UWB-Based Single-Anchor Indoor Localization Using Reflected Multipath Components

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***Abstract*—Indoor localization has many applications in the context of smart buildings that interact with objects and humans. Due to their resilience to multipath fading, high penetration rate and low duty cycles, Ultra-wideband (UWB) radio have been utilized in indoor localization. In the presence of Line-of-Sight (LoS) signals, UWB-based indoor localization system can locate a target with small errors ($< 5cm$) but in situations with Non-Line-of-Sight (NLoS) signals, UWB systems work at a much reduced accuracy. In this work, NLoS signals are utilized to improve the robustness of the positioning system. The proposed system uses the statistical characteristics of Reflected Multipath Components (RMCs) of UWB signals in different locations as fingerprints and locates the target node based on previously seen locations. We implement and evaluate our proposed system on Decawave platform. Our evaluation shows that the proposed solution can locate objects within squares of $20cm \times 20cm$, with an accuracy of 96% using only one anchor which outperforms existing solutions in robustness and accuracy.**

***Index Terms*—Indoor Localization, UWB, Channel Impulse Response**

I. Introduction

Indoor localization is a critical component of many smart building applications. Due to their exceptional accuracy, scalability, and communication capabilities, wireless indoor localization solutions are dominant techniques in the indoor localization area. The fundamental technique in wireless indoor localization relies on accurately estimating the distance between transmitter and receiver of the signal by using Line-of-Sight (LoS) signal.UWB signals are sent in short pulses in a very large frequency bandwidth (>500 MHz) which makes them resilient against multipath fading. Features like high penetration rate, resilience to multipath fading, and low power consumption make UWB signals an excellent choice for many applications including indoor localization.

The recent studies in UWB-based indoor localization have reported errors of less than 40 cm for 3d localization [1]. Most of UWB-based indoor localization techniques need to process LoS signals to accurately locate the target. However in indoor environments, the reception of LoS signals is not guaranteed in every location e.g. LoS either is blocked by obstacles or is not distinguishable from NLoS signals. Recent work in UWB-based positioning approached this challenge either by increasing the chance of receiving LoS signal through addition of extra antennas and channels, or utilizing NLoS signals to improve the robustness of the localization system. Despite these improvements, creating a UWB-based indoor localization solution that is robust, reliable, scalable, and accurate remains unsolved. Most of existing works require a large number of UWB anchors and communication links to achieve accurate results and perform poorly when the network is sparse.

In this work, we increase the robustness of UWB-based indoor localization by reducing the number of required anchors. Most of existing works are not able to locate the target without having data from at least 3 anchors. Our approach requires only one node with known location (anchor) to locate the target node. Our main idea is utilizing the unique features of UWB signals by extracting high-resolution images of Reflected Multipath Components (RMC) to accurately estimate the location of the target node. Shape and number of received RMCs are dependent on the location of sender and receiver of the signal. Our hypothesis is that the differences in RMC patterns in different places can be utilized as reliable fingerprints to locate targets based on previously seen patterns. We study the characteristics of each reflected multipath components in each location and extract and use statistical features of those components as fingerprints. Later on, to find the location of a target, the RMCs in the received signal are compared with a list of previously seen clusters in the same area and the best match is selected as the estimated target location.

We designed and implemented our single anchor UWB-based indoor localization system on Decawave platform and evaluated its performance in different indoor environments. Our results show that the proposed system can locate the target within a $20cm \times 20cm$ area with an accuracy of 96% using only one anchor node. Our contributions are:

- Proposed a robust single anchor UWB-based indoor localization technique by utilizing differences in statistical characteristics of reflected multipath components in different locations using only one anchor node.
- Generated fingerprints using statistical characteristics of amplitude and phase information for each reflected component which increases the resilience of generated fingerprints to temporal changes in the environment and also significantly reduces the model size.
- Evaluated the reliability and accuracy of using reflected multipath components as fingerprints in different environments with frequent temporal changes.

