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INDOOR POSITIONING WITH BLUETOOTH LOW ENERGY AND EXTENDED KALMAN FILTER

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ABSTRACT

Background. Indoor positioning systems based on Bluetooth Low Energy (BLE) beacons widely rely on estimating distance using the received signal strength indicator (RSSI). However, RSSI measurements in indoor environments are significantly affected by multipath propagation, shadowing, interference, and absorption by obstacles, resulting in high variability of signal strength and substantial distance estimation errors. The nonlinear logarithmic relationship between RSSI and distance further complicates the application of conventional linear filtering techniques such as the classical Kalman Filter, which requires prior transformation of measurements and may lead to loss of optimality.

Materials and Methods. This study proposes a distance estimation method based on the Extended Kalman Filter (EKF), which directly processes RSSI measurements using the nonlinear log-distance path loss model. The experiment was performed in an indoor office environment using two Silicon Labs EFR32BG22 BLE beacons and a Nordic nRF52840 receiver. The EKF parameters were selected based on prior calibration of the propagation model coefficients.

Results and Discussion. The experimental results demonstrate that the EKF effectively smooths RSSI. For the beacon with lower RSSI dispersion, the root mean square error (RMSE) reached 0.14 m, for the second beacon, the RMSE was 0.53 m. The analysis confirms that estimation accuracy strongly depends on signal stability and calibration quality. Compared to direct RSSI-to-distance conversion and the classical Kalman Filter approach reported in related work, the EKF-based algorithm reduces the mean absolute distance estimation error by approximately 20–30%, validating the advantages of nonlinear filtering.

Conclusion. The proposed EKF-based method improves the accuracy and robustness of RSSI-based distance estimation in BLE indoor positioning systems. When model parameters are properly calibrated, the achieved accuracy is sufficient for practical applications such as smart building navigation, asset tracking, and robotic localization. The algorithm can be implemented on resource-constrained embedded platforms and serves as a foundation for further development of multisensor indoor positioning systems.

Keywords: positioning, Bluetooth, BLE, RSSI, Kalman filter, Extended Kalman Filter

INTRODUCTION

Indoor positioning systems are becoming increasingly widespread due to the development of Internet of Things (IoT) technologies [1,3]. Unlike satellite navigation systems such as GPS, which are ineffective in indoor environments because of signal attenuation, low-power wireless communication technologies, in particular Bluetooth Low Energy, offer a cost-effective solution for object positioning in enclosed spaces [2,4].

One of the main challenges in BLE-based positioning systems is the estimation of the distance to beacons using measurements of the Received Signal Strength Indicator (RSSI). This metric exhibits significant variability due to multipath propagation, interference, signal absorption by obstacles, and other environmental factors [5]. Typical RSSI fluctuations can reach ±10 dBm even when the receiver remains stationary, resulting in distance estimation errors of several meters [1].

To reduce the impact of noise in RSSI measurements, various filtering techniques are traditionally employed, including the moving average, median filter, and Kalman filter [6]. The classical Kalman Filter is effective for linear systems; however, the relationship between RSSI and distance is inherently nonlinear, which limits its applicability in this context [7].

The Extended Kalman Filter (EKF) is an adaptation of the classical Kalman Filter for nonlinear systems achieved through linearization of the model around the current state estimate [8]. In the context of RSSI-based distance estimation, the EKF enables direct processing of the nonlinear logarithmic signal propagation model, which theoretically provides higher accuracy compared to linear approaches [9].

This work aims to develop and investigate an indoor positioning system based on a distance estimation algorithm for BLE beacons using the Extended Kalman Filter, as well as to compare its performance with traditional RSSI filtering methods.

