Dariusz JANCZAK

Bialystok University of Technology
ORCID: 0000-0001-5183-6017

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Indoor Positioning Based on Bluetooth maxRSSI Distance Estimator

Abstract*. The subject of the paper concerns the estimation of the indoor position of an object using the received signal strength indication (RSSI) of Bluetooth transmission. The object is equipped with a Bluetooth device, the signal of which is received by the set of locator nodes. The paper proposes an object-locator distance estimation algorithm based on a single-parameter logarithmic propagation model. The multilateration method is used to determine the position. The accuracy of position estimates is improved by the proposed distance estimator based on the maximum value of RSSI determined in the sliding window (maxRSSI). The effectiveness of the developed methods was confirmed through experimental tests carried out in a prototype evacuation supervision system.*

Streszczenie. *Tematyka artykułu dotyczy estymacji położenia obiektu wewnątrz budynku przy wykorzystaniu mierzonego RSSI sygnału Bluetooth. Obiekt wyposażony jest w moduł Bluetooth, którego sygnał odbierany jest przed sieć lokalizatorów. W artykule zaproponowano algorytm estymacji odległości obiekt - lokalizator oparty na jednoparametrycznym logarytmicznym modelu propagacji. Do wyznaczania położenia zastosowano metodę multilateracji. Poprawę dokładności estymacji położenia uzyskano poprzez zaproponowanie estymatora odległości bazującego na wartości maksymalnej RSSI wyznaczanej w ruchowym oknie (maxRSSI). Efektywność działania opracowanych metod potwierdzono poprzez badania doświadczalne przeprowadzone w prototypowym systemie nadzoru ewakuacji. (****Pozycjonowanie wewnątrz pomieszczeń na podstawie Bluetooth maxRSSI Distance Estimator****)*

Keywords: indoor positioning system, Bluetooth Low Energy, RSSI, multilateration.
Słowa kluczowe: lokalizacja wewnątrz budynku, Bluetooth Low Energy, RSSI, multilateracja.

Introduction

Estimation of indoor position using received signal strength indicator (RSSI) of a Bluetooth or Wi-Fi system is widely known and used in selected technical solutions [1, 2, 3, 4]. The main advantage of systems based on this solution is the widespread availability of RSSI and the relatively low cost of components. This results in lower cost of the user's system. Unfortunately, due to the propagation properties of the Bluetooth or Wi-Fi signal in indoor areas, the RSSI value, even for a stationary transmitter and receiver, is characterized by large fluctuations, which means that the use of this indicator does not allow for achieving high accuracy of position determination [5, 6, 7]. Improving accuracy is quite a challenge and is the subject of numerous research. However, the publications usually cover studies conducted for idealized scenarios [8, 9, 10, 11], hence there is a need for methods that can be applied to practical systems installed in typical buildings [12,13].

There are two types of RSSI-based distance measurement systems discussed in the literature. The first one involves the use of propagation relationships [6, 14, 15]. The second one, called fingerprinting [16, 17, 18], is based on carrying out a series of measurements of the signal strength received from a transmitter placed at various points of a given building and saving them in a database. In this case, the transmitter location is determined by comparing the measured RSSI with the values from the database and appropriate position interpolation. This method is algorithmically simpler and, with a dense grid of points, allows for greater accuracy. Unfortunately, the main drawback of this method is the need to conduct a series of detailed RSSI measurements for a dense grid before starting the system. Moreover, any change in the environment causes deterioration of positioning accuracy and requires re-conducting RSSI measurements. For practical reasons, launching the positioning system at any target location should be simple. This entails the requirement to minimize initialization procedure in each specific building. Due to the fact that creating a database of RSSI in a new system location requires time-consuming performance of a large number of measurements, the fingerprinting method is of limited practical significance.

Methods based on equations describing propagation dependencies, i.e. the dependence of received signal power on distance, do not have these disadvantages. In this case, two types of methods can be found in the literature: those using a reference station [15, 19, 20], and those based on identification of the parameters of the $RSSI=f(d)$ relationship model [6, 14, 21]. The method with using the reference station, despite the undoubted advantage of not having to conduct preliminary tests to identify system parameters, has a number of disadvantages. They result from the sensitivity of the entire system to the stability of RSSI measurements from the reference station and problems occurring in the event of its damage or changes in the conditions in which it operates. Therefore, in the case of large systems implemented in practice, an approach based on propagation relationship with preliminary identification of parameters seems to be more advantageous.

