ADVANCES IN CYBER-PHYSICAL SYSTEMS

Vol. 10, No. 1, 2025

INDOOR POSITIONING WITH BLUETOOTH LOW ENERGY: A PRELIMINARY SYSTEM DESIGN AND RESULTS

Tadei-Nazarii Kalynchuk, Volodymyr Shevchyk

Ivan Franko Lviv's National University, 1, Universytetska str., Lviv, 79000, Ukraine

Authors' e-mails: *tadejj@ukr.net, volodymyr.shevchyk@lnu.edu.ua*

https://doi.org/10.23939/acps2025.01.028

Submitted on 08.04.2025

***Abstract*: This study explores indoor positioning in enclosed environments using Bluetooth Low Energy technology. A system based on two Thunderboard Sense 2 beacons and a Nordic nRF52840-DK device has been proposed. The positioning method relies on signal characteristics to estimate the location of an object. Related research has been reviewed, and the technical implementation of the preliminary system has been presented. The results demonstrate the potential of Bluetooth Low Energy for accurate and energy-efficient indoor positioning and provide a basis for further experimental validation.**

***Index terms*: indoor positioning, Bluetooth low energy, BLE, RSSI, Beacon, SiLabs Thunderboard Sense 2, Nordic nRF52840-DK.**

I. INTRODUCTION

The demand for accurate indoor positioning has grown rapidly with the proliferation of location-based services across sectors such as healthcare, logistics, retail, and smart buildings. While Global Navigation Satellite Systems (GNSS), including GPS and Galileo, have revolutionized outdoor navigation, they fall short in indoor environments where signal attenuation, multipath propagation, and obstructed line-of-sight to satellites hinder reliable localization [1, 2]. These limitations have spurred the development of alternative indoor positioning systems (IPS) based on wireless technologies.

Among the various wireless technologies investigated for IPS – such as Wi-Fi [3], Ultra-Wideband (UWB) [4], Zigbee [5], and Bluetooth Low Energy (BLE) [6] – BLE has attracted significant attention. Its appeal lies in its low energy consumption, widespread support across smartphones and IoT devices, and straightforward infrastructure requirements. BLE beacons periodically transmit advertising packets, and a mobile device can estimate its distance from the beacon by measuring the Received Signal Strength Indicator (RSSI).

However, the relationship between RSSI and physical distance is non-linear and highly sensitive to environmental conditions, including the presence of obstacles, device orientation, and signal reflections [7]. These factors introduce instability in RSSI-based distance estimation and can lead to inaccurate positioning. To mitigate these issues, signal processing methods such as averaging, moving averages, and more sophisticated techniques like the Kalman filter [8], [9] are employed to smooth fluctuations and produce more reliable distance estimates.

Recent research efforts have explored hybrid approaches combining BLE with other sensor modalities (e. g., inertial measurement units, magnetometers) or incorporating machine learning techniques to improve accuracy [10]. Nevertheless, many of these solutions require additional hardware or complex models, limiting their accessibility and scalability in practical deployments.

II. LITERATURE REVIEW AND PROBLEM STATEMENT

Indoor environments present a unique set of challenges for positioning systems. Unlike outdoor spaces where GNSS signals are readily available, indoor spaces often cause severe signal degradation due to structural obstacles and multipath reflections [1, 11]. These phenomena result in non-line-of-sight (NLOS) conditions that complicate distance estimation and lead to inaccuracies. As a consequence, indoor positioning systems must incorporate robust algorithms to mitigate such effects and provide reliable location estimates.

BLE is a wireless personal area network technology designed for short-range communication and low power consumption. Introduced as part of the Bluetooth 4.0 specification, BLE has evolved to support a variety of applications, including health monitoring, asset tracking, and indoor navigation [12].

One of the main advantages of BLE is its widespread adoption in modern smartphones and IoT devices, which facilitates large-scale deployments without significant additional infrastructure costs. However, the simplicity of RSSI-based ranging also introduces uncertainties. Environmental conditions, device heterogeneity, and interference from other wireless signals can result in significant fluctuations in RSSI measurements [13]. Researchers have proposed various solutions, including fingerprinting, Kalman filtering, and machine learning approaches, to enhance accuracy and robustness [14].