MATERIALS AND METHODS

Radio Signal Propagation Model

The relationship between the received signal strength (RSSI) and the distance to the transmitter under indoor radio wave propagation conditions is traditionally described by the logarithmic path loss model (log-distance path loss model) (1) [10]:

$$RSSI(d) = A - 10 \cdot n \cdot \log_{10}(d) + X_{\sigma}, \tag{1}$$

where $RSSI(d)$ denotes the received signal power at distance d(dBm); A is the received signal strength at a reference distance of 1 meter from the transmitter (dBm); n is the path loss exponent, which depends on the propagation environment; d is the distance between the transmitter and the receiver (m); and X_{σ} is a random Gaussian noise variable with zero mean and standard deviation σ (dBm).

For free-space propagation, the path loss exponent is approximately $n \approx 2$, whereas in indoor environments, its value typically ranges from 2 to 4, depending on the presence of obstacles, wall materials, and equipment [11]. The parameter A is determined as the measured RSSI at the reference distance of 1 meter and depends on the transmitter power and antenna characteristics.

Model (1) is statistical in nature and accounts for random signal fluctuations caused by multipath propagation. For practical applications, the parameters A and n must be estimated through calibration in the specific environment under consideration [12].

Kalman Filter

The Kalman Filter is a recursive algorithm for optimal state estimation of a linear dynamic system in the presence of Gaussian noise [13]. For a discrete-time system of the form:

$$\begin{aligned} x_k &= F_k x_{k-1} + B_k u_k + w_k, \\ z_k &= H_k x_k + v_k, \end{aligned} \tag{2}$$

where x_k is the state vector, z_k is the measurement vector, and w_k and v_k represent white Gaussian process and measurement noise, respectively. The Kalman Filter computes the state estimate $\hat{x}_k$ in two stages.

Prediction:

$$\begin{aligned} \widehat{x_k^-} &= F_k \widehat{x_{k-1}} + B_k u_k, \\ P_k^- &= F_k P_{k-1} F_k^T + Q_k. \end{aligned} \tag{3}$$

Update (Correction):

$$\begin{aligned} K_k &= P_k^- H_k^T \left(H_k P_k^- H_k^T + R_k\right)^{-1}, \\ \widehat{x_k} &= \widehat{x_k^-} + K_k(z_k - H_k \widehat{x_k^-}), \\ P_k &= (I - K_k H_k) P_k^-, \end{aligned} \tag{4}$$

where Q_k is the process noise covariance matrix, R_k is the measurement noise covariance matrix, K_k is the Kalman gain, and P_k is the estimation error covariance matrix [14].

In the case of RSSI-based distance estimation, the application of the classical Kalman Filter requires a prior nonlinear transformation of the measured RSSI values into distance estimates, which results in a loss of filter optimality [15].

Extended Kalman Filter

The Extended Kalman Filter (EKF) is a generalization of the classical Kalman Filter for nonlinear systems [16]. For a system described by nonlinear state transition and measurement functions $f(\cdot)$ and $h(\cdot)$, respectively:

$$\begin{aligned} x_k &= f(x_{k-1}, u_k) + w_k, \\ z_k &= h(x_k) + v_k. \end{aligned} \tag{5}$$

The EKF performs linearization of these functions around the current state estimate by computing the corresponding Jacobian matrices [17]:

$$F_k = \frac{\partial f}{\partial x}\Big|_{\widehat{x_{k-1}}}, \quad H_k = \frac{\partial h}{\partial x}\Big|_{\widehat{x_k^-}}. \tag{6}$$

The EKF algorithm consists of the following steps.

Prediction:

$$\begin{aligned} \widehat{x_k^-} &= f(\widehat{x_{k-1}}, u_k), \\ P_k^- &= F_k P_{k-1} F_k^T + Q_k. \end{aligned} \tag{7}$$

Update (Correction):

$$\begin{aligned} K_k &= P_k^- H_k^T \left(H_k P_k^- H_k^T + R_k\right)^{-1}, \\ \widehat{x_k} &= \widehat{x_k^-} + K_k \left(z_k - h(\widehat{x_k^-})\right), \\ P_k &= (I - K_k H_k) P_k^-. \end{aligned} \tag{8}$$

The main difference from the classical Kalman Filter lies in the use of nonlinear functions for computing the state prediction and the innovation (i.e., the difference between the measurement and the prediction), while the covariance matrices are calculated using the linearized system matrices [18].

