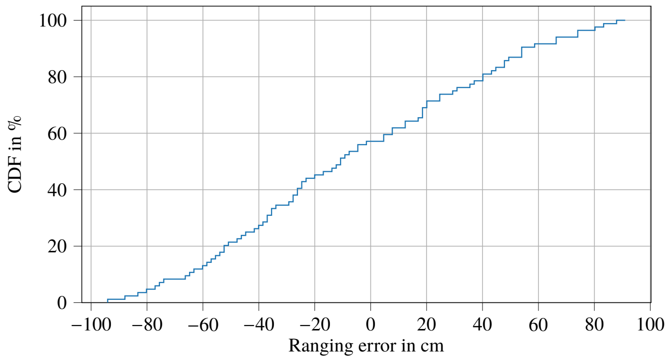

Figure 6: Ranging errors in NLOS conditions with the time-based approach.

Table IV: Confusion matrix for LOS/NLOS classification.

	LOS	NLOS
LOS	88.56 %	11.44 %
NLOS	14.95 %	85.05 %

Figure 2. Moreover CIR data is obtained for 50 particular positions.

Results are presented in Table IV. Overall, the ANN is able to predict the measurement condition with an accuracy for LOS and respectively NLOS cases of 88.5 % and 85 %. As reviewed in Section II, those values are in line with similar studies from the literature. Those results also illustrates that an ANN-based approach is indeed relevant for processing and extracting relevant information from raw CIR data.

2) ANN localization results in NLOS conditions: CIR data for each anchor is obtained at 100 different positions with the corresponding x and y coordinates in a 2 m by 3 m area. Also, 50 CIR data is obtained for a particular position.

Results of the localization using the ANN are presented in Figure 7. In average, 12.3 cm error is achieved, showing large improvement compared to the 43.2 cm average of the time-based approach. For 80 % of the measurements, a maximum error of 21.1 cm is accomplished.

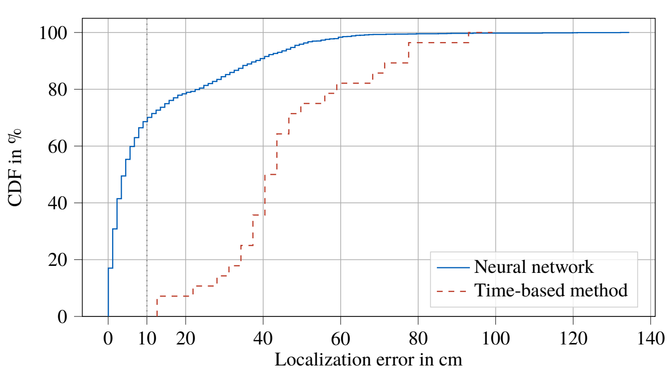

Figure 7: CDF of 2D position error in NLOS conditions.

Overall, those results indicate that the ANN is able to compensate and correct for the NLOS conditions, making our UWB-based localization system satisfy most of the accuracy requirements presented in Table I.

VI. Conclusion

We proposed and evaluated in this paper a positioning system for in-cabin aircraft use-cases. UWB-based localization was used in order to cope with the challenging accuracy requirements for our in-cabin use-cases, mainly because of its promising results in the literature and its upcoming mass market adoption. The Decawave EVB1000 platform was selected to build our IPS and perform indoor measurement and in-cabin measurements. We introduced in this paper two different approaches for performing localization based on ranging measurement performed by the Decawave nodes.

We first illustrated our multilateration approach using the ToF and evaluated its performance for both 2D and 3D scenarios by considering a LOS and an NLOS conditions respectively. In LOS conditions, a maximum localization error of 6.5 cm and 13 cm was achieved for 80 % of the measurements in 2D and 3D respectively. When it comes to the NLOS condition, the performance degrades drastically with a maximum localization error of 60 cm for 80 % of the measurements.

In order to overcome those issues, an ANN-based localization was considered to reduce the high localization error for NLOS conditions. To train the ANN, CIR data was collected in various LOS and NLOS conditions in a cabin mock-up. We showed that the ANN can be trained to predict LOS or NLOS condition with an accuracy of more than 85 %. We then trained the ANN to directly predict the coordinate of a node. Our results show that our approach is able to reach an average localization error of 12.3 cm for the NLOS condition instead of the original 43.2 cm error in average, resulting in a reduced error approximately by 70 %.

Our measurements and evaluation makes us conclude that our ANN approach is able to compensate for the difficult NLOS conditions of an aircraft cabin. Even though the system requirement, which states that the localization error should be below 10 cm, was not fully fulfilled, there are still some applications for the FAL case where this accuracy is enough. Seat-level accuracy of 30 cm accuracy is possible with our approach, enabling the majority of the use-cases investigated in this paper.

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