2023 IEEE International Mediterranean Conference on Communications and Networking (MeditCom) | 979-8-3503-3373-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/MeditCom58224.2023.10266625

A Hybrid WiFi/Bluetooth RSS Dataset with Application to Multilateration-Based Localization

Giovanni Pettorru, Virginia Pilloni and Marco Martalò
Department of Electrical and Electronic Engineering, University of Cagliari, Italy
and Consorzio Nazionale Interuniversitario per le Telecomunicazioni (CNIT), Italy
E-mail: {giovanni.pettorru,virginia.pilloni,marco.martalo}@unica.it

***Abstract*—Given the growing importance of Location-Based Services (LBS) in the broader Internet of Things (IoT) context, efficient and optimized location algorithms are essential. To address this, a hybrid WiFi/Bluetooth (BLT) localization algorithm is experimentally investigated in this paper. This approach uses Received Signal Strength (RSS) information to estimate target-anchors' distances, which are then fed at the input of a Least Squares (LS)-based localization algorithm to finally estimate the target position. The study relies on a dataset created by the authors with the goal of developing and evaluating RSS-based localization algorithms that incorporate the fusion of data from different technologies. The experimental results presented in this paper confirm that such an approach improves the accuracy, resilience, and robustness of location estimation and optimizes IoT services based on contextual information with respect to schemes based on a single technology.**

***Index Terms*—Received Signal Strength (RSS), Location-Based Services (LBS), dataset, Internet of Things (IoT), WiFi, Bluetooth, multilateration.**

I. Introduction

In recent times, we have observed an exponential growth of the Internet of Things (IoT) affecting every aspect of our lives, from homes to medical facilities, fitness centers, and even the industrial sector. While the expansion of this technology was left unrestrained in the past, the need to optimize its applications and set limits has now emerged. For instance, optimizing these applications can lead to more efficient resource allocation, greater energy efficiency, and a reduction in the overall environmental impact of IoT networks. As a result, the concept of Green IoT has arisen as a sustainable evolution of IoT, aimed at promoting energy efficiency and minimizing greenhouse gas emissions [1].

Green IoT can be empowered by contextual information to enable networks of IoT devices to understand and respond to their surroundings, improving the performance and efficiency of the services and functions they perform. One key context-aware service is provided by Location-Based Services (LBS), which gives information on objects' positions. This can enable the network to perform more complex functions, such as optimizing resource allocation, including spectral bandwidth, computational capacity, and energy consumption, meeting Green IoT requirements.

Received Signal Strength (RSS)-based localization is one of the simplest approaches used to determine the location of a target in hostile IoT environments, such as indoors, where more sophisticated technologies like satellite-based positioning cannot be used. This method is based on measuring the RSS from multiple anchors, calculating the distances between the target and each anchor, and finally using multilateration techniques to estimate the position of the target. These techniques are typically based on Maximum Likelihood (ML) estimation with the goal of minimizing differences between true and estimated distances, taking into account that these are affected by errors due to signal propagation in a non-ideal environment [2].

The primary objective of this study is to investigate a hybrid localization approach that can improve the resilience, robustness, and accuracy of RSS-based algorithms. There have been several prior studies suggesting the utilization of hybrid approaches, which combine information from multiple sources, as a means of enhancing the precision and resilience of indoor and outdoor localization systems. In [3], a framework was proposed to integrate different sources, including WiFi and Bluetooth (BLT), quick response codes, and microelectromechanical system sensors for indoor localization. Another example is the hybrid indoor positioning system proposed in [4], which uses acoustic and RSS signals for accurate indoor location estimation. In [5], a hybrid localization algorithm, which combines Angle of Arrival (AoA) and RSS information, was introduced to minimize the localization error of nodes in a wireless sensor network.

To understand the potential of the proposed approach, we investigate the modification of the Least Squares (LS)-based localization algorithm present in the literature and evaluate its performance using a dataset obtained from indoor and outdoor practice environments [6]. Our work distinguishes itself from the existing literature by presenting a hybrid approach based on two easily accessible technologies, WiFi and BLT, that are compliant with IoT devices, enabling low computational complexity and low power consumption. Unlike many previous studies that focus on specific environments, our approach is designed to be robust and reliable in a range of scenarios, including indoor/outdoor, and considering the presence/absence of obstacles. Furthermore, to ensure the reliability of our results, we collect data from real scenarios rather than relying solely on simulations, which often fail to accurately represent real-world conditions.

