Static and Dynamic Comparison of Pozyx and DecaWave UWB Indoor Localization Systems with Possible Improvements

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Abstract. This paper investigates static and dynamic localization accuracy of two indoor localization systems using Ultra-wideband (UWB) technology: Pozyx and DecaWave DW1000. We present the results of laboratory research, which demonstrates how those two UWB systems behave in practice. Our research involves static and dynamic tests. A static test was performed in the laboratory using the different relative positions of anchors and the tag. For a dynamic test, we used a robot that was following the EvAAL-based track located between anchors. Our research revealed that both systems perform below our expectations, and the accuracy of both systems is worse than declared by the system manufacturers. The imperfections are especially apparent in the case of dynamic measurements. Therefore, we proposed a set of filters that allow for the improvement of localization accuracy.

Keywords: UWB, Indoor Localization, EvAAL

1 Introduction

Localization in GPS-denied areas, such as indoor localization, has attracted much attention due to its possible commercial applications [1]. There are several technologies which allow objects localization in such areas: Bluetooth [2], WiFi [3], Ultra-wideband (UWB) [4], inertial navigation [5], Li-Fi [6], LiDAR [7], visual monitoring [8].

This article focuses on UWB technology, which is economically justified and comprehensive as it combines reasonable costs and relatively good localization accuracy [9-10]. Such a kind of indoor localization system is based on anchors (beacons), placed in known locations, and tags which positions are determined relative to those anchors. The position of tags is calculated using signal flight time between devices (TOF) [10]. Two nodes exchange messages and based on received and sent timestamps of those messages, devices can calculate the round trip time of the signal. The final tag position is obtained based on the trilateration algorithm that combines data acquired from the anchors [12]. Several commercial products use this technology

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to localize objects, such as Pozyx [13], DecaWave [14], Zebra UWB Technology [15], Ubisense [16], BeSpoon [17], NXP's automotive UWB [18]. Interesting examples on this topic can also be found in [20-21].

This paper compares the new commercially available UWB system — Pozyx and DecaWave DW1000, which is the best UWB localization system to our knowledge. The localization accuracy is compared under the same conditions. Experiments include both static and dynamic localization of the UWB tag relative to fixed anchors in a two-dimensional area. Tag node is localized in one of nineteen fixed points inside or at a short distance from the triangle marked by anchors in static experiments. A line-follower robot moves along the known EvAAL-based [34] track in close to constant linear speed motion in dynamic ones. Due to the fact, the theoretical position at any moment of the robot is known, we can evaluate the difference between the measured and actual position. The reason behind these differences are reflections, signal attenuation, clock delays, and imperfect characteristics of antennas mounted in the UWB device generating measurement noise, which influences localization accuracy [19]. Since interferences depend on both environmental and hardware factors, it is almost impossible to avoid them. Several methods can improve wireless localization accuracies, such as optimizing sensors number and position [22], antenna gain [23], machine learning [24], and filters. We have decided to apply the last option because we believe it is the most universal; it can work in real-time with a very short delay and often gives satisfactory results. We use the following filtering algorithms: median, ARMA, and Kalman filters [27], preceded by trilateration techniques.

The research, which is similar to the one presented in this article, has been performed by Simedroni et al. In [28], the authors studied DecaWave-family UWB device – MDEK 1001 [31] with 16 cm static average error results. In [29] the variance of static experiments is about 10 cm, and the accuracy of dynamic experiments is 65 cm for 100% samples (4 anchors). Both static [28-29] and dynamic [29] measurements differ from our research in the way the antennas are arranged, the size of the scene, the devices used, and the track shape. Most importantly, the results are also difficult to reproduce, as the ground truth trajectory has a very unregular shape. Jian Wang et al. in [30] conducted the experiment in which they investigated the UWB system accuracy. Still, they focused on improving the accuracy by fusing the data from separate anchors, treating them as independent systems. Unfortunately, the method of obtaining the ground-truth path is unclear. Here we decided to perform UWB systems' comparison using the robot following the EvAAL track to ensure ground truth localization.

The organization of this paper is given as follows. In Section 2, Pozyx UWB and DecaWave TREK1000 are described shortly. In Section 3, the experimental setup is defined. The results of real-time localization and error analysis are presented in Section 4. In Section 5, we conclude and sketch the directions for further research.

