Improving UWB Indoor Localization Accuracy Using Sparse Fingerprinting and Transfer Learning

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Abstract. Indoor localization systems become more and more popular. Several technologies are intensively studied with application to high precision object localization in such environments. . Ultra-wideband (UWB) is one of the most promising, as it combines relatively low cost and high localization accuracy, especially compared to Beacon or WiFi. Nevertheless, we noticed that leading UWB systems' accuracy is far below values declared in the documentation. To improve it, we proposed a transfer learning approach, which combines high localization accuracy with low fingerprinting complexity. We perform very precise fingerprinting in a controlled environment to learn the neural network. When the system is deployed in a new localization, full fingerprinting is not necessary. We demonstrate that thanks to the transfer learning, high localization accuracy can be maintained when only 7% of fingerprinting samples from a new localization are used to update the neural network, which is very important in practical applications. It is also worth noticing that our approach can be easily extended to other localization technologies.

Keywords: Indoor Localization, Transfer Learning, UWB.

1 Introduction

Nowadays, it is possible to localize objects around the world using GPS. It is a low-cost and easy to use solution available for everybody. However, it is still challenging to localize objects in GPS-denied environments located in buildings or underground. It is necessary to use other technologies to make it possible, such as dead reckoning, LiDAR-based, magnetic-field-based, or radio-frequency-based technologies [1]. Here we focus on radio-based ultra-wideband (UWB) technology, which is especially promising for indoor localization. It combines relatively low cost and good localization accuracy, especially when compared to WIFI or Bluetooth. Such systems can be used in small-scale areas, where full coverage can easily be assured by a small number of anchors. Nevertheless, the concepts presented here are general and can be applied to other local-

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ization technologies. Despite its relatively good performance, UWB localization accuracy can be improved using fingerprinting [2] as localization errors in buildings and underground areas are often caused by systematic errors. Systematic errors are difficult to reduce, as they are usually caused by the surrounding environment, especially in radio-based localization systems. They cannot be reduced by using well-known filtering techniques such as Kalman filters or particle filters.

Here we introduce the algorithm which takes advantage of fingerprinting and Transfer learning to reduce systematic errors and Kalman filtering to reduce random errors. We demonstrate that it can improve the localization accuracy by 31% compared to the state of the art UWB localization system – Pozyx [5].

2 Related Studies

There are several UWB-based localization system, to name only: Pozyx [5,10], Zebra UWB Technology [6], DecaWave [11], BeSpoon [7], Ubisense [8], NXP's automotive UWB [9,12]. According to [13], especially after taking over DecaWave, it performs best in terms of localization accuracy of all above. The localization accuracy of the UWB system can be improved in many ways, but reflections and multi-path propagation make high accuracy localization very challenging. In all possible concepts, two approaches are mainly used for this purpose: deterministic and probabilistic. Both of them follow the fingerprinting as a source of reference data [14], and the localization improvement is achieved thanks to matching the current measurement with this in a previously prepared database [14]. In the deterministic approach, the measurement's mathematical model is known [15]. As a result, the first possible way to achieve it is to find the closest database fingerprint location using a relevant similarity metric for comparison. For this purpose, it is possible to use large numbers of distance metrics (e.g. Euclidean distance, taxicab geometry, etc.) [16]. The second one uses deterministic methods represented by machine learning algorithms such as the support vector machine (SVM) [16], decision trees [18], and k-nearest neighbors (KNN) [19]. Another approach includes probabilistic algorithms, which use measurement values represented as a probability distribution. In such a case, the output localization is calculated using the signal's statistical properties based on the current online measurements and fingerprinting results from the database. The probabilistic approach is more expensive than deterministic. It can also provide higher accuracy even with the increasing number of lost samples or incompatible data [20].

