

1-1-2018

BVIRE improved algorithm for indoor localization based on RFID and a linear regression model

NOOR BAHAAALDIN

ERGUN ERÇELEBİ

Follow this and additional works at: <https://journals.tubitak.gov.tr/elektrik>



Part of the [Computer Engineering Commons](#), [Computer Sciences Commons](#), and the [Electrical and Computer Engineering Commons](#)

Recommended Citation

BAHAAALDIN, NOOR and ERÇELEBİ, ERGUN (2018) "BVIRE improved algorithm for indoor localization based on RFID and a linear regression model," *Turkish Journal of Electrical Engineering and Computer Sciences*: Vol. 26: No. 6, Article 13. <https://doi.org/10.3906/elk-1505-52>
Available at: <https://journals.tubitak.gov.tr/elektrik/vol26/iss6/13>

This Article is brought to you for free and open access by TÜBİTAK Academic Journals. It has been accepted for inclusion in Turkish Journal of Electrical Engineering and Computer Sciences by an authorized editor of TÜBİTAK Academic Journals. For more information, please contact academic.publications@tubitak.gov.tr.

BVIRE improved algorithm for indoor localization based on RFID and a linear regression model

Noor BAHAALDIN^{1*}, Ergun ERÇELEBİ²

¹Department of Computer Engineering, University of Technology, Baghdad, Iraq

²Department of Electrical and Electronic Engineering, Faculty of Engineering, Gaziantep University, Gaziantep, Turkey

Received: 06.05.2015

Accepted/Published Online: 01.03.2016

Final Version: 29.11.2018

Abstract: Traditional indoor location technologies such as infrared technology and ultrasonic technology are complex, expensive, or having unsatisfactory location accuracy. Radio frequency identification (RFID) technologies are very popular in many areas since their costs are very low. The tag in such technologies acts as the transmitter, and the radio signal strength indicator (RSSI) information is measured at the reader. However, RSSI information suffers strictly from the multipath circumstance and circumferential elements. Therefore, the localization accuracy of the boundary will be affected severely. In order to solve this problem, we introduce the boundary virtual reference label (BVIRE) algorithm to well utilize RFID techniques for locating the tracking object, which inserts some virtual reference tags on the boundary by establishing a linear regression model that eliminates unwanted tag information from the estimation procedure. The positioning accuracy of the boundary tags and stability have been improved significantly, at least 78%, without adding extra reference tags or radio frequency interference. Also, the estimation errors of our improved BVIRE are much smaller compared to the virtual reference label, location identification based on the dynamic active RFID calibration (LANDMARC), ultrawide band, RADAR, and PinPoint algorithms.

Key words: BVIRE algorithm, linear regression model, RFID, indoor location, RSSI

1. Introduction

In recent years, along with wireless and other various technologies, the rapid development of mobile computing and radio frequency identification (RFID) technology has received an increased attention with respect to the indoor positioning technology [1]. This technology has many benefits like the multiobject recognition, contactless line of sight, scalability, and long transmission range, which promises cost efficiency with a high degree of accuracy in widely used applications. Therefore, it is considered as a feasible and popular nominee for indoor location's sensing. Typically the RFID system consists of a reader, tag, and application software system as shown in Figure 1. The reader is fixed at a position that scans the nearby tags. When the tag is scanned, the distance from the tag to the reader can be calculated by the radio signal strength indicator (RSSI). However, such technologies have some drawbacks since RSSI is easily affected by the environmental factors such as radio signal reflection, refraction, and scattering by the object within the room. Also, the signal arrives at the receiver along more than one path [2]. In this paper, different indoor location methods have been demonstrated such as the dynamic active RFID calibration (LANDMARC), virtual reference label (VIRE), and others. The

*Correspondence: eng.iraq209@yahoo.com

LANDMARC algorithm is one of the most well-known indoor localization techniques using active RFID tags [3]. When it locates a tracking tag, it compares its RSSI value at known locations with the reference tags. Every reader can get the RSSI readings from some reference tags and one tracking tag. Numbers of readers can organize the tracking-tag's readings to identify some adjacent reference tags, and then the tracking-tag's location can be estimated by those nearby reference tags whose location is fixed. Nevertheless, LANDMARC has a defective performance in a closed region of severe radio signal multipath influences. Thus, to achieve a better accuracy, more fixed reference tags are required, which is costly and requires additional radio frequency (RF) interference [4]. Also, it computes all the reference tags as the candidate for the neighbour tags, which causes some unnecessary computation [2,5]. To overcome these issues, the VIRE was introduced that depends on the basis of the LANDMARC algorithm using virtual reference tags [6]. The VIRE applies some virtual reference tags to provide denser reference coverage rather than using numerous real reference RFID tags within the sensing region. Each reader produces a proximity map formed using virtual tags in order to reduce the effects of uncharacteristic signal behaviour. It removes the undesired locations for estimating the possible object's location precisely without any additional reference tag. Its main point is computing the RSSI of each virtual reference tag in a fast and appropriate way but with a lack of precision. In addition, there is an overhead in the computations of VIRE since only a few virtual reference tags closer to the tracking tags are occupied in the location process. In addition, the accuracy of the VIRE algorithm is low near the border, and adding an actual reference label at the border to achieve better accuracy will lead to an additional cost to the system [1]. Therefore, to improve the positioning accuracy of the boundary label system without increasing the system cost, this paper proposes a BVIRE algorithm that adds a virtual reference tag at the boundary using a linear regression model (LRM) and removes any redundant positioning information to identify and locate tracking objects. Such a methodology is suitable to be applied in a large area and operates well in complex and closed indoor environments.