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2 UWB localization systems

2.1 DecaWave

DecaWave DW1000 [33] is a fully integrated low power, single-chip CMOS radio transceiver IC compliant with IEEE 802.15.4-2011 ultra-wideband (UWB) standard [32]. The manufacturer distributes the chip as a part of microcontroller STM32F105 ARM Cortex M3 with LCD and USB interface, which can both power and transmit data to a computer [25-26]. The set is called DecaWave EVK1000. The DW1000 chip and microcontroller communicate via Serial Peripheral Interface (SPI). An Evaluation Kit DecaWave TREK1000 used during experiments consists of four EVK1000 boards. To perform 2D localization, at least three anchors and one tag is required. The UWB tag is localized relative to the fixed anchors' position. Every device can act as both an anchor and a tag. The configuration is set by changing dip switches located on the PCB board. These switches also allow the change operation channel to 2 or 5 (which correspond to center frequency 3993.6 MHz or 6489.6 MHz), data rate – 110 kb/s, or 6.8 Mb/s, and tag/anchor ID. Of paramount importance is the fact that anchors are not the same. The anchor with an ID equal to 0 is responsible for communication between other anchors and the tag. As a result, when it is powered off, interfered with obstacles, or exposed to excessive dumping, the localization system does not work. That is why anchor 0 location should be chosen wisely.

According to the documentation, the localization accuracy of the tag is ±30 cm. The maximum measurable distance is about 250 m, but it depends on the data rate and channel [28]. Moreover, in most countries, it is not possible to use that range due to legal restrictions on maximal mean Effective Isotropical Radiated Power (EIRP) of the antenna, which is usually -41.3 dBm/Mhz. As a result, the system measurable distance is even lower.

2.2 Pozyx

Pozyx is a new localization system that also uses the DW1000 chip, same as in EVK1000, but it takes advantage of STM32F401 ARM Cortex M4, which is more advanced than STM32F105. The development kit used during experiments consists of 8 transceivers. Although every node can act as both anchor and tag, the manufacturer has drawn a clear line between them and divided the set among four anchors and five tags. The tag device is constructed to be a shield compatible with Arduino. It connects the microcontroller board using long wire-wrap headers that extend through the shield. The Arduino communicates with Pozyx via Inter-Integrated Circuit (I^2C). Moreover, the tag device does not need an Arduino to work. It can be used by connecting a computer to Micro USB as a virtual COM port, which is also a power source. The tag can determine the position and report on motion data thanks to the built-in accelerometer, gyroscope, magnetometer, and pressure sensor. Unlike the tag, the anchor node is boxed and not compatible with Arduino. The only possibility to receive data from the anchor is to use the serial port.

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While TREK1000 kit configuration is based on dip switches, in Pozyx, all options are programmable. There are two dedicated libraries: C-like Arduino (Pozyx-Arduino_library) and Python (pypozyx), which allow changing the same parameters as in DecaWave, namely: channel, bitrate, and the board function to act as a tag or an anchor. There are seven independent channels that do not interfere and communicate with each other, transmitting center frequencies from 3244.8 MHz to 5948.8 MHz. Bitrate can be set to 110 kb/s, 859 kb/s or 6.8 Mb/s. Although Pozyx has many more configuration options than EVK1000, the setting up process is more complicated and longer.

The manufacturer claims that Pozyx accuracy is ±10 cm, which is better than TREK1000. The maximum measurable distance is 100 m, which is calculated, considering the legal restrictions of EIRP.

3 Experimental setup

The experiment was divided into two parts: static and dynamic. DecaWave and Pozyx sets were evaluated in both parts with the same data rate - 6.8 Mb/s and on the 5th channel. DecaWave and Pozyx systems localization was measured separately since they were operating at the same frequencies. Namely, when the robot was driving at the track, only one system was operating at a time.

In static experiments, the robot was placed at selected measuring points inside, on, or outside the track. These points are marked with yellow crosses in Fig. 1. The purpose of the experiment was to verify the static localization accuracy of both systems. To do it, we collected 200 coordinates with both Pozyx and DecaWave for each measuring point. This allows us to evaluate error distribution in different tag positions relative to both systems' anchors.

Dynamic localization tests are, in general, much more challenging to reproduce than static tests because they are often conducted using the testing environment, which is lab-specific. To avoid it, we used the experimental setup inspired by [34]. Our laboratory was too small to build a full test track from [34], so we decided to use only half of that track.