Both deterministic and probabilistic localization approaches require fingerprinting data [16]. Creating such a database is a big challenge since acquiring it can take a lot of time and effort, especially for large-scale environments and for the reference points' parameters determined manually [16]. It raises costs with the expected localization accuracy. Several methods were proposed to reduce it. One of them reduces the number of fingerprinting points and then use interpolation and extrapolation methods to recover missing data [22]. We essentially introduce a similar approach, but we apply it to UWB technology and use Kalman Filter (KF) and Transfer Learning (TL) instead of the hid-

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den Markov model. Other techniques use unsupervised learning methods for this purpose, see [23]. The authors of this article apply artificial intelligence to improve WiFi-based localization. As a result, the accuracy of the localization system is relatively low, despite using fingerprinting.

It is possible to use other solutions that can improve the results [2]. The first one is a median filter, which is an efficient nonlinear tool for removing outliers. Its efficiency depends on the window size. Unfortunately, it introduces the delay, which increases the localization error [24]. We apply a short median filter as an outline detector in our algorithm. The second one is the Autoregressive-moving-average (ARMA) filter. It specifies that the output depends linearly on a set of previous input samples. Generally, it is an infinite impulse response filter without delay, making it very useful during the localization improvement process [24]. We demonstrate that it performs worse, despite its properties, than the algorithm introduced here, in terms of localization accuracy. The third one is the k-nearest neighbors' algorithm (k-NN), which is often applied in localization algorithms [25]. In our experiment, it also performed worse than our algorithm. The fourth one is the edge detection algorithm, which detects the leading edge of the UWB pulse signal to determine the time of arrival (TOA) with higher accuracy even under low signal-to-noise ratio (SNR) conditions [27]. As this approach requires direct modifications in UWB hardware, it is beyond the scope of this article. The fifth one is the Kalman filter, a real-time solution widely used in indoor and outdoor positioning systems for signal filtering and data fusion. It effectively reduces Gaussian errors, but it has also proved to perform well in other conditions [3]. We use it as one of the reference methods in our research. Other algorithms use machine learning (ML) methods. They are used in data analyzing, data processing, autonomous driving, and much more. Of course, it has found its adaptation in indoor localization [31]. We essentially adapt and extend these concepts to improve UWB localization accuracy. Another solution is the use of deep learning methods. Unfortunately, they require a large amount of training data [32] or external sensors [33]. Therefore, they are not applicable in our case, as we want to reduce the effort necessary to improve the accuracy and use UWB and inertial measurement unit (IMU) sensors solely. Interesting examples on this topic can also be found in [35-36].

3 The algorithm

Our localization algorithm combines the Kalman Filter (KF) filter to reduce stochastic, Gaussian localization errors followed by a neural network (NN) to minimize the deterministic localization errors. In order to reduce the effort necessary to perform fingerprinting, we use transfer learning to adapt the network to the new operating environment of the UWB system. Unlike [21], we do not focus on distinguishing LOS, NLOS, MP signals but on determining deterministic and stochastic components of the signal, which we believe is a more general approach in terms of measurement theory.

In UWB-based localization, the leading research in localization accuracy improvement focuses on the analysis of line-of-sight (LOS), non-line-of-sight (NLOS), and multi-path analysis (MP) [28]. Here we introduce a more general approach. According

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to the convention of the 1998 ANSI/ASME guidelines [29], the errors that arise in the measurement process can be categorized into systematic and random errors. Therefore, instead of identifying LOS, NLOS, and MP signals, we apply separate tools for reducing systematic and random errors separately despite their origin. It leads to a distance measurement filtration algorithm, which is shown in

. It takes raw localization data (x_i,y_i) from the UWB system. The first step removes outliers by removing the samples that exceed the theoretically maximal velocity of the object. Second, we use the Kalman Filter (KF) to remove random errors. We consider the KF to be the best choice here, as it is the mathematically optimal filter for removing random error with Gaussian distribution for robot movement at fixed speed along the track [29], which is considered in this paper. KF cannot remove systematic errors, which means that after applying KF filtration, the signal still contains systematic errors. Therefore, after KF filtration, we use a neural network to remove systematic errors. As a result, we obtain corrected localization (x'_i, y'_i), which better reflects the object's actual localization.