II. Related Work

Literature in NLoS handling area can be categorized in two groups: Avoiding NLoS signals [2]–[4] and utilizing NLoS signals [5], [6]. In avoiding NLoS category, the key idea is increasing the chance of receiving LoS signal by adding more channels and links. In utilizing NLoS category, the main idea is estimating the error caused by presence of NLoS signals then correcting it in range measurements. Despite the accurate results achieved by approaches in both categories, the scalability of such techniques is under question. These approaches require at least 3 anchors to work. To reduce the number of required anchors to make indoor localization system more robust, the idea of using virtual anchors has been explored in the literature [5], [7]. These techniques hold a lot of assumptions about the environment, such as prior knowledge about room geometry, highly reflective surfaces, and insignificance of the effects like diffraction and diffuse scattering. Although as shown in [8], other effects like diffraction and attenuation can severely impact the ranging accuracy and consequently, the overall performance of such systems.

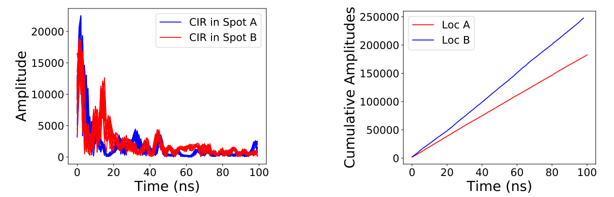
Our proposed solution as a single anchor localization solutions utilizes the unique shape of combination of NLoS and LoS signals received in each location to generate reliable and robust fingerprints. Feasibility of using information from wireless links (Bluetooth and WiFi) to generate fingerprints has been studied before [9], [10]. Features like Received Signal Strength Indicator (RSSI), Channel Frequency Response (CFR), and Channel Impulse Response (CIR) have been utilized previously. CFR is an estimation of the impact of environment on wireless signals across their bandwidth while they travel from sender to receiver. CIR is the equivalent of CFR in time domain. CIR is a very good representative of reflected multipath components (RMC) which can be used to generate fingerprints. The advantage of using CIR compared to CFR is that CFR is very dependent on temporal frequency fading and simple changes in one of the sub-carriers changes the CFR model, but CIR information is more resilient to temporal changes, since each impulse response is based on response across all the bandwidth [11]. Existing wireless fingerprinting techniques can locate the target within $75cm \times 75cm$ spot with 90% accuracy [12]. The key benefit utilized in our approach to improve accuracy is the larger bandwidth and the shorter wavelength of UWB signals compared to WiFi and Bluetooth.

Feasibility of using UWB signals to generate fingerprints has been studied before [13], [14], but the evaluation focused on signals with very large bandwidth (3 GHz to 7 GHz), and high sampling rates in the lab environment. Studies [15] showed that bandwidth of UWB signals has a huge impact on the reliability of fingerprinting approaches. To the best of our knowledge, there is no prior work in the literature that evaluates the reliability of CIR information, captured from UWB signal (IEEE802.15.4-11 standard) with the bandwidth of 500 MHz using commercial off-the-shelf DW1000 chips, to generate reliable and persistent fingerprints.

III. System Design

A. Reflected Multipath Components in UWB

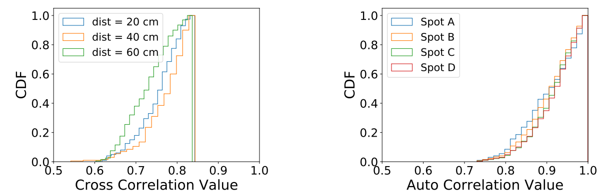
UWB refers to signals with bandwidth larger than 20% of their center frequency [16] and usage of them in WPAN networks has been standardized in IEEE 802.15.4-11 standard [17]. In UWB communication, accurate estimation of CIR is possible due to the unique shape of UWB signals (sequence of short pulses). The CIR contains high-precision information about reflected multipath components which includes first arriving path and other reflected paths. We analyze the CIR information and use information about reflected paths in different locations to generate unique fingerprints. CIR contains information from both LoS and NLoS signals and we utilize uniqueness of this combination as a key feature for generating unique fingerprints.