Please note that the same as in the static experiment, in our dynamic experiment, the anchors were placed out of the track in such a way that they formed a triangle that intersects the track. In this approach, some measurement points were inside and some outside of the triangle. To make the analysis more straightforward, we introduced a coordinate system with A_0 anchor located at (0; 0), A_1 located at (0; 4), and A_2 located in (6; 2). The track and anchor localization is shown in Fig.1. Anchors A_0, A_1, A_2 are marked with blue triangles, while the track is marked with a black line.

In dynamic experiment we used a robot – MakeBlock Robot mBot V1.1 from Fig. 2 – following the line on the floor using an optical sensor at constant linear speed. In each dynamic experiment, the robot passed the track twice, which allowed us to collect about 2400 (DecaWave) and 3200 (Pozyx) position samples in less than 4 minutes. This is equivalent to capturing 11 samples per second in DecaWave and 14 samples per second in Pozyx. We used a second optical sensor installed on the robot

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to find dynamic reference robot localization, which was triggered when crossing reference points. The reference points are marked with black lines perpendicular to the track in Fig. 1. Each time the robot was crossing the reference point, it recorded a timestamp. The average robot speed was calculated for each section between reference points basing on timestamp and section length. As a result, we were able to calculate the robot speed with precision, which was sufficient for this experiment. Using the average robot speed and the timestamps, we were able to find the robot localization at any moment. We used this localization as a reference for dynamic UWB localization in our experiment.

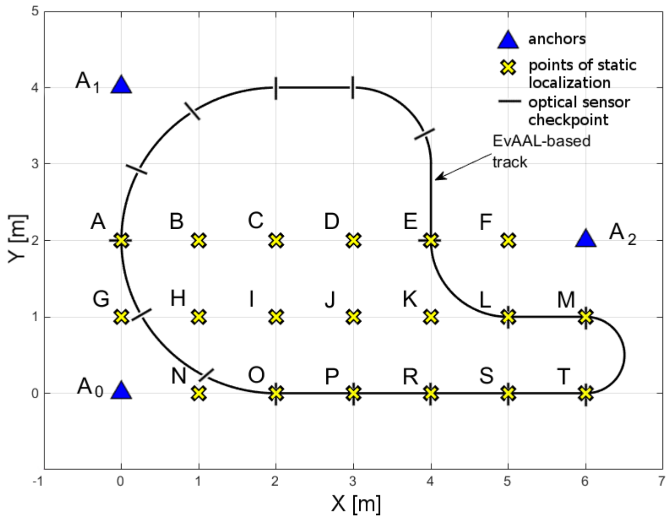

Fig. 1. Test track based on EvAAL used in experiments. Anchors A_0, A_1, A_2 are marked with blue triangles, and the track is marked with the black line. Yellow crosses mark the points of static localization. Black lines perpendicular to the track (in fact, they are white) are placed where the optical system is notified about robot localization.

4 Experiment

This section describes the results of experiments that were performed along with the explanation of the obtained results. The experiments include a static and dynamic part. Firstly, raw data from both UWB devices are compared in static and dynamic experiments. Then we demonstrate how the localization accuracy can be improved by raw data filtration. We believe that the best way to illustrate the experiment results is to present the localization coordinates on the EvAAL track and the measurement accuracy using the empirical cumulative distribution function (ECDF).

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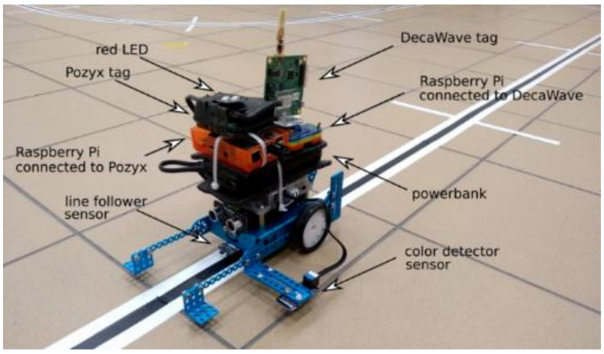

Fig. 2. Line follower robot used in experiments.

On the top, there are the DecaWave tag and Pozyx tag connected to separate Raspberry Pi. A power bank powers both computers. The robot uses the line follower sensor to track the line and color sensor to record reference point in the robot's memory and blink the red LED when it crosses the white line to notify the optical system about robot localization. Blue arms form a counterweight, which prevents the robot from tilting backward.