The scope of the paper falls within the latter category. It presents a developed method for indoor positioning, which is based on the RSSI of the Bluetooth signal received by the set of locator nodes. A method using a propagation model is proposed to estimate the distance, and a multilateration method is used to determine the position.

The contribution of this paper to the research area includes:

- improving the accuracy of position estimation by proposing a distance estimator based on the maximum value of RSSI in a sliding window (*maxRSSI*);
- proposing a distance estimator based on a single-parameter logarithmic propagation model together with a parameter identification method suitable for the *maxRSSI* estimator;
- confirmation of the performance efficiency of the developed methods through experimental tests that were carried out in a prototype system for supervising the evacuation of people from a building.

The proposed distance estimator together with modified multilateration algorithm proposed by author in [21] allowed for estimating the position of objects on a 2D plane. The paper presents the proposed methods and the analysis of the average error in determining distance and position, as well as a discussion on the selection of the estimator parameter. The proposed distance estimator is described in the next section, and the positioning algorithm is described in the following section. Then, the results of experimental tests conducted in the prototype evacuation supervision system are presented.

Distance estimation based on maximal RSSI value

The distance measurement method using propagation relationships involves the use of the dependence of the received signal power on the transmitter - receiver distance. The idea of this method is illustrated by (1), which shows the power of the received signal in the case of transmission in free space [22].

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2} \tag{1}$$

where P_r is the power of the received signal, P_t is the power of the transmitted signal, G_r G_t are the loss/gain coefficients of the receiving and transmitting paths, λ is the wavelength, d is the distance between the transmitter and receiver.

Equation (1) describes the ideal situation without taking into account interference, but allows for a general conclusion that the power of the received signal is inversely proportional to the square of the distance between the transmitter and the receiver. Therefore, assuming knowledge of the parameters P_t, G_r, G_t, λ, by measuring P_r the distance can be determined. In practice, the level of signal power is presented in decibels related to P_m=1 mW, which leads to the presentation of (1) in the form (2).

$$P_{r\,dBm} = 10\log_{10}\left(\frac{P_t G_t G_r \lambda^2}{(4\pi)^2 P_m}\right) - 20\log_{10}(d) \tag{2}$$

As follows from (2), the relationship between the received signal power and the distance takes the form of a logarithmic relationship. The power level of the received signal in commonly used devices is most often provided to the user as the RSSI parameter. It is usually expressed in dBm. Based on (2), a logarithmic model of the relationship $RSSI = f(d)$ may be formulated in the form (3).

$$RSSI_d = \beta - 20\log_{10}(d) \tag{3}$$

where *d* is the distance between the receiver and the transmitter, $RSSI_d$ is the value of the measured RSSI, and β is a parameter denoting the first part of the right side of (2).

Parameter β includes all factors which depend on the type of equipment used and the operating conditions of the system. In practice, it can be identified based on a series of RSSI measurements of the signal from transmitter located at points of known location. Based on (3), the estimate of the distance *d* between the receiver and the transmitter can be determined according to (4).

$$\hat{d} = 10^{(\beta - RSSI_d)/20} \tag{4}$$

Estimate (4) is optimal for the system operating in open space. In the case of an indoor system, the estimation error will increase due to the increase in the variance of RSSI measurements [5]. This is largely due to the multipath effect, which is caused by reflections from the walls and objects in the surroundings. The effects of this phenomenon are presented in Fig. 3 and Fig. 4 and discussed in section devoted to results of the experimental studies. Based on the analysis presented there, an estimator of the object - locator node distance is proposed. It utilizes the maximum value of RSSI determined in a sliding window of width *M*. The proposed estimator, hereinafter referred to as *maxRSSI*, has the form (5).

$$\hat{d}(k) = 10^{\left(\beta - RSSI^{max\,M}_{Loc_n}(k)\right)/20} \tag{5}$$

where $\hat{d}(k)$ is the estimated distance between the object and the locator node Loc_n at the time k, while $RSSI^{max\,M}_{Loc_n}(k)$ is determined as the maximal RSSI value in the sliding window based on the Loc_n node's RSSI levels.

$$RSSI^{max\,M}_{Loc_n}(k) = \max_{m=0,\ldots,M-1} RSSI_{Loc_n}(k-m) \tag{6}$$

where M is the width of the window of the RSSI analysis.