Compared to the approach in which RSSI measurements are first converted into distance estimates using the inverse of model (1), followed by the application of the classical Kalman Filter to the obtained distances, the EKF offers the following advantages:

1. *Direct processing of RSSI measurements*: The EKF operates directly on RSSI measurements without prior nonlinear transformation, thereby preserving the statistical properties of the measurement noise [27].
2. *Optimal linearization*: The Jacobian matrix is computed at each point along the estimated state trajectory, providing locally optimal linearization of the nonlinear model [28].
3. *Unified covariance representation*: The EKF maintains a single covariance matrix for the entire estimation process, enabling a consistent and statistically meaningful representation of distance estimation uncertainty [28].

Application of EKF for RSSI-Based Distance Estimation

In the context of estimating the distance to a BLE beacon using RSSI measurements, the system state is defined as the distance itself: $x_k = d_k$. Assuming that the beacon is static or moves slowly, the state transition function can be considered trivial (constant-position model with zero velocity):

$$f(d_{k-1}) = d_{k-1}, \tag{9}$$

which implies that $F_k = 1$.

The measurement function is represented by the nonlinear logarithmic model (with the noise component X_σ incorporated into the measurement noise):

$$RSSI(d) = A - 10 \cdot n \cdot \log_{10}(d). \tag{10}$$

Equation (10) describes the theoretical relationship between the distance d and the expected RSSI value. It represents the inverse signal propagation model: given a distance, the expected RSSI at the receiver can be predicted [19]. The logarithmic distance term $\log_{10}(d)$ reflects the exponential attenuation of signal power with distance. The use of base-10 logarithms is standard in radio engineering when working with decibel units [21].

The Jacobian of the measurement function is computed as:

$$H_k = \frac{\partial h}{\partial d}\Big|_{d=\widehat{d_k^-}} = -\frac{10 \cdot n}{d \cdot \ln(10)}, \tag{11}$$

where $\ln(10) \approx 2.302585$ denotes the natural logarithm of 10. This Jacobian expresses how RSSI varies with small changes in distance around the current predicted estimate $\widehat{d_k^-}$ [22].

Physical interpretation of the Jacobian: The negative sign indicates that the RSSI value decreases as the distance increases. The denominator $d \cdot \ln(10)$ implies that the sensitivity of RSSI to distance variations decreases with increasing distance; that is, at larger distances, small changes in position result in smaller variations in RSSI. This behavior is consistent with the logarithmic nature of the signal propagation model [23].

EKF algorithm for distance estimation:

Initialization:

$$\widehat{d_0} = d_{\text{initial}},\ P_0 = \sigma_d^2. \tag{12}$$

Prediction step (k-th iteration):

$$\begin{aligned} \widehat{d_k^-} &= \widehat{d_{k-1}}, \\ P_k^- &= P_{k-1} + Q, \end{aligned} \tag{13}$$

where Q is the process noise variance, which characterizes the model uncertainty (the assumption of a static beacon).

Update step (k-th iteration):

$$\begin{aligned} h_k &= A - 10 \cdot n \cdot \log_{10}\left(\widehat{d_k^-}\right), \\ H_k &= -\frac{10 \cdot n}{\widehat{d_k^-} \cdot \ln(10)}, \\ S_k &= H_k P_k^- H_k + R, \\ K_k &= \frac{P_k^- H_k}{S_k}, \\ \widehat{d_k} &= \widehat{d_k^-} K_k + (RSSI_k - h_k), \\ P_k &= (1 - K_k H_k) P_k^-, \end{aligned} \tag{14}$$

where R is the RSSI measurement noise variance, and S_k is the innovation (prediction error) covariance, i.e., the difference between the actual measurement and the predicted value [24]. The innovation covariance S_k consists of two components:

1. $H_k P_k^- H_k$ – the uncertainty due to the state prediction. It reflects how the distance estimation error covariance P_k^- propagates into the RSSI prediction. The Jacobian H_k transforms the uncertainty from the distance domain into the RSSI domain.
2. R – the measurement uncertainty, representing the intrinsic noise of RSSI measurements and characterizing the reliability of the receiver.