4.1 Static experiments

As described in the previous section, in static experiments, we manually place the robot in each of A-T measurement points presented in Fig. 1 and collect 200 localization samples from both localization systems. Fig. 3 shows the results of a stationary measurement in which the data collected by DecaWave is marked in red, and the data collected by Pozyx is marked in green. As illustrated in Fig. 3, the measurements from both devices accumulate at designated points. One can notice that the variance of the raw data obtained from DecaWave is, in general, much smaller than in Pozyx. Simultaneously, the center of gravity of the resultant localization samples strongly depends on the measurement point localization. For example, for measurement points I and J, the center of gravity of localization results collected by Pozyx are closer to the reference point than in the case of DecaWave. In R, S, and T points, it is the opposite, the center of gravity of points collected by DecaWave is closer to the reference points than in the case of Pozyx. Such deviations are probably the result of reflections from the walls closely surrounding the track. Moreover, the variance of DecaWave localization points is similar regardless of the measuring point is inside, on, or outside of the A_0, A_1, A_2 triangle. In contrast to DecaWave, the measurement variance for Pozyx is slightly higher when the measurement point is located outside of the A_0, A_1, A_2 triangle. For example, at point T situated outside of the track, the variance reaches 0.17 on X-axis and 0.003 on Y-axis, while for the same point in DecaWave, it is only 0.04 on X-axis and 0.0003 on Y-axis. The smallest variance of the measurement samples was obtained in point B for DecaWave (values in both axes of around 0.0001) and G for Pozyx (values around 0.001). The worst result was in point T in both cases.

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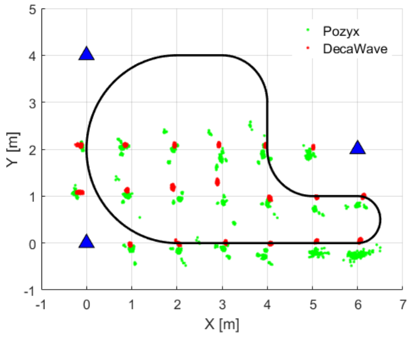

Fig. 3. Measurement points of Pozyx (marked with green dots) and DecaWave (marked with red dots) in static experiments. Anchors A_0, A_1, A_2 are marked with blue triangles, and the track is marked with the black line.

4.2 Dynamic experiments

In dynamic measurements, the robot follows the EvAAL-based track with constant velocity acquiring its position. Every correct measurement (3-5% of measurements is corrupted in the communication channel) for Pozyx and DecaWave is presented in Fig. 4. The data collected from DecaWave is marked with red dots, and the data collected by Pozyx are marked with green dots. As illustrated in Fig. 4, localization points acquired by the DecaWave system are very close to the reference track, except for the curve at the top. We suspect that this is the result of the reflection from a thick, brick wall parallel to OX, which was located next to the track. As for the Pozyx system, the measurement accuracy is significantly worse than DecaWave. Namely, most measurement points are shifted relative to the track, and the variance of the localization is much higher. On the other hand, surprisingly, the results obtained in the upper part of the track fit the reference track slightly better than in DecaWave. In general, the mean localization error for the DecaWave system is around 11 cm, and a median is approximately 7 cm. The same for Pozyx is respectively: 21 cm and 20 cm. ECDF (Fig. 5) illustrates that DecaWave mapped the track better than Pozyx, obtaining an accuracy of 32 cm when the same accuracy was achieved for Pozyx at 160 cm. However, more than 95% of the samples do not exceed a distance of 50 cm, and this value better describes the accuracy of Pozyx.

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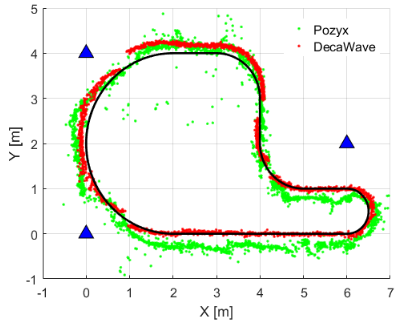

Fig. 4. Measurement points of Pozyx (marked with green dots) and DecaWave (marked with red dots) in dynamic experiments. Anchors A_0, A_1, A_2 are marked with blue triangles, and the track is marked with the black line.