(a) CIR collected from 2 Different Spots (30 cm distance)

(b) Cumulative Amplitudes of RMCs

Fig. 1: RMC Distinguishably across Spatial Change



(a) Cross correlation of RMC samples in different spots

(b) Autocorrelation of RMC samples in same spot

Fig. 2: Correlation of RMCs across Spatial Change

B. RMC Distinguishability across Spatial Changes

Two assumptions need to be true to reliably fingerprint a location using UWB. Our first assumption is RMC information in different locations are different enough and this difference can be utilized to generate unique fingerprints per location. Our second assumption is RMC information at the same location is relatively stable across time which means RMCs are resilient to temporal changes. We perform several experiments to validate our assumptions. In all the experiments, there is a pair of sender and receiver nodes. The location of the sender (anchor) is fixed but the receiver (target) is placed at different locations. Figure 1(a) shows the amplitude values for first the 100 RMC components collected from two different locations (400 samples in each location) which are 30 cm away from each other. Figure 1(b) is the cumulative amplitude of RMC samples. From Figure 1 two clusters of RMCs are clearly distinguishable. This observation supports our first assumption about distinguishability of RMCs over short spatial changes.

To validate our second assumption, we collected RMC samples at 4 different locations (each location for 1 hour). The CDF of autocorrelation between amplitude values seen for first 50 RMC components is reported in Figure 2(b) and the CDF of cross-correlation between amplitudes of first 50 RMC components in pairs of spots (distance $>$ 20 cm) are

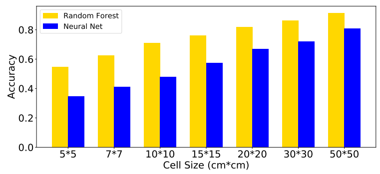


Fig. 3: Classification Accuracy-CIR Extracted Features

reported in Figure 2a. As shown in Figure 2, cross-correlation between RMCs in two different locations is much lower compared to autocorrelation across the samples collected from one location which means our second assumption is also valid in these datasets. It is also shown in Figure 2(a) that cross-correlation between RMC components decreases as the distance between the spots is increased. In conclusion, RMCs, which are reported in the form of CIR samples, are reliable sources to generate unique fingerprints per location.

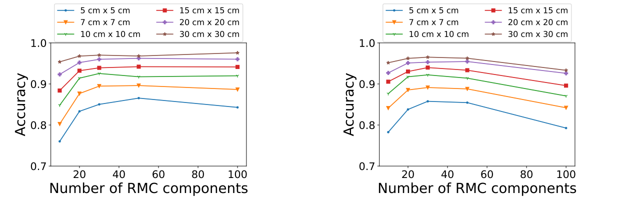
C. RMC Classification

In this section, we evaluate the feasibility of using standard classification algorithms to generate fingerprints using RMCs and accurately distinguish different spots from each other.

1) Feature Extraction: We extract the following features from RMC values: **First Path Delay & power**: The time it takes for the first arriving path to travel from sender to receiver and its received power. **Power**: Amount of power in the received signal. **Average & Std of Noise**: Average and standard deviation of the ambient noise. **Preamble Count**: UWB packets start with preambles. The accumulative correlation between received signal and expected preamble is used to estimate the CIR. The number of preambles used to estimate the CIR depends on the quality of the received signal. We utilized the number of preambles used for estimating the CIR, as a feature.