The rest of the paper is organized as follows. In Section II, we provide a system model overview, which encompasses a discussion of the reference scenario, an explanation of how the RSS-based localization algorithms work, and an introduction to the considered hybrid approach. In Section III, we discuss the setup of the devices used to collect the data, the different scenarios in which the campaign is performed, and the structure of the proposed dataset. In Section IV, results of experimental tests performed to validate the hybrid approach are shown and discussed. Finally, in Section V concluding remarks are given.

II. System Model

In this Section, we discuss the system model being used. First, the reference localization scenario is presented in Section II-A. Then, the considered RSS-based distance estimation is discussed in Section II-B, whereas the considered localization algorithms are introduced in Section II-C.

A. Reference Scenario

The reference scenario for this study involves the deployment of N_{anchors} wireless devices acting as anchors with known positions and a target, whose position has to be estimated. The considered scenario is two-dimensional, but the extension to three-dimensional localization is straightforward. The i-th anchor deployed in the environment (i = 1,2,$\ldots$,N_{anchors}) has coordinates $\boldsymbol{a}_i = [a_i^x, a_i^y]^T$, whereas the target has coordinates $\boldsymbol{t} = [t^x, t^y]^T$, being T the transpose operator. All the devices are assumed to be stationary for each localization act. The distance between the target and the i-th anchor can be expressed as

$$d_i = \|\boldsymbol{a}_i - \boldsymbol{t}\| = \sqrt{(a_i^x - t^x)^2 + (a_i^y - t^y)^2} \quad (1)$$

where $\|\cdot\|$ denotes the Euclidean norm.

In order to perform localization, the anchors send beacons to the target, which collects them to locally estimate their position using either a range-free or range-based algorithm. Even if range-free algorithms, i.e., algorithms where the position estimation is done without using any measurement, have lower complexity than range-based methods, in which the distances and/or angles measurements between the target and the anchors are used, they have lower accuracy and are more sensitive to environmental factors, such as interference or obstacles [7]. Therefore, in this paper, we focus on range-based methods. In particular, we focus on RSS-based localization, due to its inherent low complexity, which makes it suitable for IoT applications. Moreover, the RSS can be measured at the receiver antenna and used to estimate the anchor-target distance according to a specific path-loss model [8]. Note that such a metric is a measure of the signal strength received by a wireless communication system, it is usually expressed in a logarithmic scale (dBm), and quantized with a 1 dB resolution. Therefore, in the following sections, the terms RSS and received power will be used interchangeably.

Once the target-anchors' distances are estimated, they are fed at the input of the RSS-based localization algorithm. Note that, in order to locate its position within the scenario, the target will need to be able to estimate its distance from at

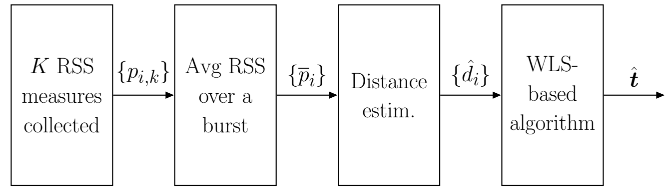


Fig. 1: General scheme of the RSS-based localization method.

perché per 3 punti passa uno ed un solo piano 2D

least 3 anchors if a two-dimensional scenario is considered. A general scheme of the considered RSS-based localization method is presented in Fig. 1 and described in more detail in the following sections.

B. Target-Anchor Distance Estimation

At each localization act and for each considered communication technology, the target collects K consecutive RSS values for the i-th anchor, as shown in the first block of Fig. 1, denoted as $\{p_{i,k}\}$ $(k = 1, 2, \ldots, K)$. The k-th power value of the beacon received by the i-th anchor can be written, according to a standard path loss model [9], as

$$p_{i,k} = p_0 - 10n \log_{10} d_i + \varepsilon_{i,k} \quad (2)$$

where p_0 is the power received at a reference distance, typically 1 m, n is the path loss exponent whose value is normally in the range of 2 to 4, and $\varepsilon_{i,k} \sim \mathcal{N}(0, \sigma^2)$ is an additive noise term due to typical phenomena in propagation such as shadowing or mirroring.

Moving on to the second block of the general scheme of Fig. 2, the average RSS over the burst of K consecutive measurements, denoted as $\overline{p}_i$, is computed as

$$\overline{p}_i = \frac{1}{K} \sum_{k=1}^{K} p_{i,k} = p_0 - 10n \log_{10} d_i + \varepsilon_i \quad (3)$$

where, according to the path loss model (2), the noise term is $\varepsilon_i \sim \mathcal{N}(0, \sigma^2/K)$.