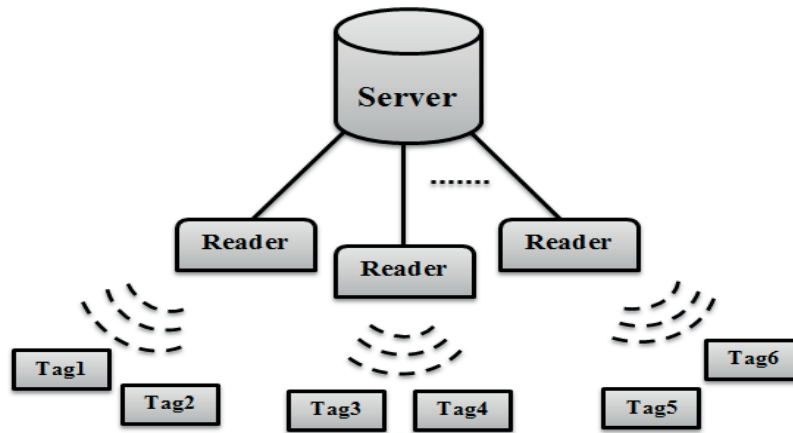


Figure 1. RFID system.

2. Related works

In recent years, lots of indoor location methods have been proposed to achieve accurate ways of determining indoor location [2,7], each having their own strengths in addition to the limitations in improving the accuracy of location such as ultrawide band (UWB) [8], RADAR [9], PinPoint [10], LANDMARC [3], and VIRE [6]. UWB

is a viable algorithm for short-range wireless indoor communication. UWB technology has a short-range data communication technology of accuracy that reaches to 15 cm. The advantage of UWB is that the direct line of sight (LOS) is not required between the readers and tags. The positioning system has the ability to track and achieve a high accuracy. However, UWB technology requires a lot of bandwidth, and may create a disturbance to other communication devices. So, the frequency permission issue of UWB technology has been debated unceasingly. In addition, the average power system of UWB is very low, a very short pulse duration causes the instantaneous peak power to be significantly large, and it will affect the normal ability of civil aviation and many other systems to work properly [11]. The RADAR method is an RF based system for tracking and locating persons inside buildings. The key powers of this system are that it is easier to setup, needs only a few base stations, and utilizes similar infrastructure of general wireless networking in the building. However, its complexity appears when the object being tracked should be supported by a Wave LAN NIC, which is not practical for small or power constrained devices. Therefore, it is costly and has high energy consumption. Also, RADAR's implementation has a poor overall accuracy that determines the object's location by 3 m deviation from its actual location [12]. The PinPoint method is similar to RADAR with respect to its use of a wireless local network technique. The positioning algorithm depends on a time difference, where it computes the distance of various objects by the RF signal transmission time. It deploys an antenna array during the measurement at the known location positions to perform multilateration. Its controller is equipped with a battery, where the radio frequency signal is transmitted to a different antenna in order to track the target location. The system positioning accuracy is approximately from 1 to 3 m and has a very strong adjustment, and it is mainly used in supermarkets, hospitals, and other indoor environments. However, the system suffers from a disadvantage in which each antenna has a narrow cone of influence that leads to an expensive deployment and a larger system investment [13].

3. The background of the VIRE algorithm

The environmental layout of the VIRE algorithm shown in Figure 2 demonstrates four readers placed within the boundary area with 16 actual reference labels, according to and based on the grid arrangement of the registration area. The core idea of the VIRE algorithm is that every four reference labels are considered as a unit grid, and that grid will be further divided into $N \times N$ small subgrids. A small grid of the virtual reference tag is shown in Figure 3, where the virtual reference tags are evenly distributed between the cells in the grid [14]. Because the position coordinates of the actual reference label are known, the coordinates of the grid virtual reference label can be easily computed, which is equivalent to adding a large number of reference labels.