Estimates (5) of the distance between an object and set of locator nodes allow the determination of the object's coordinates, which is the topic of the next section.

Determining Cartesian coordinates of object location based on distance estimates

Cartesian coordinates of the object location can be determined using the multilateration method [6, 15, 23]. In this case, a set of appropriately placed locator nodes with known coordinates is used. Using the measured distances between the object and the locator nodes, spheres of the object's potential location can be established around each locator node. The object will be located at the point where the spheres intersect. This situation is described by a system of equations (7).

$$\begin{aligned} (x_o(k)-x_{L_1})^2 + (y_o(k)-y_{L_1})^2 + (z_o(k)-z_{L_1})^2 &= d_1^2(k) \\ (x_o(k)-x_{L_2})^2 + (y_o(k)-y_{L_2})^2 + (z_o(k)-z_{L_2})^2 &= d_2^2(k) \\ &\vdots \\ (x_o(k)-x_{L_N})^2 + (y_o(k)-y_{L_N})^2 + (z_o(k)-z_{L_N})^2 &= d_N^2(k) \end{aligned} \tag{7}$$

where $x_o(k)$, $y_o(k)$, $z_o(k)$ are the Cartesian coordinates of the object, x_{Li}, y_{Li}, z_{Li} are the coordinates of the Loc_i locator node, $d_i(k)$ is the distance between the *i*-th locator node and object, k is the index denoting the current time moment, N is the number of locator nodes used in the system.

Unfortunately, in practice, the distances d_i determined on the basis of RSSI are subject to error, which can be modeled as (8).

$$\hat{d}_i(k) = d_i + v(k) \tag{8}$$

where d_i is the actual distance, $\hat{d}_i(k)$ is the distance estimate determined on the basis of RSSI, and $v(k)$ is the estimation error.

Due to the distance estimation error, the spheres of the object's potential location do not intersect at one point. This is illustrated in Fig. 1 for the 2D case and 3 locator nodes.

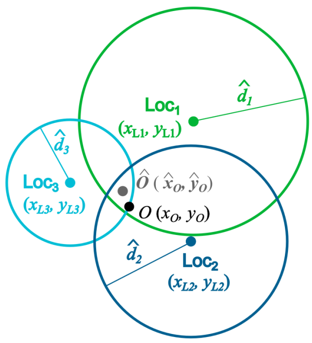

Fig. 1. Estimation of Cartesian coordinates of point O with using distance estimates

As can be deduced from Fig. 1, the system of equations (7) will not enable obtaining an analytical solution. Therefore, to obtain the coordinates of an object, an approximate solution should be used, such as the maximum likelihood estimator, or an estimator that determines the centroid of the confidence region or the center of the space formed by the intersections of spheres [24, 25, 26]. Such a position estimation algorithm was developed by the author and presented in [21]. The algorithm was designed based on a modified multilateration method. The modification involves taking into account the known heights of hanging the locator nodes and assuming the average height of the object, e.g. a wristband or a mobile phone. The above allows for the reduction of the 3D algorithm to a 2D algorithm. Due to this, an algorithm for determining object position on the floor level was achieved, while practically maintaining the accuracy of the 3D algorithm and significantly reducing the computational load. The resulting estimates of the Cartesian coordinates of the object's position can be calculated as (9).

$$\begin{bmatrix} \hat{x}(k) \\ \hat{y}(k) \end{bmatrix} = \frac{1}{2}\left(U^T U\right)^{-1} U^T V(k) \tag{9}$$

where $\hat{x}(k), \hat{y}(k)$ are estimates of the Cartesian coordinates of the object position, while the matrices *U* and *V(k)* are calculated [21] as (10) and (11).