In the third block, neglecting the thermal noise, the distance between the target and the i-th anchor can be estimated by inverting (3) as

$$\hat{d}_i \simeq 10^{\frac{\overline{p}_i - p_0}{10n}} \quad (4)$$

Once all the distances are obtained, an RSS-based multilateration algorithm, as described in the following Section, can be used to estimate the position of the target in the environment [10].

C. RSS-Based Multilateration

In this paper, we do not aim at designing a novel localization algorithm. On the other hand, we rely on an existing RSS-based multilateration algorithm to show its performance in a realistic experimental setup. Moreover, we propose an extension of such an algorithm to incorporate hybrid WiFi/BLT measurements. In particular, we exploit the Weighted Least Squares (WLS) localization algorithm proposed in [11], which extends upon the LS method to take into account the reliability caused by various factors, such as the target-anchor distance and obstacles and environmental conditions on RSS measurements. As a result, the WLS algorithm produces more accurate location estimates than methods that do not consider the variability of these data.

More precisely, given N with reference points with coordinates $\{\boldsymbol{a}_i\}$ and corresponding estimated distances from the target $\{\hat{d}_i\}$, the WLS method solves, in an LS sense, a system of equations with matrix $\boldsymbol{A}$ and vector b defined as follows:

$$\boldsymbol{A} = \begin{pmatrix} -2\boldsymbol{a}_1^T & 1 \\ -2\boldsymbol{a}_2^T & 1 \\ \vdots & \vdots \\ -2\boldsymbol{a}_N^T & 1 \end{pmatrix} \qquad \boldsymbol{b} = \begin{pmatrix} \hat{d}_1^2 - ||\boldsymbol{a}_1||^2 \\ \hat{d}_2^2 - ||\boldsymbol{a}_2||^2 \\ \vdots \\ \hat{d}_N^2 - ||\boldsymbol{a}_N||^2 \end{pmatrix} \tag{5}$$

If we consider a diagonal matrix $\boldsymbol{W}$ whose elements are the inverse of the variance of $\hat{d}_i^2$ [11, eq. (4)], the output of the WLS algorithm is

$$\hat{\boldsymbol{\varrho}} = \left(\boldsymbol{A}^T\boldsymbol{W}\boldsymbol{A}\right)^{-1}\boldsymbol{A}^T\boldsymbol{W}\boldsymbol{b} \tag{6}$$

and the final position estimation is

$$\hat{\boldsymbol{t}} = [\hat{\varrho}_1, \hat{\varrho}_2]^T \tag{7}$$

i.e., the first two elements of $\hat{\boldsymbol{\varrho}}$.

In the remainder of this paper, if a pure WiFi (BLT, respectively) localization scheme is considered, the solution (6) is obtained starting from $N = N_{\text{anchors}}$ data corresponding to RSS measurements given by the WiFi (BLT, respectively) interface of the employed wireless devices. However, by combining RSS data from WiFi and BLT a more accurate estimate of the physical location of the device can be obtained [12]. This is because different communication technologies can be affected by interference at different times, and by combining information from both sources, these effects can be mitigated.

As a very simple, yet effective, hybrid WiFi/BLT approach, we consider a WLS algorithm in which we virtually combine the number of available anchors from the two technologies, resulting in a more robust, resilient, and accurate estimate of device location. In particular, we construct (5) with $N = 2N_{\text{anchors}}$ inserting, for each anchor, two equations, one employing the WiFi-based distance estimation and one with the BLT-based one.[1] At this point, the same solution in (6) can be applied to the corresponding data.

III. Experimental Setup

Some previous works in the literature have proposed datasets that can be used for RSS-based localization algorithms, focusing on very specific scenarios [13]–[19]. Our objective is to overcome the limitations of currently available datasets by providing a more diverse range of environmental conditions and communication technologies. Our dataset is designed to be more generalized, allowing for broader applicability to various scenarios and settings.

[1]The definition of a more powerful hybrid algorithm, e.g., by selecting subsets of WiFi and BLT distance estimates based on their reliability, goes beyond the scope of this manuscript and will be the subject of future work.

A. Proof of Concept

Two types of devices are used to conduct the acquisition campaign. The target is implemented on a Raspberry Pi 4 Model B, utilizing its internal BLT interface and an external Realtek RTL8812BU USB WiFi interface. Each anchor is implemented on a Raspberry Pi Zero W, which uses the internal WiFi and BLT interfaces. The first device requires more computational capability due to its role in taking measurements and estimating its position. On the other hand, the second device does not require high computational complexity and it is a cost-effective solution in terms of functionality. To perform the data acquisition phase, all devices are placed on a tripod at a height of 1.5 meters above the ground.