Physical interpretation: The innovation covariance S_k answers the question “How much can the prediction be trusted?”. In the Kalman gain equation (K_k, Eq. 14), the value of S_k in the denominator normalizes the gain: the larger the prediction uncertainty, the less the filter corrects its estimate based on the new measurement.

Important implementation aspects:

1. *Value constraints*: Since the logarithm is undefined for $d \leq 0$, constraints on the minimum distance (e.g., $d_{\min} = 0.1\text{m}$) and maximum distance (e.g., $d_{\max} = 50\text{m}$) must be introduced to prevent filter instability.
2. *Parameter tuning*: The parameters Q and R define the trade-off between noise smoothing and responsiveness to changes. A larger value of Q relative to R indicates that the filter relies more on measurements, whereas a smaller value implies stronger noise smoothing [26].

3. *Model calibration*: The parameters A and n must be calibrated for a specific environment by measuring RSSI at known distances and applying the least squares method for logarithmic regression [12].

RESULTS AND DISCUSSION

To experimentally validate the proposed algorithm, a test system was implemented using the following components:

- *BLE beacons*: Two Silicon Labs EFR32BG22 transmitters configured for continuous transmission of advertising packets with an interval of 100 ms.
- *Receiver*: A Nordic nRF52840 DK board supporting Bluetooth 5.0 and running the Zephyr RTOS. The receiver was configured for passive scanning with a scan window of 30 ms and a scan interval of 30.

The parameters of the Extended Kalman Filter were selected based on prior calibration: $R = 5\text{dB}$ (measurement noise), $P_0 = 1$ (initial estimation error), $Q = 0.5$ (process noise), $n = 3.4$ (path loss exponent), $A = -65\text{dB}$ for Device 1, and $A = -62\text{dB}$ for Device 2.

The experiment was conducted according to the following procedure:

1. The beacons were placed at a fixed distance of 1.00 m from the receiver (reference distance).
2. The system collected RSSI measurements.
3. For each RSSI measurement, the EKF algorithm computed a distance estimate.
4. All data were stored for subsequent statistical analysis.

In total, 742 RSSI measurements were collected. The measured RSSI values are shown in **Fig. 1**, while the corresponding estimated distances are presented in **Fig. 2**. Quantitative metrics of the collected data are summarized in **Table 1**.

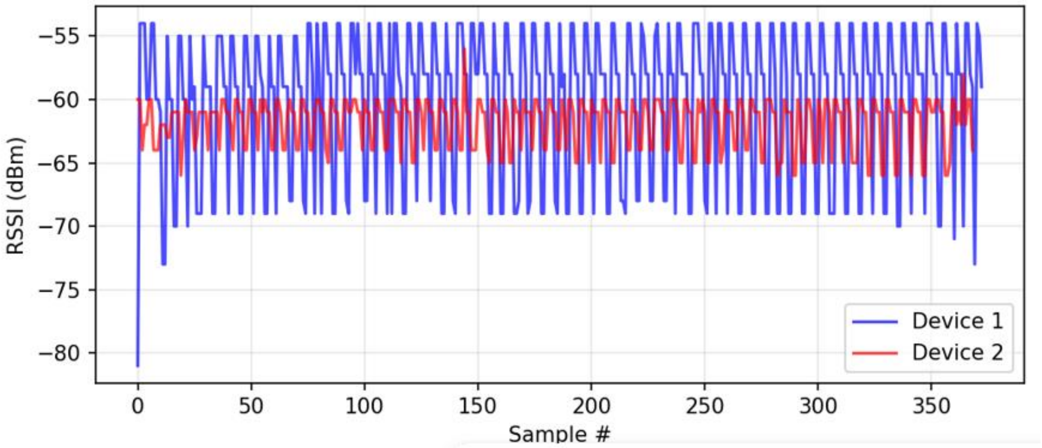

Fig. 1. Measured RSSI values.