4.3 Accuracy improvement

The raw measurement presented in section 4.2 appears to be far from the declared measurement accuracy of a maximum of 30 centimeters in Pozyx and close to it in the case of DecaWave. The problem for the Pozyx system is a high variance of measurement error. Subsequent position samples do not reflect the robot movement in detail. On the other hand, the DecaWave system has many more failed acquisitions that must be removed in the localization process. The ideal solution would be to achieve Decawave accuracy with Pozyx reliability. To meet our expectations, we decided to improve measurement accuracy for Pozyx applying filters. At the same time, we check how the same filters affect DecaWave and whether it is possible to further improve the results.

As a data source for the experiment, we take the raw measurement results from our experiment described in section 4.2 as filtration inputs. Then we process data with median filter, ARMA filter, and Kalman filter. Both series are filtered the same algorithms that, in our opinion, should improve location accuracy by reducing distribution error. To present the results, the measuring points on the track are presented, as well as the empirical cumulative distribution functions that allow checking the filtration effect.

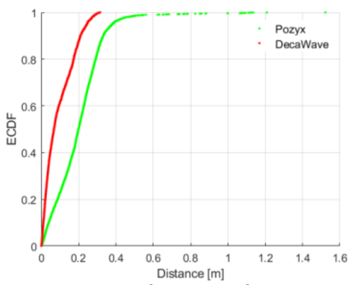

Fig. 5. The empirical cumulative distribution function of the localization error for Pozyx (green dots) and DecaWave (red dots) error accuracy in dynamic experiments.

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Median filter

The median filter is a nonlinear method for noise suppression. It operates as neighborhood averaging, which allows for the removal of out-of-range measurement samples. The number of averaging measurements is defined with window size *w*. For a sufficiently large window, the median filter can suppress random noise. The side effect of this is the delay, which is the result of the filter construction. In our case, the average delay is $\frac{100w}{2}$ ms, and the robot's maximum speed is around 1 m/s. In the series of experiments, we used window size $w = 7$, assuming that the delay of 350 ms is still acceptable in our case. The median filtering results are illustrated in Fig. 7 for Pozyx and Fig. 8 for DecaWave (green dots). In the Pozyx system, the filter results in the elimination of random measurement errors and thus an improvement of accuracy up to 42 cm, taking into account all samples and 32 cm at 95% of the samples. With DecaWave, the improvement is unnoticeable, and the localization accuracy improves by 2 cm for 100% samples and less than 1 cm for 95% of samples.

ARMA filter

The autoaggressive (AR) and moving average (MA) model specifies that the output variable depends linearly on its previous values and also linearly on a set of previous inputs. In general form, ARMA filter is an infinite impulse response filter (IIR) defined as follows (1):

$$Y(z) = H(z)X(z) = \frac{\beta(1)+\beta(2)z^{-1}+\dots+\beta(n+1)z^{-n}}{\alpha(1)+\alpha(2)z^{-1}+\dots+\alpha(n+1)z^{-m}}X(z) \quad (1)$$

where $\beta(i)$ (MA part) and $\alpha(i)$ (AR part) are filter coefficients and n, m define filter order. Looking for desired filter properties (low pass filter with a gain of 1), we decided to simplify it to the form (2):

$$Y(z) = \frac{\beta}{1-\alpha(z^{-1})}X(z) \quad (2)$$

where $\beta=\alpha\text{-}1$.

Filtering in such a way is based on fitting the appropriate α coefficient. For small α (close to zero), the filtration effect is stronger, but it is impossible to detect rapid movements of tracking objects. Unlike the median filter, the ARMA filter has zero-delay, and its computing performance makes it an efficient way to improve localization accuracy. In the experiments, we use $\alpha = 0.8$. The results of ARMA filtering are illustrated in Fig. 9 for Pozyx and Fig. 10 for DecaWave (red dots). In the case of Pozyx, the result is very similar to that obtained for median filtration. 95% of samples obtain an accuracy of 32 centimeters, and 100% of samples have an accuracy of 46 cm. In DecaWave, the difference is even less visible and almost impossible to note.