The Kalman filter is a recursive algorithm designed to estimate the state of a dynamic system from a series of noisy measurements [8]. In the context of BLE-based indoor positioning, the Kalman filter is applied to smooth the RSSI readings obtained from the mobile node. By predicting the expected RSSI value and then updating this prediction with the actual measured value, the Kalman filter effectively reduces measurement noise and provides a more stable input for distance estimation.

This filtering is especially critical when using RSSI-based techniques, as the raw RSSI values can be highly erratic due to multipath effects and other interference. The filtered RSSI data are then used in the distance estimation formula:

$$d = 10^{(RSSI-A)/(-10n)}. \quad (1)$$

Equation (1) calculates the estimated distance in meters (*d*). *RSSI* is the Received Signal Strength Indication in dBm, *A* is the RSSI value at 1 meter from the transmitter, often referred to as the *RSSI* intercept or reference value. Also, equation contains n – the path loss exponent, which depends on the environment and is typically between 2 and 4 for indoor environments.

Several studies have investigated BLE as a medium for indoor positioning. Liu et al. [11] provided a comprehensive survey of indoor positioning techniques, highlighting the benefits and limitations of using wireless signals in enclosed spaces. Subsequent research by Faragher and Harle [13] examined the accuracy of BLE-based positioning systems and identified key factors affecting signal stability. Other works have proposed hybrid solutions that combine BLE with other sensor modalities (e. g., inertial measurement units or Wi-Fi) to improve localization accuracy in complex environments [14, 15].

These studies underscore the potential of BLE for indoor positioning while also illustrating the need for improved algorithms and hardware calibration. Our work builds on these insights by proposing a simple yet effective system architecture that leverages two BLE beacons (Thunderboard Sense 2) and a mobile node (nRF52840-DK). This configuration is intended to serve as a testbed for developing and validating enhanced positioning algorithms, with the goal of addressing the inherent challenges of indoor localization.

III. SCOPE OF WORK AND OBJECTIVES

A. PRELIMINARY SYSTEM DESIGN

This article aims to review the foundational concepts behind BLE-based indoor positioning and outline a preliminary system design using commercially available development kits. The proposed system architecture is based on a dual-beacon setup combined with a mobile node for position estimation: the two Thunderboard Sense 2 are configured to act as the BLE beacon, while the nRF52840-DK serves as the mobile node or "searching object". In this section, we briefly outline the system components and their roles in the indoor positioning framework.

Hardware Components:

- BLE Beacons – Thunderboard Sense 2. The Thunderboard Sense 2 is a versatile development kit equipped with multiple sensors and BLE connectivity. In our system, these devices are configured to operate as beacons that broadcast advertising packets at predefined intervals. Their low power consumption and ease of configuration make them ideal candidates for indoor positioning applications.
- Mobile Node – nRF52840-DK. The nRF52840-DK from Nordic Semiconductor serves as the mobile unit or "searching object" in our setup. This development kit features a powerful multi-protocol system-on-chip (SoC) that supports BLE 5.0, enabling it to scan for BLE advertisements and measure the corresponding RSSI values. The collected signal data forms the basis for subsequent distance estimation and positioning algorithms.

B. SIGNAL PROCESSING AND DISTANCE ESTIMATION

Given the inherent variability and noise in RSSI measurements due to environmental factors and interference, robust signal processing is crucial for accurate distance estimation. In our system, we first apply a Kalman filter to the raw RSSI data to reduce noise and provide a more stable estimate before converting these values into distances.

The Kalman filter is a recursive algorithm that estimates the state of a dynamic system – in this case, the true RSSI value – based on a series of noisy measurements. For our application, we assume a simplified model where the state variable $x_{k/k}$ represents the true RSSI value at time step K_k. The basic equations governing the Kalman filter are as follows next.

First goes *State Transition (Prediction)* step. We assume that the RSSI value changes slowly over time (I e. g., a nearly constant process model). The state prediction is given by:

$$x_{k|k-1} = x_{k-1|k-1}, \quad (2)$$

and the predicted error covariance is updated as:

$$P_{k|k-1} = Q + P_{k-1|k-1}. \quad (3)$$

At equation (2) $x_{k|k-1}$ is the predicted state at time k given the previous state. At equation (3) $P_{k|k-1}$ is the predicted error covariance and Q is the process noise covariance, which reflects the uncertainty in the state transition.