As can be seen from **Table 1**, the measured RSSI values exhibit significant variability, which confirms the necessity of applying filtering techniques to reduce the impact of noise and multipath signal propagation.

The following accuracy metrics were computed: Mean Error (ME), Standard Deviation (SD), and Root Mean Square Error (RMSE).

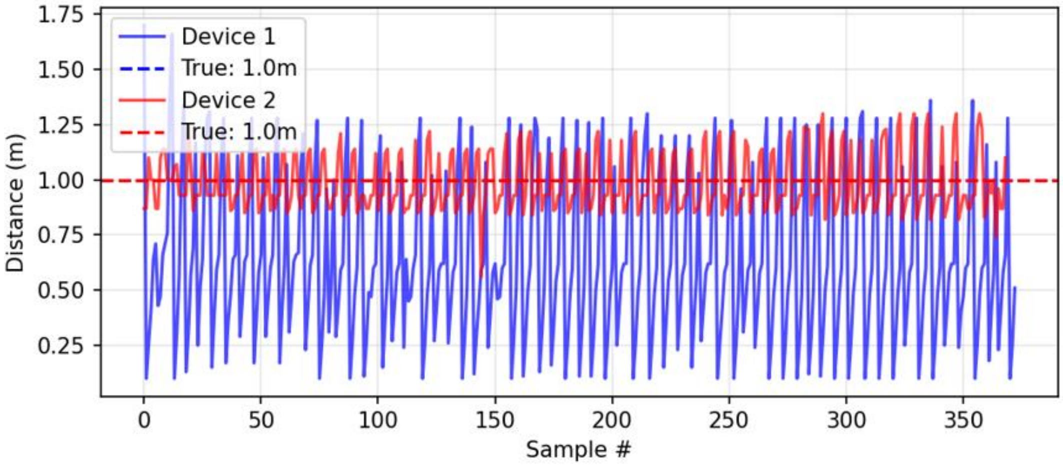

Fig. 2. Estimated distance values.

Table 1. **Measurement results**

Beacon	Number of measurements	RSSI range, dBm
Device 1	373	−81 … −54
Device 2	369	−66 … −56
Total	742	−81 … −54

The results of applying the Extended Kalman Filter for distance estimation to the beacons are presented in **Table 2**. The distance estimation error obtained using the EKF is illustrated in **Fig. 3**.

Table 2. **Distance estimation accuracy metrics using EKF**

Beacon	Mean estimate, m	Estimated range, m	ME, m	SD, m	RMSE, m
Device 1	0.64	0.10 – 1.70	−0.36	0.38	0.53
Device 2	0.98	0.56 – 1.30	−0.02	0.13	0.14

Device 1: The mean estimated distance is 0.64 m at the actual distance of 1.00 m, indicating a systematic underestimation of the distance by 0.36 m. The standard deviation of 0.38 m reflects a significant spread of estimates around the mean value. The RMSE of 0.53 m characterizes the overall accuracy of the method for this beacon. The wide range of estimated distances (0.10–1.70 m) can be attributed to the high variability of RSSI measurements (from −81 to −54 dBm).