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Kalman filter

Kalman filter used in the experiment estimates a state vector based on a dynamic model. The model assumes that the velocity is constant in the sampling interval, and the system can measure only the target's position (have no sensors to measure velocity) [27]. According to the assumption, the Kalman filter can remove the signal noise when the covariance coefficients are properly selected. We propose a method for determining the covariance based on the function of the variance value from the distance of the anchor to the tag - *f*(d), where d is the distance. Given the function *f*, it is possible to calculate the covariance matrix in a two-dimensional area. Supposing that variance is a vector, one can create three vectors from measured point *T* directed towards each anchor A_0, A_1, A_2. The length of each vector is the value of function *f*. Projecting each vector on X-axis and Y-axis and averaging vector components give two variance vectors that are the basis for the covariance matrix (3) and (4).

$$\delta_x = \frac{\delta_x^{A_0} + \delta_x^{A_1} + \delta_x^{A_2}}{3} \tag{3}$$

$$\delta_y = \frac{\delta_y^{A_0} + \delta_y^{A_1} + \delta_y^{A_2}}{3} \tag{4}$$

Fig. 6 illustrates the method of determining variance in the X-axis and Y-axis.

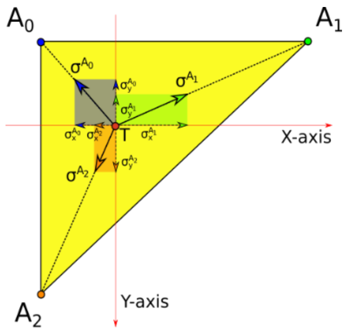

Fig. 6. Method of determining variance in X-axis and Y-axis.

Kalman filtering results are illustrated in Fig. 9 for Pozyx and Fig. 10 for DecaWave (purple dots). The Pozyx system is similar to median and ARMA filtering (around 32 cm for 95% of samples and 42 cm for 100% samples). The significantly worse improvement occurs in DecaWave, where the accuracy of localization decreases by around 6 cm to 38 cm for 100% samples and 34 cm for 95% samples.

While the Kalman filter reduces error in static measurement to 0.5 cm [35], the improvement works not as expected in dynamic measurements. Filter attracts trajectory to the most probable position, which results in smooth tracking considering inertia (Fig. 9 and Fig. 10), but it does not improve measurement accuracy. It contradicts the widespread belief that the Kalman filter always allows for a reduction in position

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measurement error. This is mainly because the measurement noise has non-Gaussian characteristics.

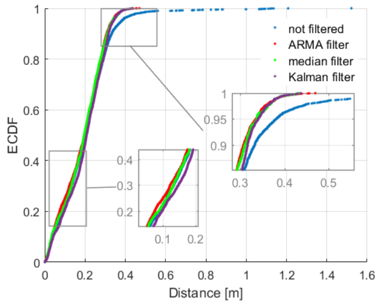

Fig. 7. Empirical cumulative distribution function of the localization error for not-filtered Pozyx data (blue dots), ARMA filtered Pozyx data (red dots), median filtered Pozyx data (green dots), and Kalman filtered Pozyx data (purple dots) in dynamic experiments.

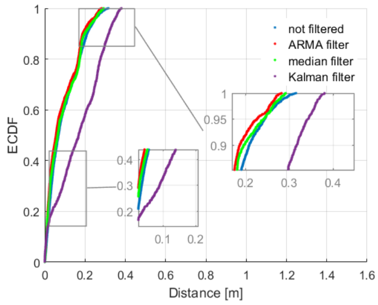

Fig. 8. Empirical cumulative distribution function of the localization error for not-filtered DecaWave data (blue dots), ARMA filtered DecaWave data (red dots), median filtered Pozyx data (green dots), and Kalman filtered DecaWave data (purple dots) in dynamic experiments.

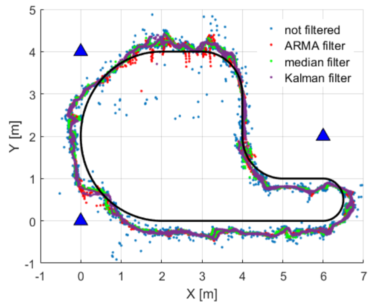

Fig. 9. Measurement points of not-filtered Pozyx data (blue dots), ARMA filtered Pozyx data (red dots), median filtered Pozyx data (green dots), and Kalman filtered Pozyx data (purple dots) in dynamic experiments. Anchors A_0, A_1, A_2 are marked with blue triangles, and the track is marked with the black line.