During the data acquisition campaign, RSS measurements are acquired for a duration of 15 minutes for each anchor-target pair. The target node is stationary for the duration of the acquisition campaign in each scenario, as described in the following section.

On the software side, Python scripts are used for both the target and the anchor node. Regarding the target, the PyShark library [20] is used to access the external interface in monitor mode, allowing it to capture all probe requests sent from devices within the coverage radius of the anchor node and related information, including RSS. The captured packets are filtered to retain only those sent by the anchor nodes, using their Medium Access Control (MAC) address as the discriminating information. A similar logic is used for BLT measurements with the Bluepy library [21].

Regarding the anchor nodes, a continuous scan of the WiFi networks and nearby BLT devices is performed using a Python script. These scans indirectly force the forwarding of Probe Request (WiFi) and Inquiry Scan (BLT) packets, allowing their capture by the target node.

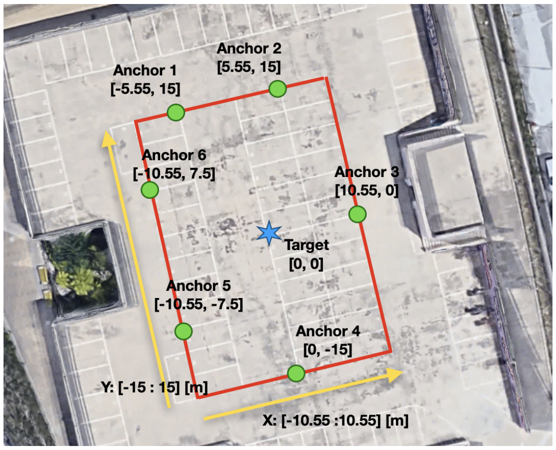
B. Scenarios and Dataset Structure

The RSS measurements are acquired in 4 different scenarios, each of them with different purposes, as described in the following. All the scenarios are implemented in the parking area of the Faculty of Engineering of the University of Cagliari, Italy.

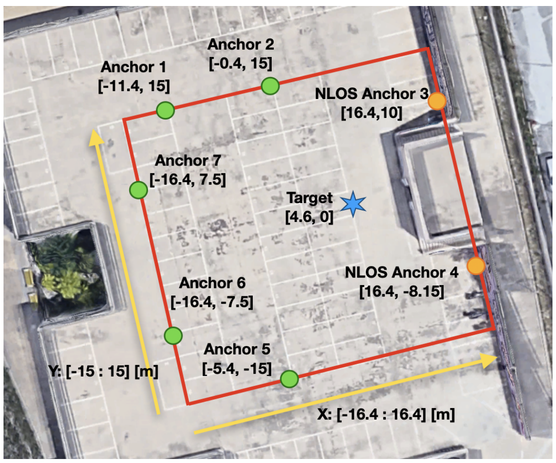
The first scenario, referred to as "Scenario A", is outdoor and all the devices are placed in parking lots along the perimeter of an approximately 21×30 m^2 rectangle. Six anchors are used and all the target-anchor communication links are in Line-Of-Sight (LOS), with the target located at coordinates $[0, 0]^T$, as shown in Fig. 2 (a).

The second scenario, referred to as "Scenario B", is still outdoor in parking lots around the perimeter of an approximately 32×30 m^2 rectangle. Seven anchor nodes are used, 5 of them in LOS and 2 in Non-Line-Of-Sight (NLOS), with the target located at coordinates $[4.6, 0]^T$, as shown in Fig. 2 (b).

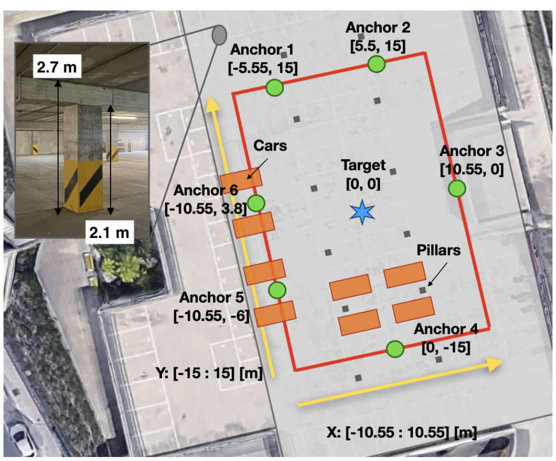
The third scenario, referred to as "Scenario C", is indoor in parking lots by trying to replicate "Scenario A" in the indoor environment (some anchors' coordinates are changed to cope with the physical constraints of the environment).