Moreover, the positioning accuracy of the indoor system has been improved in the VIRE algorithm that depends on the weight basis, which consists of two weighting factors: w_{1i} and w_{2i} . w_{1i} is used to characterize the difference between the received signal strength indication (RSSI) of the selected tag to be positioned and the smaller differential value because a smaller difference means that w_{1i} is greater [1,6]. w_{2i} is used to characterize the optimal optimization density of the selected neighbouring reference label in which a greater density results in a greater w_{2i} :

$$w_{1i} = 1 - \sum_{k=1}^K \frac{|S_k(T_i) - S_k(R)|}{K \times S_k(T_i)}, \quad (1)$$

$$w_{2i} = \frac{n_{ci}}{\sum_{i=1}^{n_a} n_{ci}}, \quad (2)$$

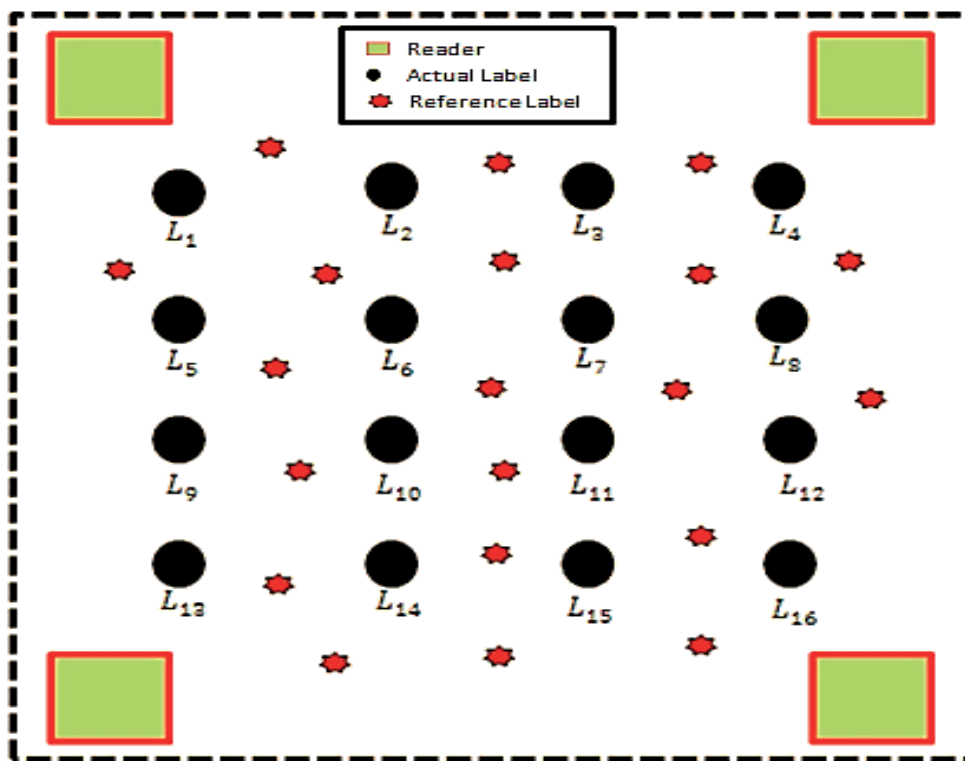


Figure 2. The VIRE reader and tag distribution system.

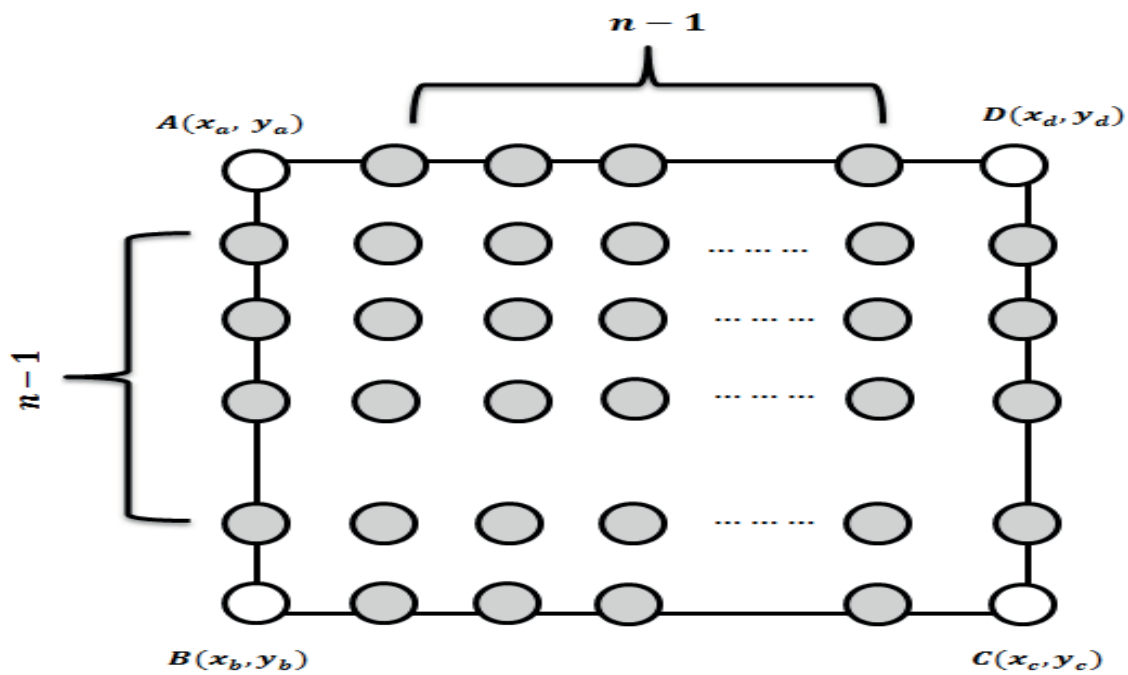


Figure 3. The distribution grid of the virtual reference label.