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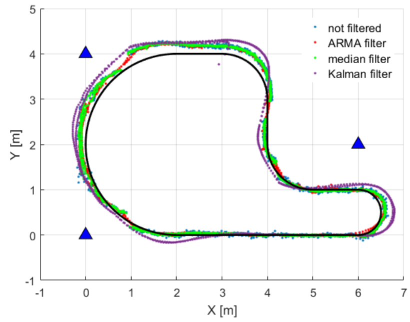

Fig. 10. Measurement points of not-filtered DecaWave data (blue dots), ARMA filtered DecaWave data (red dots), median filtered DecaWave data (green dots), and Kalman filtered DecaWave data (purple dots) in dynamic experiments. Anchors A_0, A_1, A_2 are marked with blue triangles, and the track is marked with the black line.

5 Summary

The paper investigates static and dynamic localization accuracy of two indoor localization systems based on ultra-wideband communication: Pozyx and DecaWave DW1000. The final tag position is obtained in these systems based on the trilateration algorithm that combines data acquired from three anchors. Our research shows that in both: static and dynamic experiments, the Pozyx system has a broader sample variance than DecaWave. Our research has also revealed that the accuracy of both systems is worse than declared by the manufacturers (30 cm for 100% samples). Position accuracy is 38 cm for 95% of Pozyx samples and over 1.5 m for 100% samples. Similarly, the accuracy of DecaWave is 25 cm for 95% of DecaWave samples and 32 cm for 100% samples.

To improve localization accuracy, we have applied ARMA, median, and Kalman filters. The median filter improves localization accuracies of Pozyx to 32 cm for 95% of samples. In the DecaWave, improvement is almost invisible. Similar results have been obtained in ARMA filtration. Kalman filter improves Pozyx accuracy of 95% samples to 32 cm. In the case of DecaWave, the result is significantly worse than not filtered signal – the accuracy of localization decreases by around 8 cm to 34 cm for 95% samples. It should also be noted that the filter attracts trajectory to the most probable position, which results in smooth tracking, but it does not improve measurement accuracy.

In the future, we consider extending our research by applying artificial neural networks to remove the non-gaussian error and reducing the impact of signal reflections on localization results.

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6 References

1. Mautz R.: Indoor positioning technologies, Habilitation Thesis, Institute of Geodesy and Photogrammetry, Department of Civil, Environmental and Geomatic Engineering, ETH Zurich, (2012).
2. Obreja, S., G., Vulpe, A.: Evaluation of an Indoor Localization Solution Based on Bluetooth Low Energy Beacons, 2020 13th International Conference on Communications (COMM), Bucharest, Romania, pp. 227-231 (2020).
3. Xue, J., Liu, J., Sheng, M., Shi, Y., Li, J.: A WiFi fingerprint based high-adaptability indoor localization via machine learning, in China Communications, vol. 17, no. 7, pp. 247259, July 2020, (2020).
4. Che, F., Ahmed, A., Ahmed, S., G., Zaidi, R., Shakir, M., Z.: Machine Learning Based Approach for Indoor Localization Using Ultra-Wide Bandwidth (UWB) System for Industrial Internet of Things (IIoT), 2020 International Conference on UK-China Emerging Technologies (UCET), Glasgow, United Kingdom, (2020).
5. Barbour, N., M., Stark Draper, C.: Inertial Navigation Sensors, Laboratory (P-4994), Cambridge, MA 02139, USA (2011).
6. Lam, E., W., Little, T., D., C.: Indoor 3D Localization with Low-Cost LiFi Components, 2019 Global LIFI Congress (GLC), Paris, France, 2019, pp. 1-6, (2019).
7. Opromolla, R., Fasano, G., Rufino, G., Grassi, M.. Savvaris, A.: LIDAR-inertial integration for UAV localization and mapping in complex environments, 2016 International Conference on Unmanned Aircraft Systems (ICUAS), Arlington, VA, 2016, pp. 649-656, (2016).
8. Taira, H., Okutomi, M., Sattler, T., Cimpoi, M., Pollefeys, M., Sivic, J., Pajdla, T., Torii A.: InLoc: Indoor Visual Localization With Dense Matching and View Synthesis; The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018, pp. 71997209, (2018).
9. Zimmerman, T., Zimmermann, A.: Magic Quadrant for Indoor Location Services, Global Published 13 January 2020 - ID G00385050, (2020).
10. Zhang, W., Zhu, X., Zhao, Z., Liu, Y., Yang, S.: High Accuracy Positioning System Based on Multistation UWB Time-of-Flight Measurements, 2020 IEEE International Conference on Computational Electromagnetics (ICCEM), Singapore, (2020).
11. Decawave, APS011 Application Note, Sources of Error in DW1000 Based Two-Way Ranging (TWR) Schemes, (2014).
12. Asmaa, L., Hatim, K.,A., Abdelaaziz, M.: Localization algorithms research in wireless sensor network based on Multilateration and Trilateration techniques, 2014 Third IEEE International Colloquium in Information Science and Technology (CIST), Tetouan, 2014, pp. 415-419, (2014).
13. Pozyx Homepage https://www.pozyx.io last accessed 2021/02/01.
14. Decawave DW1000 product homepage https://www.decawave.com/product/dw1000-radio-ic/ last accessed 2021/02/01.
15. Zebra Homepage https://www.zebra.com/us/en/products/location-technologies/ultra-wideband.html last accessed 2021/02/01.
16. Ubisense Home Site https://ubisense.com/dimension4/ last accessed 2021/02/01.
17. BeeSpoon Mek 1 Product Homepage https://bespoon.xyz/produit/mek1-ultra-wideband-module-evaluation-kit/ last accessed 2021/02/01.
18. NXP Homepage https://www.nxp.com/applications/enabling-technologies/connectivity/ultra-widebanduwb:UWB last accessed 2021/02/01.