Next step is *Measurement Update*. When a new RSSI measurement z_k is obtained, the Kalman gain K_k is computed as:

$$K_k = \frac{P_{k|k-1}}{P_{k|k-1}+R}. \quad (4)$$

At equation (4) R is the measurement noise covariance, representing the variance in the RSSI measurements due to environmental noise and hardware limitations.

The state is then updated using the measurement:

$$x_{k|k} = x_{k|k-1} + K_k(z_k - x_{k|k-1}), \quad (5)$$

and the error covariance is revised as:

$$P_{k|k} = (1 - K_k)P_{k|k-1}. \quad (6)$$

In this application, the Kalman filter smooths the raw RSSI values, yielding a more reliable signal strength estimate that better reflects the underlying trend despite rapid fluctuations. The effectiveness of this filter depends on appropriate tuning of the covariance parameters Q and R, which are typically chosen based on empirical observations of the RSSI behavior in the deployment environment.

After obtaining the filtered RSSI value, the next step is to estimate the distance between the mobile node and each BLE beacon. This is achieved using a widely adopted log-distance path loss model. The conversion is performed using the formula (1). This equation is derived from the logarithmic nature of signal attenuation in a multipath environment and forms the basis for estimating the distance. It is important to note that the accuracy of this model depends heavily on proper calibration to determine the correct values of A and n for the specific environment in which the system is deployed.

C. INTEGRATION IN THE SIGNAL PROCESSING PIPELINE

The overall signal processing pipeline on the mobile node (nRF52840-DK) is as follows:

1. *Data Acquisition.* The mobile node continuously scans for BLE advertising packets from the beacons and records the raw RSSI measurements.
2. *Pre-processing.* Raw RSSI values are collected and temporarily stored.
3. *Kalman Filtering.* The raw RSSI measurements are processed through the Kalman filter to obtain a smoothed RSSI estimate.
4. *Distance Estimation.* The filtered RSSI values are converted into distance estimates using the log-distance path loss formula.
5. *Localization.* The estimated distances from multiple beacons are then used in positioning algorithms such as triangulation or multilateration to infer the mobile node's location. In our case, we use triangulation with only two beacons because we know on which side of the beacons the mobile node is located.

The integration of the Kalman filter into the processing pipeline is particularly advantageous for tracking dynamic changes in signal strength when the mobile node is in motion. Its recursive nature allows for real-time updates with minimal computational overhead – a critical feature for resource-constrained devices.

By combining effective RSSI smoothing with a robust distance estimation model, the system is better equipped to handle the noisy and fluctuating nature of indoor radio signals, thereby improving the overall accuracy of the indoor positioning system.

IV. RESULT IN STATIC SYSTEM

The results of proposed method in static system is described in Figs. 1–6. The first experiment is shown in Fig. 1 and 2. In Fig. 1, "original" refers to the distance obtained from raw RSSI, while "filtered" shows the result after applying the Kalman filter. In Fig. 2 we have red dot – real object position and cluster of calculated positions.

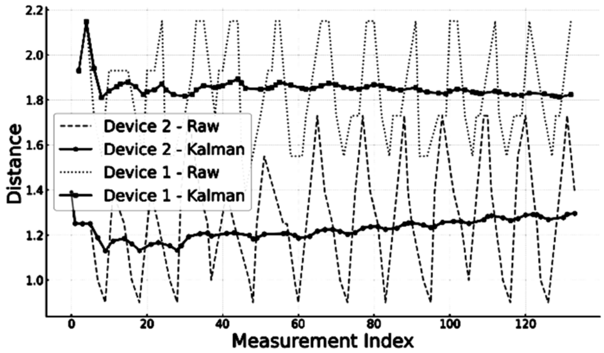

Fig. 1. First experiment, distances to anchors

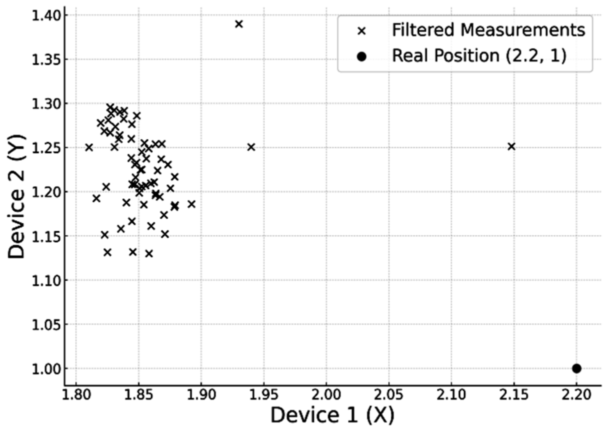

Fig. 2. First experiment, coordinates

The average distance error from the real object position is 0.41 m, with a minimum of 0.37 m and a maximum of 0.47 m.