where K represents the number of tags in the system, $S_k(T_i)$ is the RSSI value of the tag to be positioned, and $S_k(R)$ is the RSSI value of the reference tag. n_{ci} represents the number of connections with the neighbouring reference label i together in the selected region and n_a is the number of neighbouring reference labels to be positioned throughout the indoor area selected. Taking into account factors w_{1i} and w_{2i} , the following weight is obtained:

$$w_i = w_{1i} \times w_{2i}. \tag{3}$$

The coordinate values (x, y) of the label to be positioned can be calculated using the following formula:

$$(x, y) = \sum_{i=1}^{n_a} w_i (x_i, y_i), \tag{4}$$

where w_i is the weighting factor to the i th neighbouring reference tag, n_a is the number of total regions in the set of possible positions, and (x_i, y_i) denotes the coordinates of the virtual reference tag.

The estimation error between the coordinate of the label to be positioned (x, y) and the actual coordinates of the label to be located (x_0, y_0) is defined as follows:

$$e = \sqrt{(x - x_0)^2 + (y - y_0)^2}. \tag{5}$$

The visible error of the VIRE method has been effectively improved. However, Figure 4 shows that the label located near the boundary, compared with other labels, has a high positioning error, which represents a primary problem that is considered with our improved methodology. A comparison of the positioning error between VIRE and other methods is shown in above mentioned figure.

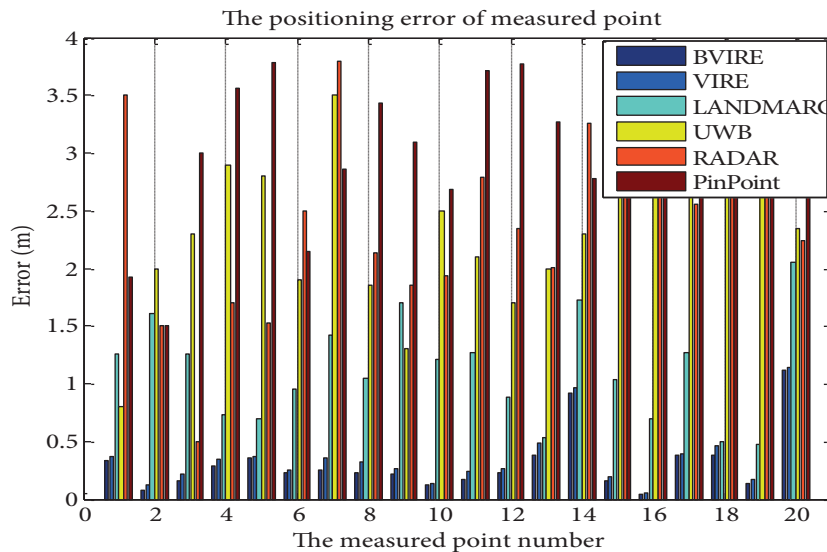


Figure 4. Comparison of positioning error with several methods.

4. Principles of our improved BVIRE algorithm

The distribution of the boundary virtual reference label is shown in Figure 5. This paper introduces 16 boundary virtual reference labels. From the coordinates of the original label value, we can easily obtain the coordinates

of virtual reference label value [15]. Additionally, according to the RSSI of the original reference label for the linear regression equations, the RSSI value of the boundary virtual reference label and the actual reference label have the same reference value. When the actual reference label position and RSSI value changes, then the tag location and the boundaries of virtual reference RSSI values can be updated in real time with a good adaptability to the environment. Therefore, a regression equation can be established based on the coordinate values and the RSSI value of the actual reference tags. The establishment of the linear regression equation, which is shown below, will solve the RSSI value of the boundary virtual reference label.