We divided the target area to grids with different sizes ($5cm \times 5cm$ to $50cm \times 50cm$). To perform data collection consistently and systematically, we used a robot (turtlebot [18]) to move around with a constant speed (0.05 cm/s) while the receiver is mounted on top of it. The sender (anchor) is in a static location and sends beacons every 50 ms. Figure 3 shows the classification accuracies achieved by running neural networks (MLP Classifier with quasi-Newton solver and with network size (5 layers, 5 neurons per layer)) and random forest (number of estimators = 10, criteria=entropy) classification algorithms on the features collected from different spots (15 spots which are at least 30 cm apart) with the same size (in each spot, at least 2000 packets used for training). The accuracies are reported after running 10-fold-cross-validation on the dataset.

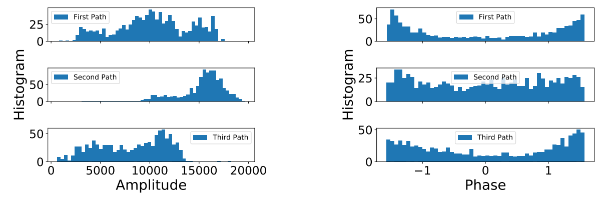
As shown in Figure 3, the best result which is approximately 84% accuracy is achieved by the random forest algorithm with the spot size of $50cm \times 50cm$. The classification becomes less accurate as we decrease the size of squares. Overall, the collected features are not reliable enough for generating fingerprints. Using other classification algorithms like SVM and Bayes Nets in scikit-learn 0.19.1 also could not improve the accuracy.



(a) Neural Net

(b) Random Forest

Fig. 4: Classification Accuracy using Raw CIR Information



(a) Amplitude Distribution

(b) Phase Distribution

Fig. 5: Histogram of First 3 RMCs over 1000 Samples

2) Over-fitting with Raw CIR: Next, we study the feasibility of using raw CIR information as classification features instead of extracting general features from CIR samples. Figure 4 shows the accuracy reported by neural net (MLP Classifier with quasi-Newton solver and with network size (5,10)) and random forest (number of estimators = 20, criteria=entropy) algorithms after feeding them with raw CIR values from previous experiment (15 spots). We also changed the number of RMCs used in training phase from 5 components up to 100 components.

As shown in Figure 4, overall accuracies improved (in average 25%) compared to previous approach (using extracted features). This observation is expected since CIR information contains more details about each location. Despite improvements in the reported accuracy, Figure 4 shows that the classification using raw CIR data suffers from overfitting. As we increase number of reflected components above 50, the accuracy starts decreasing. In other words, those algorithms do not benefit from the rest of RMC samples in the data.

3) Modeling RMCs: In next step, we try to extract generalized statistical features of each RMC component in each location. Our hypothesis here is that statistical distributions are more resilient to temporal changes and can improve the robustness of localization solution. Figure 5 shows the histogram of amplitude and phase for first three RMCs calculated from sampling 1000 packets while the locations of sender and receiver are fixed. Figure 5(a) shows that the amplitude information on each reflected component follows a mixture of Gaussian distributions. Also, the collected phase information (Figure 5(b)) follows the Beta distribution which is reasonable due to the nature of UWB signals. They are sent as sequence of 0,+1 and -1 values [17] which means the phase values are mostly around +90 degrees and -90 degrees phases. We observe the same pattern in rest of RMCs across different locations. Amplitude values for each RMC is modeled as Gaussian Mixture model. Variational Bayesian Gaussian Mixture [19] is used to find optimum number of