Experiment 2 is shown in Fig. 3 and Fig. 4. The figures are constructed in the same manner as in the first experiment. Real coordinates of object (2.2 m; 3 m).

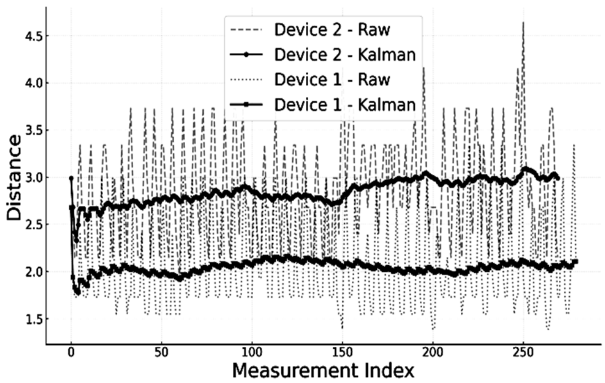

Fig. 3. Second experiment, distances to anchors

The average distance error for experiment 2 from the real object position is 0.25 m, with a minimum of 0.18 m and a maximum of 0.48 m.

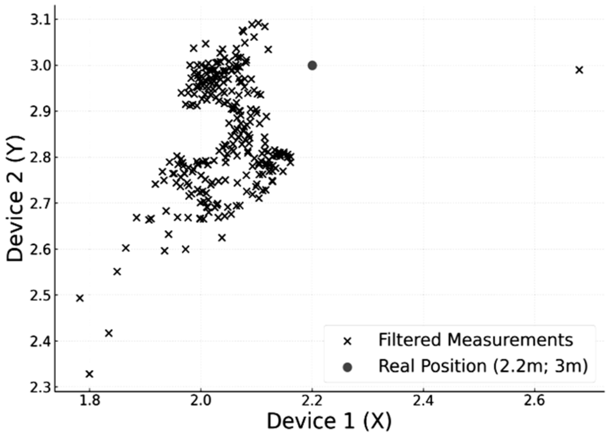

Fig. 4. Second experiment, coordinates

Experiment 3 is shown in Fig. 5 and Fig. 6. The figures are constructed in the same manner as in the first two experiments. Real coordinates of object (1.8 m; 4 m).

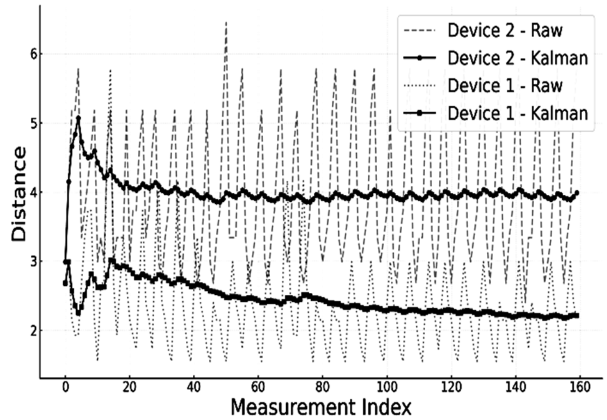

Fig. 5. Third experiment, distances to anchors

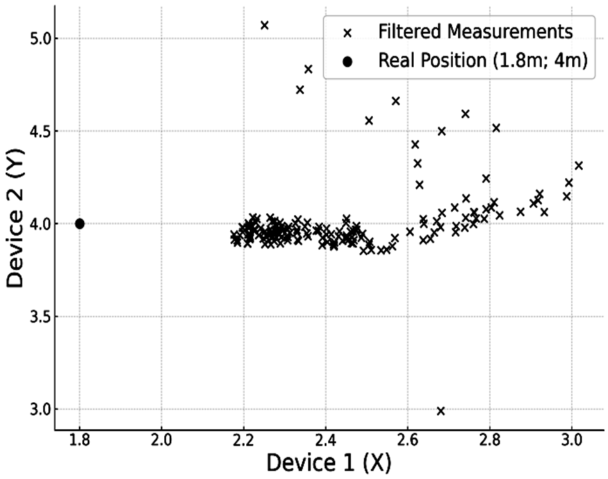

Fig. 6. Third experiment, coordinates

The average distance error for experiment 3 from the real object position is 0.85 m, with a minimum of 0.67 m and a maximum of 1.34 m. We have large error from device 1 that produce general error (0.84 m), and error from device 2 is only 0.1 m.