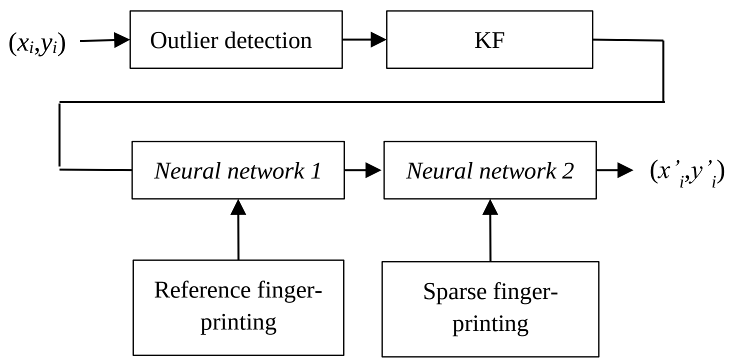

Fig. 1. Localization algorithm.

The system's critical element is the neural network. We train it using fingerprinting results. Obtaining the best results requires performing fingerprinting in each localization where the system is deployed to acquire neural network training data. We use transfer learning to avoid it, which reduces the fingerprinting density in new localizations where the system operates. We train the *neural network 1* using dense reference fingerprinting (see

). Next, we apply transfer learning by updating *neural network 1* using the more simple *neural network 2*, which is trained using just a few fingerprinting points in a new localization. It facilitates system deployment in real-life conditions without losing system accuracy. Our experiments demonstrate that our approach can significantly improve the localization accuracy and reduce the effort necessary to deploy the UWB system in different localizations, thanks to transfer learning. A similar results, but for static measurements, has been introduced in [28].

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4 Experiment

Our research focused on a dynamic localization algorithm that localizes the object in movement using the UWB Pozyx localization system. Pozyx is a localization system that uses a DW1000 chip and STM32F401 ARM Cortex M4. We used four anchors and a tag of Pozyx development kit. The tag is shield compatible with the Arduino board, which was used to capture the measurement data. The Arduino board communicates with Pozyx over Inter-Integrated Circuit. The tag can determine its position and motion data from an accelerometer, a gyroscope, a compass, and a pressure sensor. The anchor is not compatible with Arduino and communicates over the serial port. We used a dedicated *pypozyx* Python library to configure the system parameters: channel, bitrate, and function.

We divided the experiment into four parts:

1. static fingerprinting in reference, indoor localization - *testbed 1*,
2. static fingerprinting in another localization, in which the system operates - *testbed 2*,
3. dynamic localization of the robot in motion on *testbed 1*,
4. dynamic localization of the robot in motion on *testbed 2*.

The fingerprinting was used to capture the data, which was then used for training the *neural network 1*. The localization of the fingerprinting points together with the points' ID's are marked with green dots in Fig. 2. The localization of anchors A0, A1, A2, A3 is marked with red triangles. Please note that the fingerprinting area goes beyond the rectangle bounded by the anchors. Even though this is incompatible with the Pozyx documentation, the system's localization accuracy in the rectangle area and beyond is at the same level. For each fingerprinting point from Fig. 2 on both tracks, we collected 200 measurements. The measurements from testbed 1 were then used to train the *neural network 1* from