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19. Decawave, APS006 Application Note Channel effects on communications range and time stamp accuracy in DW1000 based systems, https://www.decawave.com/wpcontent/uploads/2018/10/APH001_DW1000-HW-Design-Guide_v1.1.pdf. last accessed 2021/02/01.
20. Glonek, G., Wojciechowski A.,: Kinect and IMU sensors imprecisions compensation method for human limbs tracking, International Conference on Computer Vision and Graphics, ICCVG 2016; Poland (2016).
21. Daszuta, M., Szajerman, D., Napieralski, P.:New emotional model environment for navigation in a virtual reality Open Physics, vol. 18, no. 1, (2020).
22. Zhao, Y., Li, Z., Hao, B., Wan, P., Wang, L.: How to select the best sensors for TDOA and TDOA/AOA localization?, China Communications Year: Vol. 16, Issue:2, Feb. (2019).
23. Sinha, P., Yapici, Y., Guvenc, I.: Impact of 3D Antenna Radiation Patterns on TDOA-Based Wireless Localization of UAVs IEEE INFOCOM 2019 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS) (2019).
24. Bibb, D., A., Yun, Z., Iskander, M., F.: Machine learning for source localization in urban environments MILCOM 2016 - IEEE Military Communications, (2016).
25. Decawave, APS006 Part 2 Application Note, Non Line of Sight operation and optimization to improve performance in DW1000 Based systems, version 1.5, 2014.
26. Decawave, APH001 Application Note, DW1000 hardware design guide, version 1,1, 2018.
27. Saho, K.: Kalman Filter for Moving Object Tracking: Performance Analysis and Filter Design, December 2017, Kalman Filters, Theory for Advanced Applications, (2017).
28. Simedroni X..L.: Indoor Positioning using Decawave MDEK1001, 2020 International Workshop on Antenna Technology (iWAT), Bucharest, Romania, (2020).
29. Delamare Y., Boutteau M., Savatier R., Iriart N.: Static and Dynamic Evaluation of an UWB Localization System for Industrial Applications. Sci (2020).
30. Wang J., Wang M., Yang D. , Liu F., Wen Z. UWB positioning algorithm and accuracy evaluation for different indoor scenes, International Journal of Image and Data Fusion, (2021).
31. MDEK1001 Kit User Manual Module Development & Evaluation Kit for the DWM1001 Version 1.2
32. IEEE Standard for Local and metropolitan area networks— Part 15.4: Low-Rate Wireless Personal Area Networks (LR-WPANs).
33. DecaWave, DW1000 User Manual, version 2.11, 2017.
34. Porti, F., Sangjoon, F., Ruiz, A., R., Barsocchi, P.: Comparing the Performance of Indoor Localization Systems through the EvAAL Framework. Sensors 2017, 17, 2327 (2017).
35. Morawska, B.: Reduction of measurement error in spatial objects' positioning, BSc Thesis, Faculty of Technical Physics, Information Technology and Applied Mathematics of the Technical University of Lodz, (2020).

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