Device 2: The mean estimated distance of 0.98 m with the standard deviation of 0.13 m indicates stable estimates with low variability. An RMSE of 0.14 m demonstrates high estimation accuracy. The narrower range of distance estimates (0.50–1.30 m) and

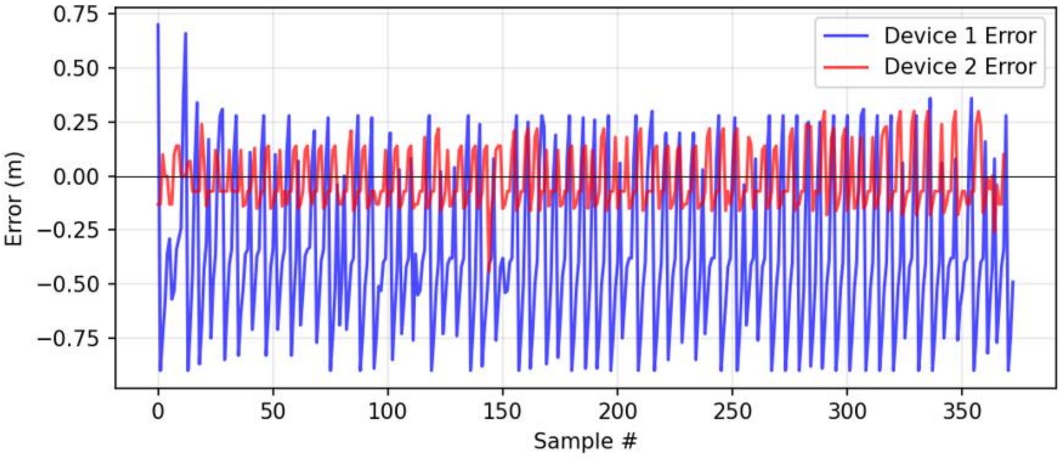

Fig. 3. Distance estimation error.

RSSI values (−66 to −56 dBm) suggests more stable signal propagation conditions for this beacon.

The substantial difference in estimation accuracy between the two beacons (with RMSE differing by 0.39 m) can be explained by the following factors:

1. *Different RSSI variability*: The RSSI range for Device 1 is 27 dBm, whereas for Device 2 it is only 10 dBm. Lower signal variability leads to more stable distance estimates.
2. *Calibration accuracy*: The reference RSSI parameter A for Device 2 (−62 dBm) better matches the actual propagation conditions, which is confirmed by the near-zero mean error.

Despite significant fluctuations in the input RSSI measurements, the estimated distances exhibit a smoothed trajectory without abrupt jumps, which positively demonstrates the effectiveness of the EKF-based approach. The proposed algorithm efficiently filters out anomalous RSSI measurements that may occur due to short-term interference.

Overall, the Extended Kalman Filter demonstrates varying effectiveness for the two beacons. For Device 2, the method provides high accuracy (RMSE = 0.14 m), which is sufficient for indoor navigation and positioning applications. For Device 1, the accuracy is lower (RMSE = 0.53 m), indicating the need for further parameter tuning or the application of more advanced calibration methods.

CONCLUSION

This paper investigated the application of the Extended Kalman Filter to improve the accuracy of distance estimation based on Bluetooth Low Energy RSSI measurements. A mathematical EKF model adapted to the nonlinear logarithmic relationship between signal power and distance was developed, including a detailed derivation of the measurement function Jacobian and a physical interpretation of the signal propagation model parameters.

The proposed algorithm was experimentally validated in a real office environment using two Silicon Labs EFR32BG22 BLE beacons and a Nordic nRF52840 receiver. A total of 742 measurements were collected and analysed at a reference distance of 1.00 m. The results demonstrated varying effectiveness for the two beacons: for Device 2, an RMSE of

0.14 m with a mean error of −0.02 m was achieved, whereas for Device 1, the RMSE was 0.53 m with a mean error of −0.36 m.

The obtained results confirm that the EKF effectively handles the nonlinear relationship between RSSI and distance when the signal propagation model parameters are properly calibrated. For the beacon with optimally tuned parameters, an accuracy of approximately 0.14 m (RMSE) was achieved, which is sufficient for most indoor positioning applications, including smart building navigation, asset tracking, and robotic localization.