$$U = \begin{bmatrix} \left(x_{L_2} - x_{L_1}\right) & \left(y_{L_2} - y_{L_1}\right) \\ \vdots & \vdots \\ \left(x_{L_N} - x_{L_1}\right) & \left(y_{L_N} - y_{L_1}\right) \end{bmatrix} \tag{10}$$

$$V(k) = \begin{bmatrix} x_{L_2}^2 - x_{L_1}^2 + y_{L_2}^2 - y_{L_1}^2 + \left(z_{L_1} - z_0\right)^2 - \\ -\left(z_{L_2} - z_0\right)^2 + \hat{d}_1^2(k) - \hat{d}_2^2(k) \\ \vdots \\ x_{L_N}^2 - x_{L_1}^2 + y_{L_N}^2 - y_{L_1}^2 + \left(z_{L_1} - z_0\right)^2 - \\ -\left(z_{L_N} - z_0\right)^2 + \hat{d}_1^2(k) - \hat{d}_N^2(k) \end{bmatrix} \tag{11}$$

where x_{Li}, y_{Li}, z_{Li} are the Cartesian coordinates of the Loc_i locator node, z_o is the average height of the object's location, $\hat{d}_i(k)$ is the estimate of the distance between the object and the Loc_i locator node.

Results of experiments

The proposed RSSI-based distance estimation algorithm (5)-(6) and the object positioning algorithm (9)-(11) were tested for a real RSSI of Bluetooth signal with using a prototype evacuation supervision installation. The installation includes five locator nodes arranged as shown in Fig. 2. The locator nodes are based on modules using ESP32 chips. They are equipped with Bluetooth Low Energy (BLE) communication modules and Wi-Fi modules that enable cooperation with a data server using the MQTT protocol. The located object was a wristband based on the nRF52832 module. The wristband periodically broadcasts BLE advertisements containing its ID, and the locator nodes determine the RSSI of the received signal. A more detailed description of the experimental installation can be found in the author's publications [2, 5, 27]. In the current section, at first, the experimental results which allowed the formulation of the distance estimation method (5)-(6) (*maxRSSI* method) will be described. Then, the identification process of the model (3) β parameter will be presented. Next, the results of research on the accuracy of distance estimation using the proposed method will be presented, followed by results showing the position estimation error.

1) Experimental results enabling the development of a distance estimation method

As part of the investigation on improving the quality of the distance estimation algorithm based on the RSSI, research was carried out on the RSSI distribution for object located at the same distance from the locator node, but for a different nature of the surroundings. Examples of histograms of the RSSI value distribution for the actual transmitter-receiver distance d = 2.5 m and d = 4.0 m are shown in Fig. 3 and Fig. 4.

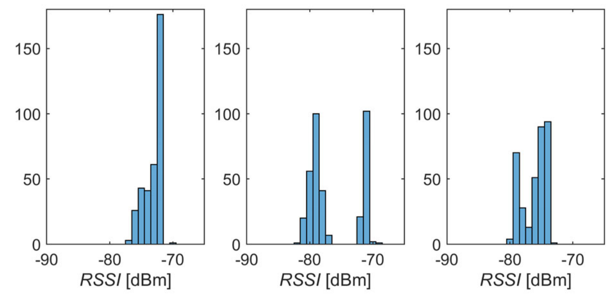

Fig. 3. Histograms of the RSSI value distribution for points of the object location at a distance of d = 2.5 m from the locator node