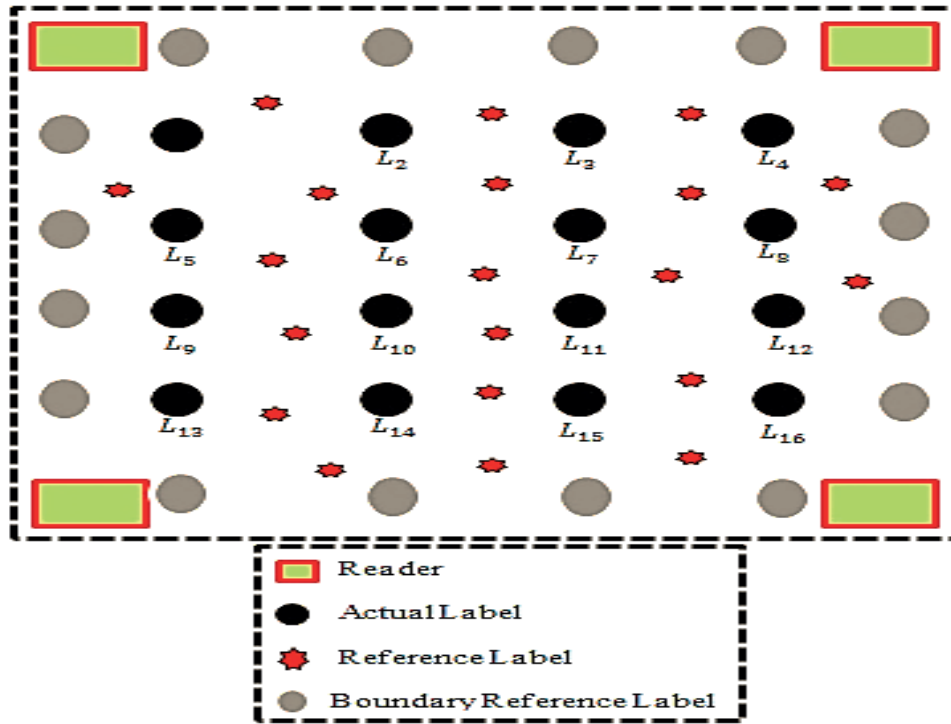


Figure 5. The position distribution of BVIRE system.

- (1) Building the binary linear regression equation for two dimensions (2D), the mathematical relational expression is:

$$S_{binary(two\ coordinate)} = B_0 + B_1x + B_2y, \tag{6}$$

where

$$B = (X^T X)^{-1} X^T \tag{7}$$

$$X(2D) = \begin{pmatrix} 1 & x_{11} & y_{21} \\ 1 & x_{12} & y_{22} \\ \vdots & \vdots & \vdots \\ 1 & x_{1n} & y_{2n} \end{pmatrix} \tag{8}$$

$$\hat{\beta}_2 = \frac{\sum_{i=1}^n x_i S_i - n\bar{x}\bar{S}}{\sum_{i=1}^n x_i^2 - n\bar{x}^2} = \frac{\sum_{i=1}^n (x_i - \bar{x})(s_i - \bar{s})}{\sum_{i=1}^n (x_i - \bar{x})^2}, \quad \hat{\beta}_1 = \bar{s} - \hat{\beta}_2 \bar{x} \hat{\beta}_0 = \bar{s} - \hat{\beta}_1 \bar{x} \quad (9)$$

$$\hat{\beta} = \begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \end{pmatrix} \quad (10)$$

$$S_{|b(\text{two coordinate})|} = \hat{\beta}_0 + \hat{\beta}_1 x_{b1} + \hat{\beta}_2 y_{b1}, \quad (11)$$

where S_{Binary} is the RSSI value of the actual reference label (x, y) . B_0, B_1, B_2 are the regression coefficients of the actual reference label. $X(2D)$ is the tag coefficients for two dimensions. $S_{|b(\text{two coordinate})|}$ is the RSSI value of the boundary virtual reference label. In the previously mentioned Figure 4, the label shows that by using the coordinate values and the RSSI value of the 16 actual reference tags we obtain $\hat{\beta}$ that represents the regression coefficients of the boundary virtual reference label. According to Eq. (11), the horizontal tag and the vertical coordinates tag (x_{b1}, y_{b1}) are used to determine RSSI value $S_{|b|}$ using reader R_1 .

(2) Establishment of one linear regression equation:

$$S_{binary} = B_0 + B_1 x, \quad (12)$$

where

$$X(1D) = \begin{pmatrix} 1 & x_1 & y_1 \\ 1 & x_2 & y_2 \\ \vdots & \vdots & \vdots \\ 1 & x_n & y_n \end{pmatrix} \quad (13)$$

$$S_{|b(\text{binary})|} = \hat{\beta}_0 + \hat{\beta}_1 x_{b1}, \quad (14)$$

where S_{Binary} is the RSSI value of the actual reference label (x, y) for one dimension. B_0 and B_1 are regression coefficients for the actual reference label. $X(1D)$ is the tag coefficients for one dimension. $S_{|b(\text{binary})|}$ is the one dimension RSSI value of the boundary virtual reference label. For example, consider the first row labels are $L_1 L_2 L_3$, and L_4 on the reader R_1 that has RSSI values $s_1 s_2 s_3 s_4$; then, the coordinates of RSSI values will be $(x_1, s_1) (x_2, s_2) (x_3, s_3), (x_4 s_4)$, and by substituting these values into Eq. (6), a group of $\hat{\beta}_0$ and $\hat{\beta}_1$ values is obtained. Additionally, tag x_{b1} can be obtained on the reader R_1 with the RSSI value $S_{|b|}$. The same procedures can be performed from three other readers.