(a)



(b)



(c)

Fig. 2: Scenarios for data acquisition: (a) Scenario A, (b) Scenario B, and (c) Scenario C.

This scenario is depicted in Fig. 2 (c) and includes various obstacles, such as cars and pillars within the environment.

Finally, another scenario, referred to as "Scenario 0", is also considered for preliminary analysis on the propagation model. In particular, in this outdoor scenario, the target remains fixed and the anchor is moved along a line at a distance ranging from 5 to 25 meters with intermediate steps of 5 meters.

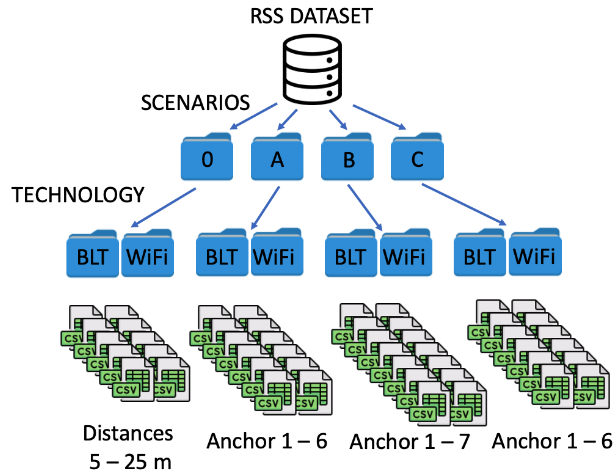


Fig. 3: Structure of the RSS dataset.

The dataset is publicly available [6]. It is organized into directories, each of which corresponds to a specific scenario. In addition, these are further divided into subdirectories based on the type of technology analyzed, WiFi or BLT. Finally, each subdirectory includes a CSV file for each anchor node that is part of the scenario. The structure is graphically described in Fig. 3.

IV. Experimental Performance Analysis

A. *Preliminary Dataset Statistical Analysis*

As a preliminary performance assessment, we investigate the statistical characteristics of the collected dataset. In particular, it has been observed in Section II that the mean and standard deviation of the RSS measurements are of interest for localization purposes. These quantities are presented in Fig. 4 and Fig. 5, respectively.

In particular, in Fig. 4 the mean RSS is shown, as a function of the time, in Scenario A[2] for both WiFi and BLT technologies. For a fixed technology, each line corresponds to a specific anchor. It can be observed that WiFi technology provides higher received power compared to BLT in the analyzed scenarios. This has to be expected since WiFi technology uses higher transmission power as per the standard. However, due to the stronger WiFi interference present in these scenarios (e.g., concurrent WiFi university connectivity), BLT technology produces more stable measurements with less fluctuation over time.

In order to obtain a comprehensive understanding of the RSS data, a statistical analysis is conducted by separately considering each anchor and scenario. Fig. 5 shows the average standard deviation (over time) of the RSS measurements for each scenario and anchor. It is worth noting that BLT is, on average, more stable (for fixed conditions) than WiFi in all the considered scenarios, thus confirming the observations carried out in Fig. 4.

[2]Similar considerations hold for the other scenarios.

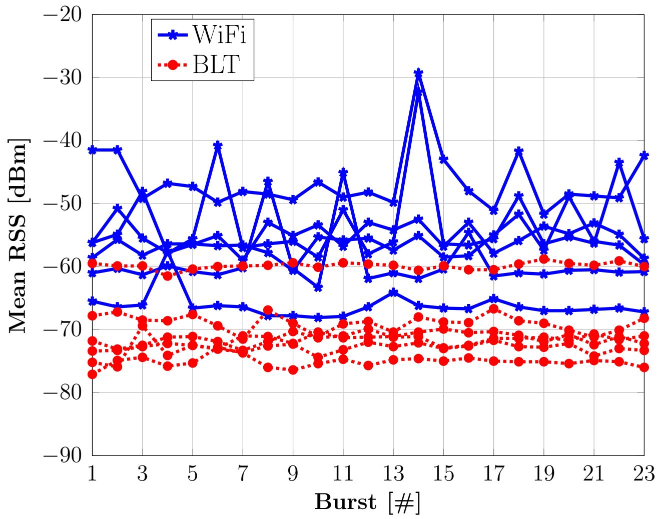


Fig. 4: Mean RSS, as a function of the time, in Scenario A for both WiFi and BLT technologies.