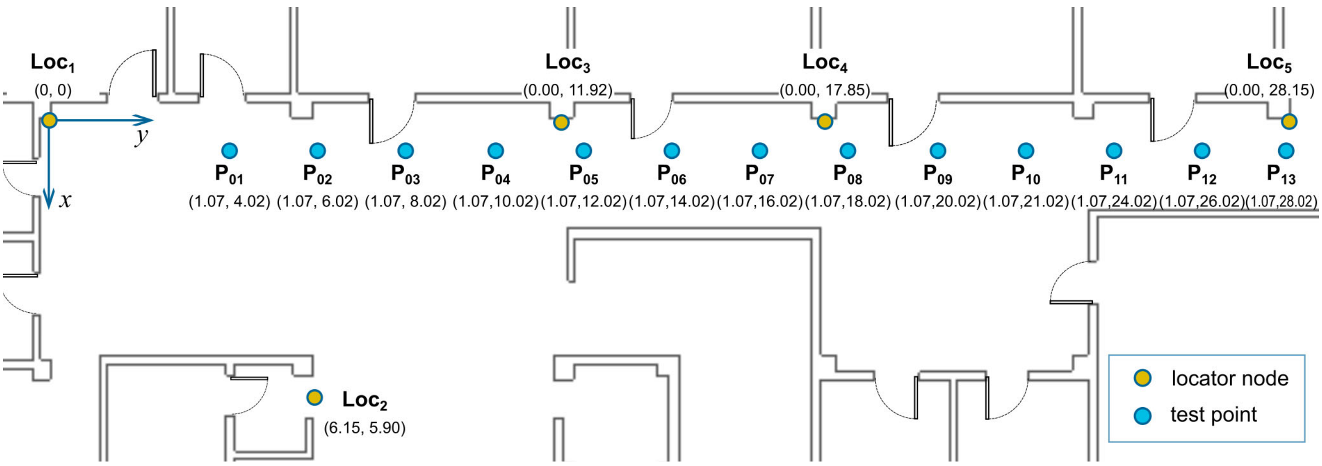

Fig. 2. Location of Loc_i locator nodes in the experimental installation and P_n points of the object's location during a series of tests

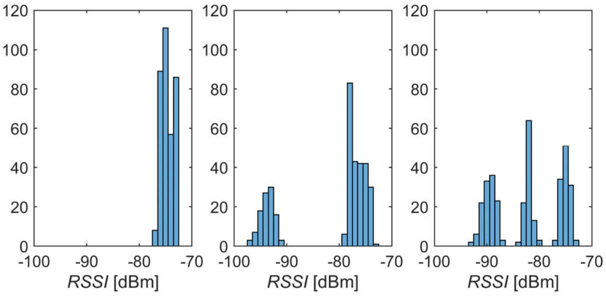

Fig. 4. Histograms of the RSSI value distribution for points of the object location at a distance of d = 4.0 m from the locator node

Analyzing the histograms presented in Fig. 3 and Fig. 4, one can identify separate or overlapping groups of RSSI measurements. The analysis of the surrounding leads to the conclusion that among histogram bins there is a group of RSSI measurements originating from direct transmission and emerging groups of RSSI measurements coming from multipath. The analysis also leads to the observation that in the tested system, measurements from direct transmission constitute the RSSI group with the highest power. This observation allowed the formulation of an algorithm for RSSI analysis in a sliding window with determination of maximum value. The proposed method is supposed to filter out measurements from multipath transmission. The proposed distance estimator $\hat{d}(k)$ has the form (5)-(6), as presented in previous section. The width of the sliding window can be selected depending on the probability of RSSI measurements resulting from multipath, which can be estimated based on statistical analysis.

2) Identification of the distance model parameter

The estimator (5)-(6) requires the identification of the β parameter of model (3), which is specific for each type of BLE transmitter - receiver pair. In order to identify the parameter, several series of approx. N_s=800 RSSI measurements were carried out for an object placed at points with known location. The identification process is illustrated in Fig. 5. The blue dots on the graph represent the average of the maximum values (6) determined for RSSI measurements carried out by the *m*-th locator node (Loc_m) for BLE signal from wristband located at the *n*-th point (P_n). The width of the sliding window was set to M = 10. The black line represents model (3), for which the β parameter was identified using the nonlinear least squares method with the Levenberg-Marquardt algorithm.