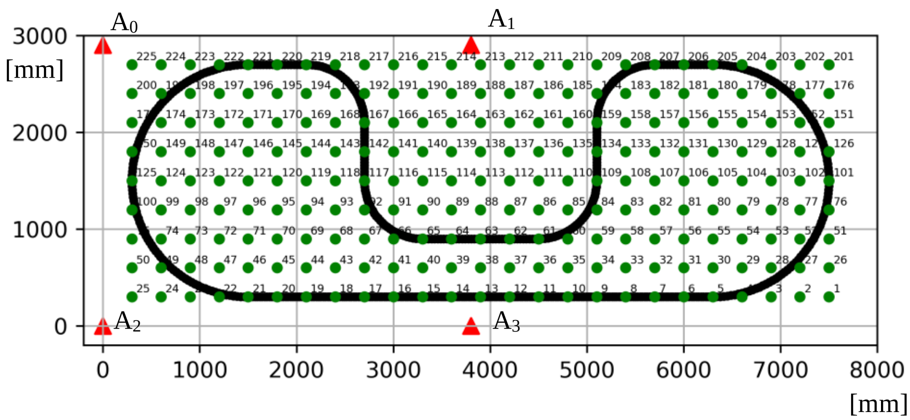

Fig. 2. The localization of anchors (red triangles), fingerprinting points (green dots), and EvAAL-based track (black lines) in both testbeds.

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Our dynamic experiments used the EvAAL-based test track from [31], which is marked as a black curve in Fig. 2. We shrank the original EvAAL track to fit the size of our laboratories. Finding the reference localization of the object in dynamic localization tests is challenging as reference localization accuracy must be more precise than the localization of the UWB system, which requires the reference's centimeter accuracy. We achieved this by using MakeBlock Robot mBot V1.1, which followed the line on the floor using an optical sensor at constant linear speed. It leads to the reference measurement variance below 1cm, which is sufficient when considering that UWB dynamic localization accuracy is about 50cm, according to our measurement results. We captured the measurements data for six laps. Half of the lap passes were captured for the robot moving clockwise, the other half for the robot moving counterclockwise. The localization sampling frequency was around 16Hz.

We carried out the experiment using the same Pozyx development kit, test track, and relative anchors localization in two different testbeds localized in two different laboratories. The fingerprinting results from the first testbed were used to teach the neural network. We used the TensorFlow library to optimize the neural network architecture and learn it. The resultant NN parameters are summarized in Table 1.

Table 1. The architecture of *neural network 1*.

Layer	Number of neurons	Activation function
1	2	tanh
2	82	selu
3	152	relu
4	2	relu
5	2	relu

The resultant *neural network 1* was used to improve the dynamic localization accuracy in testbed 1. The dynamic experiment was carried out with the robot following the EvAAL-based test track with constant velocity. The Pozyx localization system, which was mounted on the robot, was acquiring its position. The single run localization results of the robot on the test track are presented in Fig. 4.

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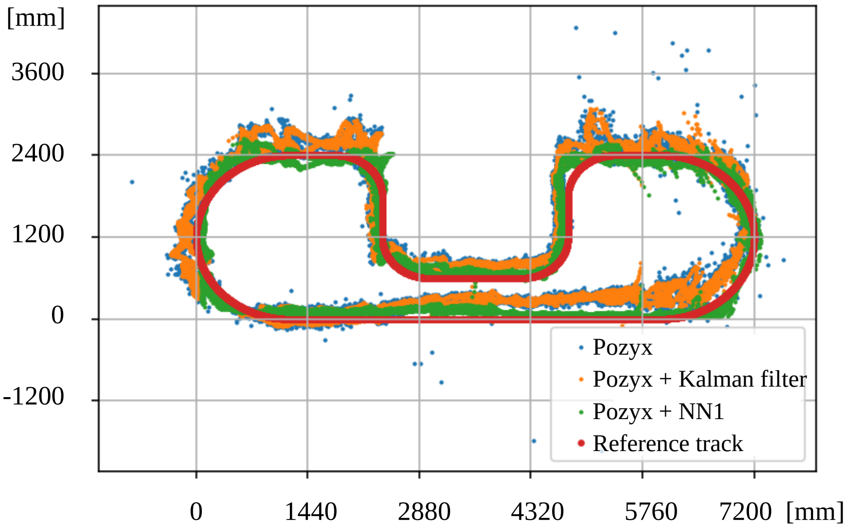

Fig. 3. The robot's localization results for EvAAL-based track, laboratory number one, run one; gray dots – Pozyx localization results, red dots - our algorithm.