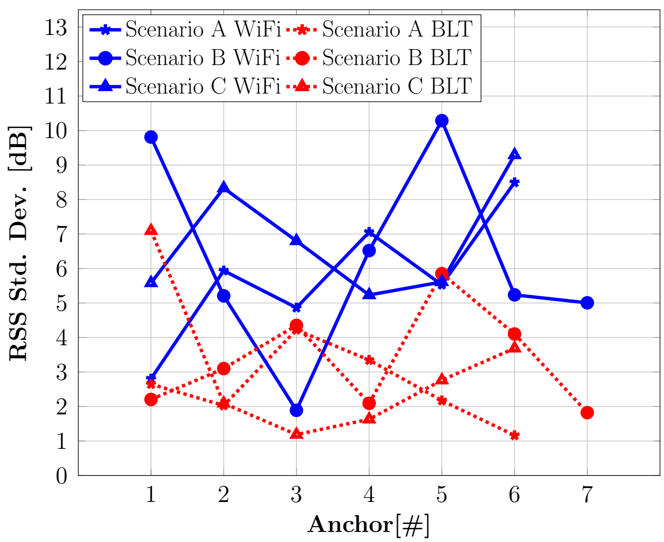


Fig. 5: Average standard deviation (over time) of the RSS measurement for each scenario and anchor.

B. Localization Performance

The goal of this section is to demonstrate the effectiveness and feasibility of the WLS-based approaches presented in Section II-C on the experimental dataset introduced in Section III. To this end, we consider an illustrative scenario in which measurements are collected in bursts of $K = 10$ consecutive samples.[3] Using the data in Scenario 0, we determine that the optimal values for p_0 and n in (4) are -40 dBm and 4, respectively. For what concern the value of σ, required by the WLS algorithm, we decide to use 2 dB mainly taking into consideration the shadowing phenomenon. The localization performance is assessed in terms of the Root Mean Square Error (RMSE, dimension [m]), defined as

$$\Theta = \sqrt{\frac{1}{N_{\text{burst}}} \sum_{\ell=1}^{N_{\text{burst}}} ||\boldsymbol{t} - \hat{\boldsymbol{t}}_\ell||^2} \quad (8)$$

where N_{burst} is the number of collected bursts (i.e., performed localization acts) and $\hat{\boldsymbol{t}}_\ell$ is the estimated position at the ℓ-th burst. In other words, the RMSE provides an indication of the average squared discrepancy between the estimated and actual location. Note that N_{burst} for each scenario and reference technology is limited by the minimum number of measurements available for each anchor.

The localization performance of the considered WLS-based algorithms in the investigated experimental scenarios are presented in Fig. 6. In particular, the clouds of estimated positions are placed on the map and the corresponding RMSE for pure WiFi, pure BLT, and hybrid approaches are indicated. In all cases, the RMSE of the hybrid approach has intermediate values between WiFi and BLT, due to the fact that the algorithm is somehow limited by the worst technology. However, it is worth noting that in some cases (Scenario B) pure WiFi is better than pure BLT, whereas in some other cases (Scenario A and Scenario C) the opposite happens. This means that the hybrid approach is "on average" effective in all scenarios, and this is especially useful when no information on which technology has better performance is available.

V. Conclusions

This paper investigated a hybrid localization approach that combines WiFi and BLT RSS measurements and validated it through experimental tests. The primary objective of this paper was to showcase the effectiveness of data fusion by combining RSS measurements from both WiFi and BLT interfaces and utilizing them as inputs for multilateration-based algorithms. Additionally, we collected a hybrid dataset that includes both WiFi and BLT RSS measurements to assist researchers in evaluating and enhancing the accuracy of RSS-based localization algorithms in indoor and outdoor environments.

Using a hybrid version of the WLS algorithm, we demonstrated the feasibility and effectiveness the considered approach. Our results showed good performance in terms of RMSE of target location estimation, highlighting the potential advantages of the hybrid approach in scenarios where there is limited prior knowledge of the environment.

Overall, this study makes a significant contribution to the field of context-aware services and has the potential to pave the way for future investigations into the development of innovative hybrid algorithms and methods for RSS-based localization in IoT environments.

Looking ahead, it would be valuable to investigate the development of hybrid WiFi/BLT algorithms exploiting the reliability of the data coming from multiple interfaces. Additionally, the integration of other promising technologies like Ultra Wideband (UWB) could help to further enhance the overall system performance.

[3]Similar considerations can be carried out for other values of K.