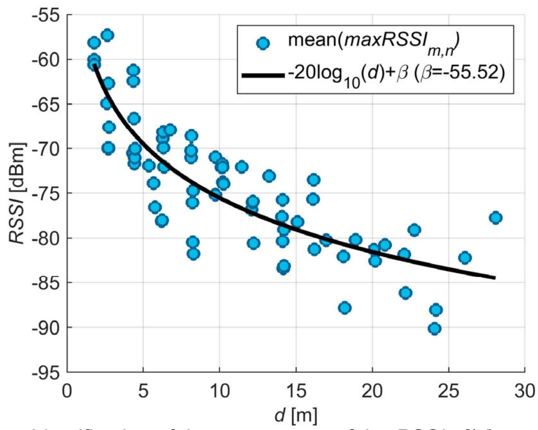

Fig. 5. Identification of the parameter β of the *RSSI*= f(d) model

In the identification process illustrated in Fig. 5, the parameter value β = -55,52 was obtained, which minimized the mean square matching error. This value used in the proposed method (5)-(6) allows obtaining an estimate of the distance based on the RSSI.

3) Distance estimation using the maxRSSI algorithm

The efficiency of indoor positioning based on Bluetooth RSSI depends largely on the quality of the estimates of distance between object and locator node. Therefore, tests on the distance estimation error were carried out. These tests were conducted in the experimental installation shown in Fig. 2. The diagram shows the location of the Loc_m locators and P_n test points. As mentioned earlier, the choice of the width M of the RSSI analysis window (see (6)) is an important factor influencing the estimation error. Therefore, a study was carried out on the dependence of the distance estimation error on the selected M. The results are presented in Fig. 6, which shows the mean absolute error (MAE) of the estimates of the distance between P_n and Loc_m depending on the window width M. The MAE was determined according to (12).

$$(12)\quad MAE\left(\hat{d}(k)\right)=\frac{1}{N_m N_n N_k}\sum_{m=1}^{N_m}\sum_{n=1}^{N_n}\sum_{k=1}^{N_k}\left|\hat{d}_{m,n}(k)-d_{m,n}\right|$$

where $\hat{d}_{m,n}(k), d_{m,n}$ are the distance estimate and the actual distance between Loc_m and P_n, while N_m is the number of locator nodes, N_n is the number of object positions, and N_k is the number of RSSI measurements taken by Loc_m for a given object position P_n.

The MAE of estimates obtained using the proposed *maxRSSI* method were compared with the MAE of the distance estimates obtained using two other methods. The first is the widely used distance estimation based on raw RSSI measurements, and the second one is the distance estimation presented in [21], whose algorithm is based on Gaussian modeling of the RSSI distribution. The results obtained for the three methods are shown in Fig. 6, where the MAE in the case of the proposed estimator (5)-(6) is marked as *maxRSSI*, in the case of the estimator [21] it is marked as *meanRSSI*, and in the case of the raw RSSI as *rawRSSI*.

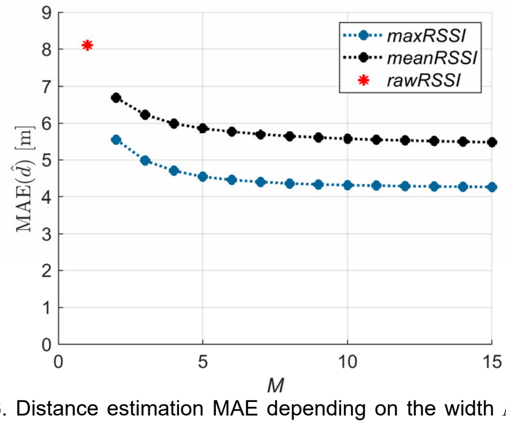

Fig. 6. Distance estimation MAE depending on the width M of the sliding window

The comparison of results presented in Fig. 6 indicate the advantage of the developed *maxRSSI* method over other methods. The *maxRSSI* method shows approximately 20% improvement in distance estimation accuracy compared to the method [21] based on the Gaussian model of RSSI and approximately 50% lower MAE when using raw RSSI values. Moreover, the dependence of the distance estimation error on M shown in Fig. 6 allows for the formulation of the range of window width M that should be used in practice. As can be seen for the *maxRSSI* graph, increasing the window width from M = 2 to M = 6 results in a significant reduction of MAE. The changes are small in the range of $7 \le M \le 10$. Increasing M above 10 provides negligible benefits. From the above analysis it follows that in practice the value of M should be taken in the range 7÷10.