(3) Establishment of quadratic linear regression equation:

$$\begin{aligned} S_{quadratic} &= B_0 + B_1 x + B_2 x^2 \\ &= B_0 + B_1 x_1 + B_2 x_2 \rightarrow (x = x_1, x^2 = x_2) \end{aligned} \quad (15)$$

where $S_{quadratic}$ is the quadratic RSSI value of boundary virtual reference label. x_1x_2 can work as new independent variables, so the above equation can be rewritten as:

$$S_{quadratic} = B_0 + B_1x_1 + B_2x_2 \rightarrow (x = x_1, x^2 = x_2) \tag{16}$$

From the observations shown before, we used the same steps of regression Eq. (1) to get an RSSI value of the quadratic linear regression equation.

(4) Establishment of a logarithmic curve equation:

$$S_{logarithmic} = B_0 + B_1 \log x \tag{17}$$

Suppose $x' = \lg x$, then the above equation can be rewritten as:

$$S_{logarithmic} = B_0 + B_1 \hat{x} \tag{18}$$

The linear regression equations with these formulas represent the specific approach model. The abbreviations of the common formulas are given in Table 1.

Table 1. Abbreviations for common formulas.

Abbreviation	Definition
w_{1i}, w_{2i}	Weighting factor
K	Number of total tags (labels)
$S_k(T_i)$	RSSI value of the label to be positioned
n_a	Number of the neighbouring reference label
w_i	Weight at time i
(x_i, y_i)	Coordinates of the virtual reference tag
(x_0, y_0)	Actual coordinates of the tag to be located
e	Estimation error
S_{Binary}	RSSI value of tag linear regression equation
B_0, B_1, B_2	Regression coefficients of actual reference label
$S_{ b(two\ coordinate) }$	RSSI value of boundary virtual reference label
$\hat{\beta}$	Regression coefficients of boundary virtual reference label
x_{b1}, y_{b1}	Horizontal and vertical coordinate of tag
R_1	RFID reader
$S_{quadratic}$	RSSI value of quadratic linear regression equation
$S_{logarithmic}$	RSSI value of logarithmic curve equation
σ_x^2, σ_y^2	Estimated variance of 2D position
σ_s	Distance error of the standard deviation

4.1. Adding grid virtual reference tags

After computing the boundaries of the virtual reference label layout, the next step is estimating the coordinates of the start value and the RSSI value of the virtual reference tag at the $n \times n$ grid, as shown in the previously

mentioned Figure 3. Each of the four virtual reference labels or boundary virtual reference labels consists of a boundary unit grid that is evenly spaced within the grid virtual reference tags [16].

Then, each cell in the grid will be added to the $[(n + 1)^2 - 4]$ virtual reference grid label. In addition to the many actual reference labels, a unit grid refinement propagation environment can effectively weaken the estimation error in the location system caused by the multipath effect. The consideration is based on the simplified order of complexity [7], using a linear data interpolation algorithm to calculate their coordinates and the RSSI values. In the horizontal direction, the RSSI value of the virtual reference tags can be calculated based on the equation below:

$$\begin{aligned}
 S_k(T_{p,b}) &= S_k(T_{p,b}) + P \times \frac{S_k(T_{a+n,b}) - S_k(T_{p,b})}{n} \\
 &= \frac{P \times S_k(T_{a+n,b}) + (n + 1 - p) \times S_k(T_{p,b})}{n}.
 \end{aligned}
 \tag{19}$$

In the vertical direction, the RSSI value of virtual reference tags can be calculated based on the equation below:

$$\begin{aligned}
 S_k(T_{a,q}) &= S_k(T_{p,b}) + q \times \frac{S_k(T_{a,b+n}) - S_k(T_{a,b})}{n} \\
 &= \frac{q \times S_k(T_{a,b+n}) + (n + 1 - q) \times S_k(T_{a,b})}{n},
 \end{aligned}
 \tag{20}$$

where $S_k(T_{i,j})$ is the RSSI value for the i th row and the j th column of the virtual label on the reader R_k , and $a = \lfloor i/n \rfloor$, $b = \lfloor j/n \rfloor$ for $0 \leq P = i \bmod n \leq n - 10 \leq q = j \bmod n \leq n - 1$.

4.2. Selection of the neighbouring reference labels

All of the reference labels (actual reference label, virtual reference label, and boundary virtual reference label) have been obtained using the steps above for the location coordinates and the RSSI values. Additionally, each reader has an access to all of the RSSI values of the labels to be positioned. For the reference label and the label to be positioned for each reader, the RSSI values must be compared to obtain the absolute difference value. The difference between the position of the label and the label to be positioned must be smaller and closer to the location.

A fuzzy map has been established with a reference label centred in the area that has a number of equal sized areas. We select a certain threshold value that must be smaller than the absolute differential value. The position of this threshold value was set to 2, and the absolute differential value is greater than the threshold value when the position is set to 0. For each label to be positioned, k can be formed on the k fuzzy map reader, and the adjacent intersection for each fuzzy maps is ultimately optimizing the neighbouring reference label by setting all k on the fuzzy map to position 1 to remove redundant position information.