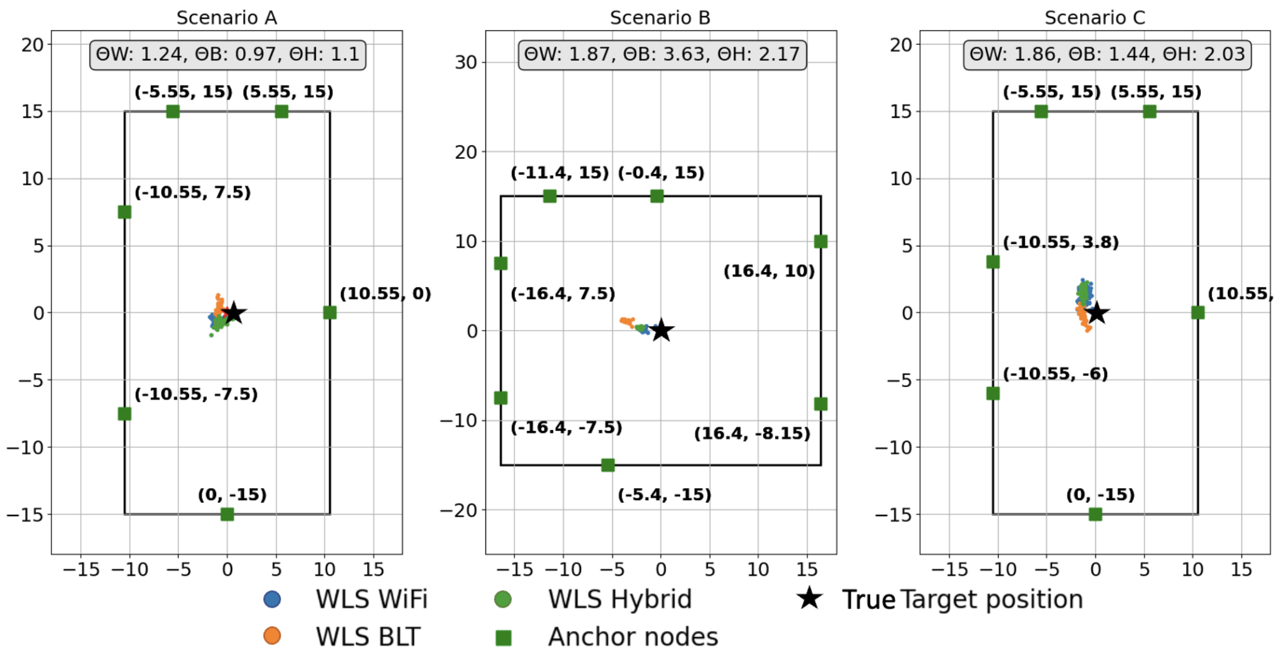


Fig. 6: Localization performance of the considered WLS-algorithms in the investigated experimental scenarios. θW, θB, and θH refer to the RMSE with, respectively, pure WiFi, pure BLT and hybrid localization.

ACKNOWLEDGMENTS

This work was partially supported by M.D. 351, National Recovery and Resilience (NRRP) funded by the European Union, NextGenerationEU.

REFERENCES

[1] F. K. Shaikh, S. Zeadally, and E. Exposito, "Enabling technologies for Green Internet of Things," *IEEE Systems J.*, vol. 11, no. 2, pp. 983–994, June 2017, DOI: 10.1109/JSYST.2015.2415194.

[2] L. Asmaa, K. A. Hatim, and M. Abdelaaziz, "Localization algorithms research in wireless sensor network based on multilateration and trilateration techniques," in *IEEE Int. Colloquium in Information Science and Technology* (CIST), Tetuan, Morocco, October 2014, pp. 415–419, DOI: 10.1109/CIST.2014.7016656.

[3] Y. Yu, Y. Zhang, L. Chen, and R. Chen, "Intelligent fusion structure for Wi-Fi/BLE/QR/MEMS sensor-based indoor localization," *MDPI Remote Sensing*, vol. 15, no. 5, 2023, DOI: 10.3390/rs15051202.

[4] S. Li and R. Rashidzadeh, "Hybrid indoor location positioning system," *IET Wireless Sensor Systems*, vol. 9, no. 5, pp. 257–264, October 2019, DOI: 10.1049/iet-wss.2018.5237.

[5] A. Singh, S. Kumar, and O. Kaiwartya, "A hybrid localization algorithm for wireless sensor networks," *Procedia Computer Science*, vol. 57, pp. 1432–1439, 2015, DOI: 10.1016/j.procs.2015.07.464.