The data collected by Pozyx are marked with blue dots. The localization obtained from Kalman filtration of Pozyx localization results are marked with orange dots. The results obtained from Pozyx, followed by Kalman filtration and *neural network 1* are marked with green dots. It is noticeable that our algorithm outperforms Pozyx in terms of localization accuracy, which proves that the neural network learned with fingerprinting data can improve the dynamic localization accuracy of the UWB system. The comparison of the localization accuracy is shown in Fig. 4. It proves that the NN can correct systematic errors, which cannot be removed using KF.

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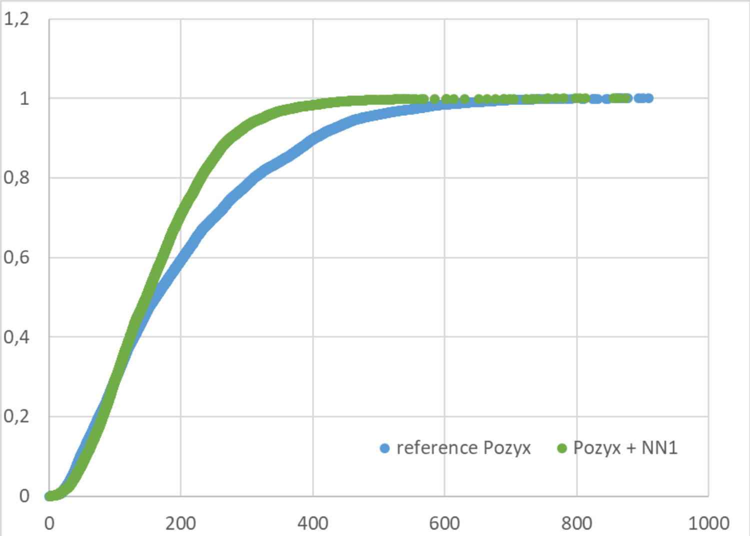

Fig. 4. Cumulative Distribution Error for the dynamic experiment on testbed 1. Comparison of Poxyx localization and Pozyx + NN1.

Next, we repeated the fingerprinting on testbed 2, which was situated in the laboratory with different size and similar shape as in testbed 1. . In this scenario, the distance from walls to the track was around twice more significant than in testbed 1. In this case,we didn't use all the fingerprinting points from testbed 2 to learn the *neural network 2*. We increased the density of fingerprinting gradually. The *neural network 2* was updated in consecutive steps using fingerprinting results of higher density. In each step, we performed neural network architecture optimization and learning using TensorFlow. The resultant NN2 responsible for transfer learning consisted of 4 layers, consisting of 22, 62, 12, 2 neurons, respectively. The list of chosen points in each step and the localization error of the 95% test samples is shown in Table 2. Corresponding CDF functions for each step are presented in Fig. 5. Please notice that the localization accuracy is much below the accuracy declared in Pozyx documentation. Localization accuracy does not change significantly in steps 6 – 11, which means that localization accuracy achieved thanks to *neural network 1* can be maintained for lower fingerprinting density thanks to transfer learning.

Table 2. List of fingerprinting points that were used to train the neural network in testbed two.

Step	List of localization points/algorithm	Localization error at 95%
0	Pozyx (reference)	472mm
1	13, 101, 125, 213	470mm

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2	13, 19, 25,113, 125, 213, 225	365mm
3	1, 13, 25, 101, 125, 201, 213, 225	360mm
4	13, 19, 25, 113, 119, 125, 213, 219, 225	330mm
5	1, 13, 25, 101, 113, 125, 201, 213, 225	355mm
6	1, 7, 13, 19, 25, 101, 107, 113, 119, 125, 201, 207, 213, 219, 225	323mm
7	1, 7, 13, 19, 25, 54, 60, 66, 72, 101, 107, 113, 119, 125, 154, 160, 166, 172, 201, 207, 213, 219, 225	323mm
8	1, 5, 9 ,13, 17, 21, 25, 51, 55, 59, 63, 67, 71, 75, 101, 105, 109, 113, 117, 121, 125, 151, 155, 159, 163, 167, 171, 175, 201, 206, 209, 213, 217, 221, 225	323mm
9	1, 3, …, 25, 51, 53, … , 75, 101, 103, …, 125, 151, 153, …, 175, 201, 203, … 225,	323mm
10	1, 3, 5, 7, …, 225,	322mm
11	All fingerprinting points in testbed two	323mm