A comparison of the mean distance estimation errors obtained using EKF in this work and those reported for the classical Kalman Filter in [29] indicates that, on average, the EKF-based algorithm reduces the mean absolute distance estimation error by 20–30% compared to the classical Kalman Filter.

The practical significance of this work lies in the feasibility of using low-cost BLE beacons to construct indoor positioning systems without the need for additional infrastructure. The proposed algorithm can be integrated into embedded systems based on microcontrollers with limited computational resources.

Future research directions include: (1) the development of automatic calibration methods for the parameters A and n to adapt to changing environmental conditions; (2) evaluation of the algorithm's performance in dynamic scenarios with moving beacons or receivers; (3) integration of the EKF with additional sensors (accelerometer, gyroscope, magnetometer) to improve robustness and accuracy through multisensor data fusion; and (4) comparative analysis with alternative nonlinear filtering techniques such as the Unscented Kalman Filter (UKF) and Particle Filter.

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COMPLIANCE WITH ETHICAL STANDARDS

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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ВИЗНАЧЕННЯ ПОЛОЖЕННЯ ОБ'ЄКТІВ В ПРИМІЩЕННІ З ВИКОРИСТАННЯМ РАДІОТЕХНОЛОГІЇ BLUETOOTH LOW ENERGY ТА РОЗШИРЕНОГО ФІЛЬТРА КАЛМАНА

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АНОТАЦІЯ

Вступ. Системи внутрішнього позиціювання на основі маяків *Блютуз з низьким енергоспоживанням* (БНЕ, Bluetooth Low Energy, BLE) часто використовують оцінку відстані за *показником потужності прийнятого сигналу* (ППС, Received Signal Strength Indicator, RSSI). Проте вимірювання ППС в приміщеннях істотно залежать від багатопроменевого поширення, затінення, інтерференції та поглинання сигналу перешкодами, що призводить до значних викидів у значеннях сигналу та суттєвих похибок оцінки відстані. Нелінійна логарифмічна залежність між ППС та відстанню додатково ускладнює застосування класичних лінійних методів фільтрації, зокрема фільтра Калмана, який потребує попереднього нелінійного перетворення вимірювань і може втрачати оптимальність.

Матеріали та методи. У роботі запропоновано метод оцінки відстані на основі розширеного фільтра Калмана (РФК, Extended Kalman Filter, EKF), який безпосередньо обробляє вимірювання ППС з використанням нелінійної логарифмічної моделі втрат потужності сигналу. Експеримент проведено в офісному приміщенні з використанням двох БНЕ-маяків Silicon Labs EFR32BG22 та приймача Nordic nRF52840. Параметри РФК визначено на основі попереднього калібрування коефіцієнтів моделі поширення сигналу.

Результати. Отримані результати показали, що РФК ефективно згладжує флуктуації ППС. Для маяка з меншою дисперсією ППС середньоквадратична похибка становила 0,14 м, а для іншого – 0,53 м. Аналіз підтверджує, що точність оцінювання суттєво залежить від стабільності сигналу та якості калібрування параметрів моделі. Порівняно з методом прямого перетворення ППС у відстань та класичним фільтром Калмана, розглянутими в попередніх дослідженнях, застосування РФК дозволяє зменшити середню абсолютну похибку оцінки відстані приблизно на 20–30%, що підтверджує переваги нелінійної фільтрації.

Висновки. Запропонований метод на основі розширеного фільтра Калмана підвищує точність та надійність оцінки відстані в системах внутрішнього позиціювання з використанням БНЕ. За умови належного калібрування параметрів моделі досягається точність, достатня для практичного застосування у навігації в будівлях, відстеженні активів та локалізації роботів. Алгоритм може бути реалізований на вбудованих платформах з обмеженими обчислювальними ресурсами та є основою для подальшого розвитку мультисенсорних систем внутрішнього позиціювання.

Ключові слова: позиціонування, Блютуз, БНЕ, ПППС, фільтр Калмана, розширений фільтр Калмана.

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