Gaussian components for each RMC component. In summary the proposed fingerprinting approach works as follow. For each location RMC information (CIR) is collected across several beacon packets sent from nearby anchor; for each RMC component, the amplitude is modeled as a Gaussian Mixture model and phase is modeled as Beta distribution with α and β parameters. We store these models for each component as fingerprints. For instance, if we decide to use information for 50 RMC components as fingerprint, at each location, we store set of 50 pairs of models (amplitude model and phase model). Later, in the online phase, to locate the target, after receiving beacon message from a specific anchor, the CIR information from test packet is investigated to find its best match with previously seen clusters which are associated with same anchor. To measure the similarity, we define the following metric:

$$S(P, U^t, V^t) = \sum_{i=1}^{N} LogLK(U_i^t, Amp_i) + \sum_{i=1}^{N} LogLK(V_i^t, Phase_i) \tag{1}$$

in which, P is the received test packet, U^t is set of Gaussian Mixture models for amplitude values in location t (one GMM per RMC), V^t is the set of Beta distributions for phase values at location t (one Beta distribution per RMC) , LogLK stands for log likelihood function, Amp_i and $Phase_i$ are amplitude and phase values of i^{th} RMC component at test packet P respectively and N is number of RMC components considered for generating fingerprint. After calculating the similarity of received test packet from specific anchor to all clusters associated with the same anchor, the location of the target is the most similar cluster. It is essential to mention that since for each spot the proposed approach only saves distribution parameters and not the raw data, the database size is significantly decreased. Small database size improves the required search time.

IV. Performance Evaluation

A. Experiment Setting

We used EVB1000 [20] nodes which are evaluation kits manufactured by DecaWave company and include DW1000 chips. DW1000 chips estimate CIR with 1 ns resolution. We collected data from different locations including office space in (i) our lab, (ii) a crowded coffee shop on campus and (iii) a large dining hall with lots of furniture. In each experiment, we compared the performance of proposed solution in accurately classifying at least 15 different spots. In each location, we collected data from up to 3 different anchors. As expected results from anchors with LoS condition outperform results from NLoS anchor; We focus on the results with the NLoS anchor. Our dataset contains 223366 packets collected from 200 different spots. The target node is placed on top of a robot which moves with constant speed (0.05 cm/s). The anchors broadcast beacons every 50 ms. The target node estimates and saves the CIR information from received beacon messages. In each environment, we made sure one of the anchors is in the NLoS condition (no visual Line-of-Sight, error in distance measurement at least twice the error in LoS condition with the same distance). In the all following sections (except those in which source of data is clearly mentioned) reported results are average performance results over all three tested environments. The anchors are deployed at the height of 160 cm and the target is deployed at the height of 70 cm.

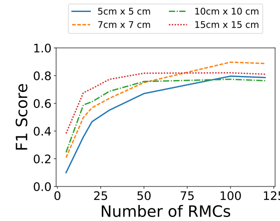
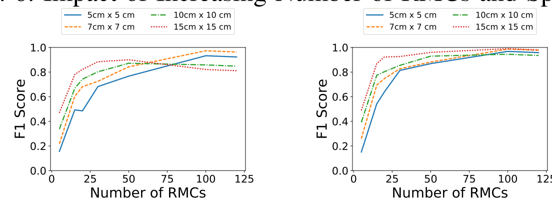


Fig. 6: Impact of Increasing Number of RMCs and Spot Size



(a) Window size = 3 (b) Window size = 5

Fig. 7: Minimum Reliably Distinguishable Spot Size

B. Impact of Contributing Factors

1) Number of RMCs and Spot Size: There are two main factors which determine the accuracy of the proposed system: number of used RMCs and spot size. Figure 6 shows the F1 score calculated from training and testing data in the coffee shop. As shown in figure 6, as we increase the number of used RMCs in fingerprint, the score goes higher but this trend stops after using 100 RMC components. Also, increasing spot size improves the performance. With spot size of $5cm \times 5cm$, the maximum score is around 0.8 which is not good enough but if we increase the spot size to $15cm \times 15cm$, the score increases to 0.95. Another interesting observation is the fact that the best classification score happens at spot size $7cm \times 7cm$. The data were collected while the nodes were communicating over channel 2 with center frequency of 3.993 GHz. The wavelength of this frequency is approximately 7 cm which is the reason spot size of $7cm \times 7cm$ has very high classification scores (0.88 with 100 RMC components in use). It is essential to mention that we verified that in average the difference between power level of 100th RMC component and noise is bigger than 10 DB in our dataset.