V. RESULT IN DYNAMIC SYSTEM

In dynamic system we have object that is moving and static anchors.

Experiment 4 is shown in Fig. 7 and Fig. 8. We have moving object that moves with stale speed. Start point 3 m from Device 1, 2 m from Device 2. Finish point 3 m from Device 1, 1 m from Device 2.

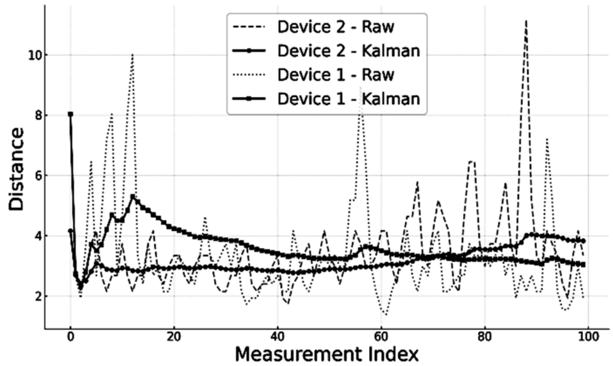

Fig. 7. Fourth experiment, distances to anchors

Let's assume that Device 1 has coordinates (0;0) and Device 2 (0; 2) distance between them 2 m. To calculate coordinates of object we need to find intersection of two circles – first one with center in Device 1, second – Device 2. Some of our distance measurement can`t move to coordinates, because circles build on calculated distances don`t intersect. For example, first measurement – distance to Device 1 – 8 m, distance to Device 2 – 4.1, according to devices coordinates we can`t find coordinates of object at that time. On Fig. 8 shown all coordinates that can be calculated.

As we can see from Fig. 8, the calculated coordinates do not correspond to the actual movement of the object. But we can observe a clear movement pattern in the coordinate graph.

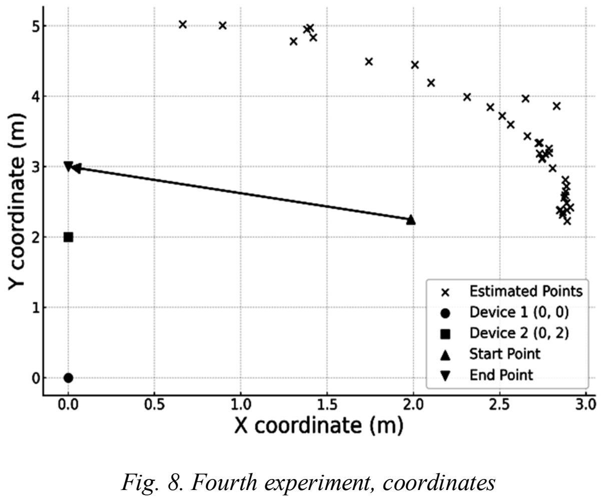

Fig. 8. Fourth experiment, coordinates

Experiment 6 is shown in Fig. 9 and Fig. 10. We have moving object that moves with stale speed. Start point 3 m from Device 1, 2 m from Device 2. Finish point 4 m from Device 1, 3 m from Device 2. On Fig. 9 displayed only filtered value for better view.