5. Evaluation of the positioning accuracy using geometric dilution of precision (GDOP)

Currently, the most common evaluation standard is the geometric dilution of precision (GDOP). GDOP is a method of distance measurement that represents the geometric relationship between the reader and the label (tag) to be positioned [17,18]. It is used to measure the impact of geometrical position on the positioning accuracy that can be expressed as follows:

$$GDOP = \sqrt{mt[(Q^T Q)^{-1}]},
 \tag{21}$$

where $mt(.)$ is the matrix of the trace, and Q is the main diagonal elements of the matrix. It is based on the coefficient matrix of series linear regression equations. The reader's position Y is known as an $R \times 1$ dimensional vector, and X is the position of the label to be located. Using the formula below the label to be positioned will be obtained:

$$X = (Q^T Q)^{-1} Q^T Y \tag{22}$$

If the estimation is unbiased in a two-dimensional hyperbolic positioning system, GDOP will be calculated as shown below:

$$GDOP = \sqrt{\sigma_x^2 + \sigma_y^2} / \sigma_s, \tag{23}$$

where σ_x^2 , σ_y^2 are the estimated variance of the two-dimensional position, and σ_s is the distance error of the standard deviation [19]. Because our study is for a two-dimensional system, the analysis firstly calculates the coordinates σ_x^2 , σ_y^2 of the three algorithms variance as shown in Table 2. The calculation of Eq. (23) is obtained under the three algorithms of GDOP value. Figure 6 shows the GDOP value of the three algorithms (BVIRE, VIRE, and LANDMARC).

Table 2. The coordinate variance and standard deviation of the three algorithms.

Symbol	LANDMARC	VIRE	BVIRE
σ_x^2	0.4261	0.0410	0.0124
σ_y^2	0.4371	0.0420	0.0189
σ_s	2.1324	0.4898	0.4236

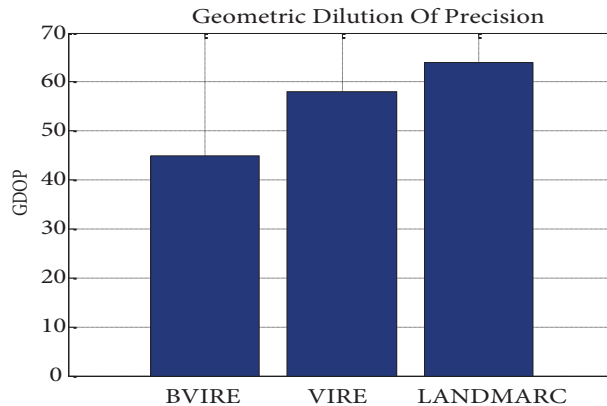


Figure 6. Geometric dilution of precision.

6. Results and analysis

The standard deployment of our system contains 16 virtual reference tags, T-RFID readers, $n \times n$ reference tags, and an object that has a tag. The region consists totally of 4 RFID readers for gathering information at 4 corners from the reference tags to be sent to the computer. Finally, the system uses the BVIRE algorithm to localize the target object. The previously mentioned Figure 4 showed a comparison between our adaptive BVIRE algorithm with other algorithms of the positioning errors that has $N=30$ intervals, and the threshold

is equal to 2. Figure 7 represents a segment of the original comparison that was shown in Figure 4 but with only six tags. Moreover, by introducing the LRM, which has an advanced utilization of more reference tags rather than a few ones, the average error in the localization accuracy of our BVIRE has been minimized to 0.31 m. Compared to LANDMARC, it enhanced the efficiency by 72.3% with an average error of 1.12 m. Also, it enhanced the efficiency by 15.14%, 86.94%, 87.5%, and 90.25% compared to VIRE, UWB, RADAR, and PinPoint respectively with an average error of 0.35 m , 2.36 m, 2.47 m, and 3.12 m. In our BVIRE algorithm, the average error of the estimated difference between the maximum and minimum value is 0.0436 m and the average error of the PinPoint algorithm estimation between the maximum and minimum is 1.22 m. When the position of the label is changed, the BVIRE algorithm has a better compatibility.

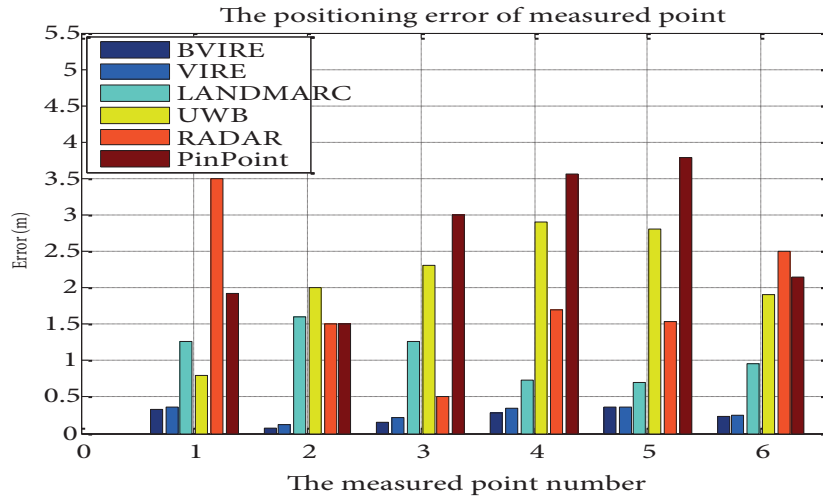


Figure 7. Comparison of positioning error with six tags.