4) Position estimation using the maxRSSI estimator

As mentioned earlier, the proposed distance estimator (5)-(6) and 2D coordinate estimator (9)-(11) enable indoor position estimation based on the RSSI of the BLE signal. The above method was implemented in the experimental installation shown in Fig. 2. The system was used to test the accuracy of 2D coordinate determination using the proposed methods for a series of RSSI measurements obtained by Loc_1-Loc_5 locators. The tests were carried out for test points P_{01}-P_{13}. For each test point location, approximately $N_s = 800$ RSSI measurements were collected. The average height of the object placement was taken as $z_o \approx 1.2$ m. The research was carried out for two different operating conditions of the multilateration algorithm. The experiments were organized in such a way that due to the mutual arrangement of locator nodes and object positions P_n, points P_{01}-P_{07} show well-conditioned multilateration geometry in the x-axis direction, while P_{08}-P_{13} - poorly conditioned. This allows testing the effectiveness of algorithms for various practical scenarios.

Table 1 shows the MAE of the Cartesian coordinates estimates of the P_n points and the error $\bar{e}_{\hat{P}_n}$ of determining the location of each P_n point. These errors were determined according to (13) and (14). The presented results were obtained for $M = 10$.

(13)
$$MAE(\hat{x}(k)) = \frac{1}{N_{P_n}} \sum_{k=1}^{N_{P_n}} \left| \hat{x}(k) - x_{P_n} \right|$$
$$MAE(\hat{y}(k)) = \frac{1}{N_{P_n}} \sum_{k=1}^{N_{P_n}} \left| \hat{y}(k) - y_{P_n} \right|$$

(14)
$$\bar{e}_{\hat{P}_n} = \frac{1}{N_{P_n}} \sum_{k=1}^{N_{P_n}} \sqrt{\left(\hat{x}(k) - x_{P_n}\right)^2 + \left(\hat{y}(k) - y_{P_n}\right)^2}$$

where $\hat{x}(k), \hat{y}(k)$ are estimates of the Cartesian coordinates of the object position, x_{P_n}, y_{P_p} are the actual Cartesian coordinates of the P_n point, and N_{P_n} is the number of RSSI measurements at a given P_n object position.

Table 1. Coordinate estimation error and the error of determining the location of each P_n point

P_n	$MAE(\hat{x}(k))$ [m]	$MAE(\hat{y}(k))$ [m]	$\bar{e}_{\hat{P}_n}$ [m]
P_{01}	5.02	0.95	5.13
P_{02}	0.82	2.26	2.49
P_{03}	5.11	2.30	5.68
P_{04}	1.33	1.32	1.90
P_{05}	1.28	3.53	3.88
P_{06}	0.77	1.72	1.91
P_{07}	0.70	3.57	3.72
P_{08}	13.32	1.06	13.36
P_{09}	10.84	5.56	12.19
P_{10}	3.10	0.70	3.28
P_{11}	3.18	1.68	3.75
P_{12}	13.39	3.89	14.29
P_{13}	5.75	5.20	8.00

As can be seen from the results presented in Table 1, when using the developed estimators (5)-(6), (9)-(11), the MAE error in estimating the x, y coordinates in the case of points with well-conditioned multilateration geometry (P_{01}-P_{07}) is in the range of 1 ÷ 5 m, the error in determining the position was below 5.7 m. However, in the case of the remaining points (P_{08}-P_{13}) for the y coordinates, the error is in a similar range, but for the x coordinates, due to the poor conditioning of the multilateration geometry, it reaches up to 13.4 m. This causes the increase of the positioning error to approximately 14.3 m in the worst case.

The next determined parameter was the average position estimation error $\bar{e}_{\hat{P}_o}$ calculated for all measurements according to (15).

(15)
$$\bar{e}_{\hat{P}_o} = \frac{1}{\sum_{n=1}^{N_n} N_{P_n}} \sum_{n=1}^{N_n} \sum_{k=1}^{N_{P_n}} \sqrt{\left(\hat{x}(k) - x_{P_n}\right)^2 + \left(\hat{y}(k) - y_{P_n}\right)^2}$$

where N_n is the number of positions P_n.