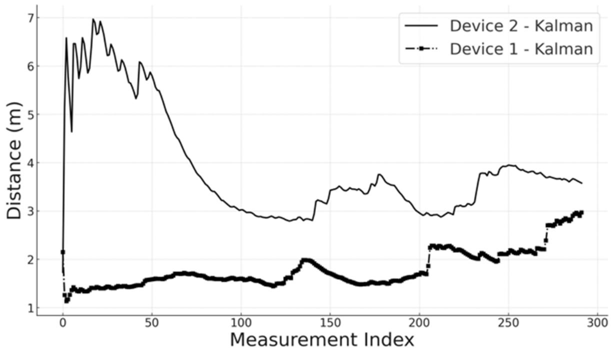

Fig. 9. Fifth experiment, distances to anchors

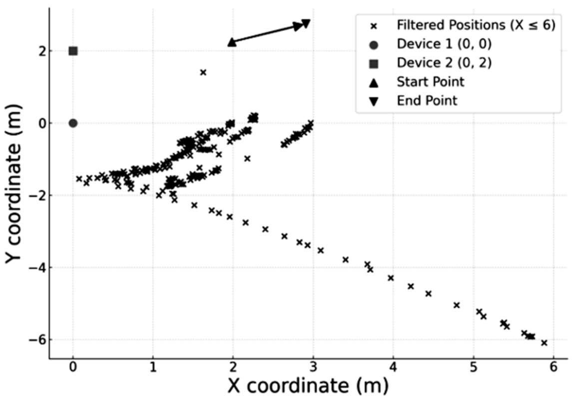

Fig. 10. Fifth experiment, coordinates

As we can see from Fig. 10, the calculated coordinates do not correspond to the actual movement of the object, and we can't observe a clear movement pattern in the coordinate graph. But we can observe pattern from filtered data (Fig. 9).

VI. RESULT IN DYNAMIC SYSTEM WITH OBSTACLE

Let's introduce an obstacle into the static system. The obstacle, 1.5 m wide, is placed between the object and the devices (anchors). The calculated distances to the anchors in this scenario are shown in Fig. 11.

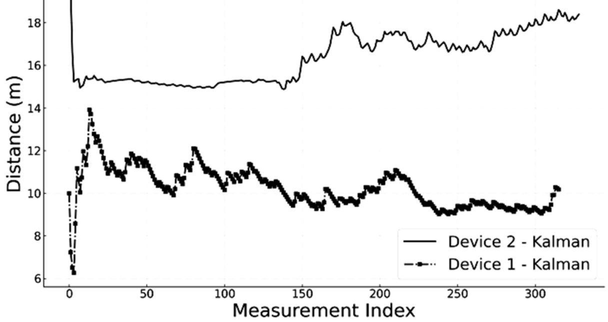

Fig. 11. Sixth experiment, distances to anchors

As we can see from Fig. 12, the calculated coordinates do not correspond to the actual position of object. Difference between real / expected coordinates is major – 12.2 m is average error.

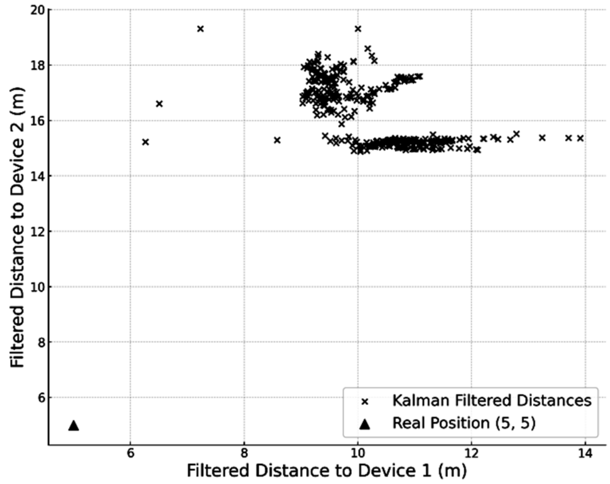

Fig. 12. Sixth experiment, coordinates

When there are obstacles between the Bluetooth transmitter and receiver, the signal strength (RSSI) is affected in the following ways: absorption, reflection, diffraction and scattering.

VII. CONCLUSION

The proposed method for indoor positioning using BLE-based distance estimation demonstrated potential in a static system, where both the anchors and the object of interest remain stationary. The average error across different experiments was 0.5 m, with a minimum of 0.25 m in Experiment 2 and a maximum of 0.85 m in Experiment 3. The integration of BLE technology for distance estimation, enhanced by the use of a Kalman filter, improved accuracy by mitigating noise and smoothing RSSI values. However, when an obstacle was introduced, the average error increased significantly to 12.2 m. In a dynamic system – where the object of interest is moving while the anchors remain static – the error becomes substantial, and even the movement patterns are difficult to observe in the resulting data.