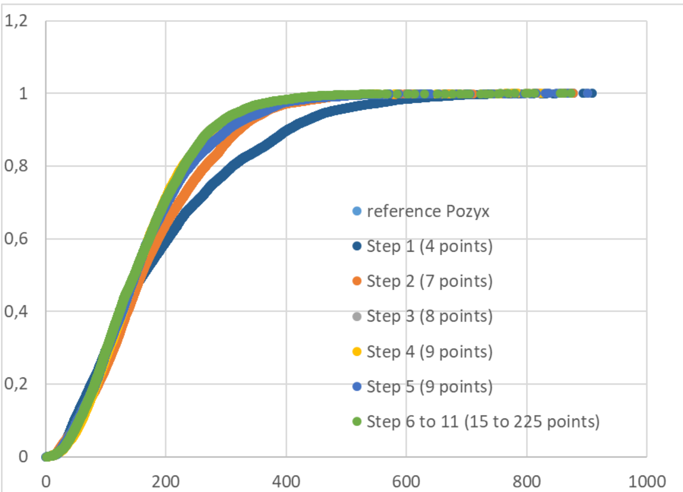

Fig. 5. Cumulative Distribution Error for the dynamic experiment on testbed 2. Localization results for steps from Table 2 and *neural network 2*.

The results presented in both Table 2 and
demonstrate that the UWB Pozyx system's localization accuracy can be improved using KF filtering and fingerprinting-based neural network. Furthermore, if the neural network is trained in a well-controlled environment, it can be easily updated by making very sparse fingerprinting, using just 7% of the samples necessary to train the neural network. The main purpose of this process was to reduce the number of points required in fin-gerprinting. As demonstrated in fig. 5, it is possible to achieve the same location ac-curacy for the 15 points as for the 225 points. As a result, the cost of fingerprinting can be significantly reduced while maintaining location accuracy. In our experiments, we used a uniform, sparse fingerprinting grid. However, the localization accuracy might

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be improved when using higher grid density in the vicinity of obstacles. The reduction of the fingerprinting points is very desirable in practical applications, as it reduces the costs of system deployment. The comparison of our algorithm with other algorithms that can be applied to improve the Poxyx localization accuracy is presented in Table 3. The localization error of our transfer learning-based algorithm is 32% lower when compared to the Pozyx system. It is also 31% lower than Kalman filtering, 30% lower than median filtering, 20% lower than ARMA filtering, 17% lower than the LOS/NLOS algorithm introduced in [21], and 7% lower than the k-NN algorithm introduced in [2].

Table 3. Comparison of the transfer learning-based algorithm with median filtering, ARMA filtering, Kalman filter, LOS/NLOS algorithm from [21], the k-NN algorithm from [2].

Localization algorithm	Localization error [mm]
Pozyx orig	472
Median	462
ARMA	415
Kalman	465
LOS/NLOS [21]	401
k-NN [2]	354
Transfer learning	**323**

5 Summary

This paper introduces a neural network-based algorithm for UWB localization improvement, reducing localization error by 32%, which outperforms the k-NN algorithm by 7%. The practical experiments demonstrated that the localization accuracy could be maintained if the UWB localization system is deployed in a new localization with only 7% of fingerprinting samples used to update the neural network parameters. It means that our approach combines higher localization accuracy than state of the art UWB Pozyx localization system with low fingerprinting complexity. Furthermore, thanks to transfer learning, it also reduces the learning time required to train the neural network, which is very important in practical applications. Our research has also proved that the combination of Kalman filter, to reduce random localization errors, with a neural network, to minimize systematic error, is an efficient approach to improve indoor localization accuracy.

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