2) Minimum Spot Size: Instead of using just one packet, we evaluated the possibility of using multiple packets and considering the majority vote as the final detected location. Figure 7 shows the F1 scores reported from window sizes of 3 and 5 packets. As we expected, the score increases to 0.96 after considering the last 3 samples for deciding the location with the spot size of $7cm \times 7cm$. Average human walking speed is 130 cm per second [21] and we are collecting data every 50 ms which means to receive 3 samples, the target has moved around 20 cm. In other words, our solution locates the target within the spot of $20cm \times 20cm$ with the F1 score of 0.96.

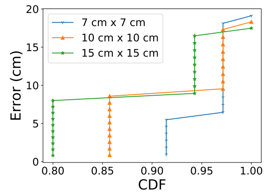
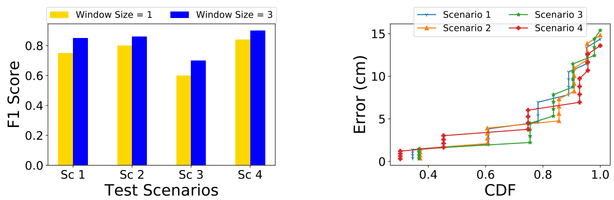


Fig. 8: Maximum Localization Error (CDF)



(a) F1 Score (b) Maximum Localization Error

Fig. 9: Resilience to Temporal Changes

C. Overall Accuracy

1) Compared to ToA Ranging: We also run two-way ranging application provided by Decawave company in the coffee shop area ($15m \times 10m$) with 3 anchors and measured its accuracy over 12 test points. The average error was approximately 45 cm.

2) Maximum Localization Error: There are cases in which the system makes misclassifies the target's location, now we study, how far is the detected location from the real location. Figure 8 shows the CDF of maximum errors. As shown in figure 8, in 92% of the times the maximum error is below 6 cm and in 97% of times, the maximum error is below 10 cm making the system useful in indoor localization applications.

3) Resilience to Temporal Changes: To evaluate the resilience of proposed method to temporal changes, we collect data from the coffee shop one week after collecting the training data creating four different scenarios: in each scenario we reorganized some pieces of furniture like tables and chairs and collected data from the same spots as training data was collected. Figure 9 reports F1 scores and maximum errors calculated from our proposed method. Despite sometimes F1 score going down to 0.6 even with window size of 3, the maximum error remains under 20 cm in all the scenarios. Periodic training could improve the classification score.

V. Discussion

The main advantage of proposed approach is reducing the number of required anchors from 3 to 1 while keeping the accuracy reasonably comparable with state of the art solutions. Also, data collected by robot is only used for training; our solution is able to locate the target with 96% accuracy by using only 3 consecutive packets which makes it practical for indoor object/human tracking. In addition, we conducted experiments using channel 2 but DW1000 chip supports 4 more frequency channels with higher central frequencies (shorter wavelengths), which means the size of the spot that reliably distinguishable from other spots can be smaller in higher frequency channels.

VI. Conclusion

In this work, we studied the feasibility of using reflected multipath components extractable from CIR information from UWB signals to implement a robust single anchor indoor localization applications. Our evaluations show that the proposed approach can locate a target inside a spot with size of $20cm \times 20cm$ with F1 score of 0.96. Our solution uses just one anchor, which is not necessarily LoS, to locate the target which significantly increases the robustness of indoor localization systems.

References

[1] "Microsoft indoor localization competition - ipsn 2017," https://www.microsoft.com/en-us/research/event/microsoft-indoor-localization-competition-ipsn-2018/, accessed: 2018-05-05.