Fig. 7 shows the dependence of the average position estimation error on the window width M.

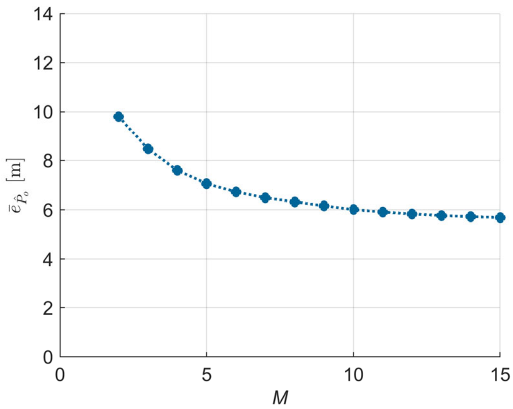

Fig. 7. Dependence of the average position estimation error on the window width M

The analysis of the positioning errors presented in Fig. 7 confirms that in practice the value of M should be set between 7 and 10.

A comparison of estimation errors using the proposed method (*maxRSSI*) with distance estimation based on raw RSSI measurements (*rawRSSI*) and the estimation presented in [21] (*meanRSSI*) was performed. Table 2 shows the MAE errors of (x, y) coordinate estimation calculated for all measurements and the average position estimation error. The position determination error was calculated according to (15), while $MAE(\hat{x}_o(k))$, $MAE(\hat{x}_o(k))$ are similarly averaged as $MAE(\hat{x}(k))$, $MAE(\hat{y}(k))$ (13). Table 2 includes the results averaged separately for the entire range of object positions (P_{01}-P_{13}) and for those with good multilateration geometry (P_{01}-P_{07}).

Table 2. Averaged MAE error of coordinate estimation (x, y) and averaged position estimation error

Method	P_n	$MAE(\hat{x}_o(k))$ [m]	$MAE(\hat{y}_o(k))$ [m]	$\bar{e}_{\hat{P}_o}$ [m]
maxRSSI	P_{01}-P_{07}	2.06	2,20	3,42
	P_{01}-P_{13}	4.87	2.61	6.01
meanRSSI	P_{01}-P_{07}	2.67	2.25	3.83
	P_{01}-P_{13}	6.73	2.98	7.85
rawRSSI	P_{01}-P_{07}	7.80	3.29	9.15
	P_{01}-P_{13}	11.89	4.74	13.68

The analysis of the results presented in Table 2 confirms high efficiency of the proposed *maxRSSI* method. The average position estimation error does not exceed 3.5 m in the case of an appropriate configuration of locator nodes that ensures good conditioning of the multilateration geometry. Moreover, the positioning error of proposed *maxRSSI* method is approximately 12% smaller than that of the *meanRSSI* method. The *maxRSSI* method allows for an approximately 2.5-fold reduction in error compared to using raw RSSI measurements.

Conclusions

The paper presents the developed algorithm for analyzing the RSSI of Bluetooth signal that allows for indoor localization. The analysis of histograms of RSSI for signals obtained in various locator nodes surroundings allowed the formulation of an object-locator distance estimator algorithm based on the RSSI maximal value determined in the sliding window. Moreover, it was proposed to use a single-parameter logarithmic propagation model for distance estimation. A parameter identification method was also proposed. The above distance estimation algorithms were included in the multilateration method in order to obtain estimates of the Cartesian coordinates of the object. The proposed approach was verified in a real experimental system of an evacuation surveillance system. The experiments revealed that the proposed method allows to achieve an average position estimation error of approximately 3.5 m and an average error in determining the x, y coordinates of approximately 2.2 m. The proposed method allows to obtain an error that is 2.5 times smaller than when processing raw RSSI and 12% smaller than when using the *meanRSSI* method. Having such advantages as a small positioning error and low demand for computational power, the proposed method can be recommended for implementation in low-budget positioning systems using Bluetooth Low Energy.

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***Author**: dr hab. inż. Dariusz Jańczak, Politechnika Białostocka, Wydział Elektryczny, ul. Wiejska 45d, 15-351 Białystok, e-mail: d.janczak@pb.edu.pl.*

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