[6] G. Pettorru. Hybrid dataset for RSS-based localization. [Online; accessed 5-May-2023]. [Online]. Available: github.com/GiovanniPettorru/HybridDataset_for_RSSbasedLocalization

[7] S. Ghorpade, M. Zennaro, and B. Chaudhari, "Survey of localization for Internet of Things nodes: Approaches, challenges and open issues," *MDPI Future Internet*, vol. 13, no. 8, 2021, DOI: 10.3390/fi13080210.

[8] F. Zafari, A. Gkelias, and K. Leung, "A survey of indoor localization systems and technologies," *IEEE Commun. Surveys & Tutorials*, vol. 21, no. 3, pp. 2568–2599, 2019, DOI: 10.1109/COMST.2019.2911558.

[9] A. Goldsmith, *Wireless Communications*. USA: Cambridge University Press, 2005.

[10] K. Cengiz, "Comprehensive analysis on least squares lateration for indoor positioning systems," *IEEE Internet of Things J.*, vol. 8, no. 4, pp. 2842–2856, 2021, DOI: 10.1109/JIOT.2020.3020888.

[11] B. Mukhopadhyay, S. Srirangarajan, and S. Kar, "RSS-based localization in the presence of malicious nodes in sensor networks," *IEEE Trans. Instrumentation and Measurement*, vol. 70, pp. 1–16, 2021, DOI: 10.1109/TIM.2021.3104385.

[12] C. E. Galván-Tejada, J. C. Carrasco-Jiménez, and R. F. Brena, "Bluetooth-WiFi based combined positioning algorithm, implementation and experimental evaluation," *Procedia Technology*, vol. 7, pp. 37–45, 2013, DOI: 10.1016/j.protcy.2013.04.005.

[13] J. Torres-Sospedra, R. Montoliu, A. Martínez-Usó, J. P. Avariento, T. J. Arnau, M. Benedito-Bordonau, and J. Huerta, "UJIIndoorLoc: A new multi-building and multi-floor database for WLAN fingerprint-based indoor localization problems," in *Int. Conf. Indoor Positioning and Indoor Navigation* (IPIN), Busan, the Republic of Korea, October 2014, pp. 261–270, 10.1109/IPIN.2014.7275492.

[14] G. M. Mendoza-Silva, P. Richter, J. Torres-Sospedra, E. S. Lohan, and J. Huerta, "Long-term WiFi fingerprinting dataset for research on robust indoor positioning," *MDPI Data*, vol. 3, no. 1, 2018, DOI: 10.3390/data3010003.

[15] E. S. Lohan, J. Torres-Sospedra, H. Leppakoski, P. Richter, Z. Peng, and J. Huerta, "Wi-Fi crowdsourced fingerprinting dataset for indoor positioning," *MDPI Data*, vol. 2, no. 4, 2017, DOI: 10.3390/data2040032.

[16] M. A. Nassar, M. Hasan, M. Khan, M. Sultana, M. Hasan, L. Luxford, P. Cole, G. Oatley, and P. Koutsakis, "WiFi-based localisation datasets for No-GPS open areas using smart bins," *Elsevier Computer Networks*, vol. 180, p. 107422, October 2020, DOI: 10.1016/j.comnet.2020.107422.

[17] P. Barsocchi, A. Crivello, D. La Rosa, and F. Palumbo, "A multisource and multivariate dataset for indoor localization methods based on WLAN and geo-magnetic field fingerprinting," in *Int. Conf. Indoor Positioning and Indoor Navigation* (IPIN), Madrid, Spain, October 2016, pp. 1–8, DOI: 10.1109/IPIN.2016.7743678.

[18] A. N. Nor Hisham, Y. H. Ng, C. K. Tan, and D. Chieng, "Hybrid Wi-Fi and BLE fingerprinting dataset for multi-floor indoor environments with different layouts," *MDPI Data*, vol. 7, no. 11, 2022, DOI: 10.3390/data7110156.

[19] Z. Tóth and J. Tamás, "Miskolc IIS hybrid IPS: Dataset for hybrid indoor positioning," in *Int. Conf. Radioelektronika* (RADIOELEKTRONIKA), Kosice, Slovakia, April 2016, pp. 408–412, 10.1109/RADIOELEK.2016.7477348.

[20] D. Green, "pyshark," https://github.com/KimiNewt/pyshark, [Online; accessed 5-May-2023].

[21] I. Harvey, "bluepy," https://github.com/IanHarvey/bluepy, [Online; accessed 5-May-2023].