[2] B. Kempke, P. Pannuto, B. Campbell, and P. Dutta, "Surepoint: Exploiting ultra wideband flooding and diversity to provide robust, scalable, high-fidelity indoor localization," in *SenSys'16*. New York, NY, USA: ACM, 2016, pp. 137–149.

[3] P. Corbalán and G. P. Picco, "Concurrent ranging in ultra-wideband radios: Experimental evidence, challenges, and opportunities," 2018.

[4] M. Mati, "Identification & mitigation of nlos information for uwb based indoor localization," Ph.D. dissertation, University of Windsor (Canada), 2016.

[5] B. Großwindhager, M. Rath, J. Kulmer, S. Hinteregger, M. Bakr, C. A. Boano, K. Witrisal, and K. Römer, "Demo abstract: Uwb-based single-anchor low-cost indoor localization system," 2017.

[6] C. Di Franco, A. Prorok, N. Atanasov, B. Kempke, P. Dutta, V. Kumar, and G. J. Pappas, "Calibration-free network localization using non-line-of-sight ultra-wideband measurements," in *IPSN'17*. IEEE, 2017.

[7] J. Kulmer, S. Hinteregger, B. Großwindhager, M. Rath, M. S. Bakr, E. Leitinger, and K. Witrisal, "Using decawave uwb transceivers for high-accuracy multipath-assisted indoor positioning," in *Communications Workshops (ICC Workshops), 2017 IEEE International Conference on*. IEEE, 2017, pp. 1239–1245.

[8] M. Heydariaan, H. Mohammadmoradi, and O. Gnawali, "Toward Standard Non-line-of-sight Benchmarking of Ultra-wideband Radio-based Localization," in *CPSBench '18*, 2018.

[9] R. Yang and H. Zhang, "Rssi-based fingerprint positioning system for indoor wireless network," in *LSMS'14*. Springer, 2014, pp. 313–319.

[10] R. Faragher and R. Harle, "Location fingerprinting with bluetooth low energy beacons," *IEEE journal on Selected Areas in Communications*, vol. 33, no. 11, pp. 2418–2428, 2015.

[11] Z. Yang, Z. Zhou, and Y. Liu, "From rssi to csi: Indoor localization via channel response," *ACM Computing Surveys (CSUR)*, vol. 46, no. 2, p. 25, 2013.

[12] S. Shi, S. Sigg, and Y. Ji, "Probabilistic fingerprinting based passive device-free localization from channel state information," in *VTC'16*. IEEE, 2016, pp. 1–5.

[13] G. Caso, M. T. Le, L. De Nardis, and M.-G. Di Benedetto, "Performance comparison of wifi and uwb fingerprinting indoor positioning systems," *Technologies*, vol. 6, no. 1, p. 14, 2018.

[14] J. Luo and H. Gao, "Deep belief networks for fingerprinting indoor localization using ultrawideband technology," *International Journal of Distributed Sensor Networks*, vol. 12, no. 1, p. 5840916, 2016.

[15] C.-C. Chong, F. Watanabe, and M. Z. Win, "Effect of bandwidth on uwb ranging error," in *WCNC 2007*. IEEE, 2007, pp. 1559–1564.

[16] X. Shen, M. Guizani, R. C. Qiu, and T. Le-Ngoc, *Ultra-wideband wireless communications and networks*. John Wiley & Sons, 2007.

[17] "Ieee802.15.4-11 standard," http://www.ieee802.org/15/pub/TG4.html, accessed: 2018-05-05.

[18] "Turtlebot," http://www.turtlebot.com/, accessed: 2018-05-05.

[19] N. Nasios and A. G. Bors, "Variational learning for gaussian mixture models," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 36, no. 4, pp. 849–862, 2006.

[20] "Evb1000 evaluational kit," https://www.decawave.com/products/evk1000-evaluation-kit, accessed: 2018-05-05.

[21] N. Carey, "Establishing pedestrian walking speeds," *Karen Aspelin, Portland State University*, vol. 1, no. 01, 2005.