References

[1] Mendoza-Silva, G. M., Torres-Sospedra, J., & Huerta, J. (2019). A Meta-Review of Indoor Positioning Systems. *Sensors, 19(20),* 4507. DOI: https://doi.org/10.3390/s19204507

[2] Mary, J. S. N. (2022). Design of digital meters for industries using data acquisition system. *IOP Conference Series: Materials Science and Engineering,* 1258(1), 012047. DOI: https://doi.org/10.1088/1757-899X/1258/1/012047

[3] Shu, Y., Bo, C., Shen, G., Zhao, C., Li, L., & Zhao, F. (2015). Magicol: Indoor localization using pervasive magnetic field and opportunistic WiFi sensing. *IEEE Journal on Selected Areas in Communications*, 33(7), 1443–1457. DOI: https://doi.org/10.1109/JSAC.2015.2430274

[4] Yang, Z., Zhou, Z., & Liu, Y. (2017). From RSSI to CSI: Indoor localization via channel response. *ACM Computing Surveys, 49(2),* 1–36. DOI: https://doi.org/10.1145/2543581.2543592

[5] Subedi, S., Gang, H.-S., Ko, N. Y., Hwang, S.-S., & Pyun, J.-Y. (2019). Improving indoor fingerprinting positioning with affinity propagation clustering and weighted centroid fingerprint. *IEEE Access*, 7, 31738–31750. DOI: https://doi.org/10.1109/ACCESS.2019.2902564

[6] Ramirez, R., Huang, C.-Y., Liao, C.-A., Lin, P.-T., Lin, H.-W., & Liang, S.-H. (2021). A practice of BLE RSSI measurement for indoor positioning. *Sensors*, 21(15), 5181. DOI: https://doi.org/10.3390/s21155181

[7] Huang, B., Liu, J., Sun, W., & Yang, F. A robust indoor positioning method based on Bluetooth Low Energy with separate channel information. *Sensors*, 19(16), 3487. DOI: https://doi.org/10.3390/s19163487

[8] Wu, C., Yang, Z., Zhou, Z., Qian, K., Liu, Y., & Liu, M. (2015). PhaseU: Real-time LOS identification with WiFi. *IEEE conference on computer communications (INFOCOM)*, 2038–2046. DOI: https://doi.org/10.1109/INFOCOM.2015.7218588

[9] Kardzhiev, R., & Stoyanov, B. (2022). New indoor positioning system using ultrasonic. *AIP Conference Proceedings*, 2505(1), 020003. DOI: https://doi.org/10.1063/5.0100660

[10] Sadowski, S., & Spachos, P. (2018). RSSI-based indoor localization with the Internet of Things. *IEEE Access,* 6, 30149–30161. DOI: https://doi.org/10.1109/ACCESS.2018.2843325

[11] Liu, H., Darabi, H., Banerjee, P., & Liu, J. (2007). Survey of Wireless Indoor Positioning Techniques and Systems. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 37(6),* 1067–1080. DOI: https://doi.org/10.1109/TSMCC.2007.905750

[12] Syazwani, N. S. C. J., Wahab, N. H. A., Sunar, N., Ariffin, S. H. S., Wong, K. Y., & Aun, Y. (2022, May). Indoor positioning system: A review. International *Journal of Advanced Computer Science and Applications*, 13(6), 515–524. DOI: https://doi.org/10.14569/IJACSA.2022.0130659

[13] He, S., & Chan, S.-H. G. (2016). Wi-Fi fingerprint-based indoor positioning: Recent advances and comparisons. *IEEE Communications Surveys & Tutorials*, 18(1), 466–490. DOI: https://doi.org/10.1109/COMST. 2015.2464084

[14] Zafari, F., Gkelias, A., & Leung, K. K. (2019). A survey of indoor localization systems and technologies. *IEEE Communications Surveys & Tutorials*, *21*(3), 2568–2599. DOI: https://doi.org/10.1109/COMST.2019.2911558

Tadei-Nazarii Kalynchuk was born in Ivano-Frankivsk, Ukraine, in 1997, is a third-year postgraduate student, Department of Radiophysics and Computer Technologies at Ivan Franko National University of Lviv. Received the B.S. degree in computer science from Ivan Franko National University of Lviv, Ukraine, in 2017 and the M. S. degree in 2018. With over 8 years with research and development experience.

Volodymyr Shevchyk, is a PhD student at the Department of Radiophysics and Computer Technologies, Ivan Franko National University of Lviv. His research interests are focused on computer systems for vibrational diagnostics, including the development of algorithms and hardware platforms for monitoring rotating machinery. He is also actively engaged in the design and implementation of cloud-based data acquisition systems.