The cumulative distribution function is commonly used to measure positioning system performance. In the analysis of the impact parameter, the BVIRE algorithm is used for the performance of CDF. Figure 8 analyses and compares the performance of CDF between BVIRE and other algorithms, where the minimum error value of our BVIRE algorithm is 0.2633 m, and the maximum error value is 0.5603 m. So, 78% of the error values have been minimized.

The data analysis of Table 3 shows that the majority of the error values in the BVIRE algorithm are within 90 cm and that the remainder of the values are within 100 cm, whereas the majority of the errors in the VIRE algorithm are within 120 cm and the remainder of the values are within 140 cm. Additionally, the probability of positioning error is larger than 120 cm, 140 cm, 160 cm, and 180 cm for LANDMARC, UWB, RADAR, and PinPoint, respectively. Therefore, the performance optimization of the BVIRE algorithm was better than the other algorithms.

Due to the addition of a virtual tag, the density has been increased without incurring any additional costs. In theory, the greater density of the virtual reference tags results in more accurate positioning. However, when the value of N is greater than a certain number, the accuracy will not be further improved. By observing Figure 9, the positioning accuracy of N=30 has been improved significantly compared with N=20. Thus, we selected N=30, based on the consideration of the computational complexity. Also, in order to remove the redundant location information, the selection of the threshold values is critical. If the chosen threshold is too large, then it will be difficult to remove the noise interference caused by the virtual reference tags. If

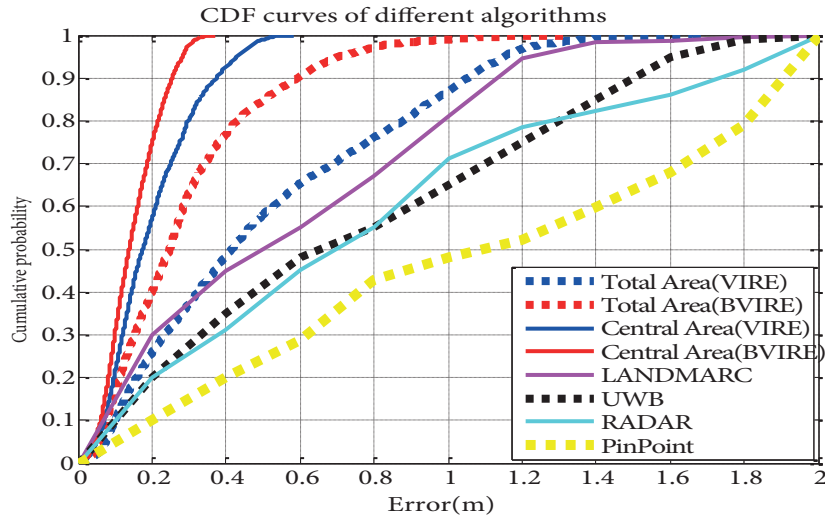


Figure 8. The cumulative distribution function of several methods.

Table 3. The details of cumulative distribution function in several methods.

	Bvire	Vire	LANDMARC	UWB	RADAR	PinPoint
CDF (20)	40%	30%	30%	20%	19%	10%
CDF (30)	65%	38%	37%	26%	25%	15%
CDF (40)	76%	48%	45%	35%	30%	20%
CDF (50)	86%	58%	50%	42%	37%	24%
CDF (60)	91%	64%	55%	48%	45%	29%
CDF (70)	95%	69%	61%	52%	50%	36%
CDF (80)	98%	75%	67%	55%	55%	42%
CDF (90)	99%	81%	71%	61%	63%	45%
CDF (100)	100%	87%	80%	66%	71%	48%
CDF (120)	100%	98%	93%	75%	78%	53%
CDF (140)	100%	100%	99%	85%	82%	59%
CDF (160)	100%	100%	99%	95%	85%	68%
CDF (180)	100%	100%	100%	99%	90%	79%
CDF (200)	100%	100%	100%	100%	100%	100%

the threshold value chosen is too small, then many neighbouring reference labels will be removed. Figure 10 shows different thresholds of BVIRE positioning algorithm results. When the threshold value is equal to 2, the arithmetic average magnitude of the error value achieved a minimum value, and when the threshold value increases to 3, 3.5, 4, 4.5, and 5 in the management of change process, the positioning error will be increased. The positioning error is relatively large if the threshold value is so small that it reaches to 0.5; this result was due to the influence of channel noise. Also, when the selection of the threshold value is too small, then this will create an omission of some neighbouring reference labels in the optimization process. Therefore, the general selection threshold value has been specified as 2.

The GDOP value of our BVIRE algorithm in the previously mentioned Figure 6 is 0.446, which has

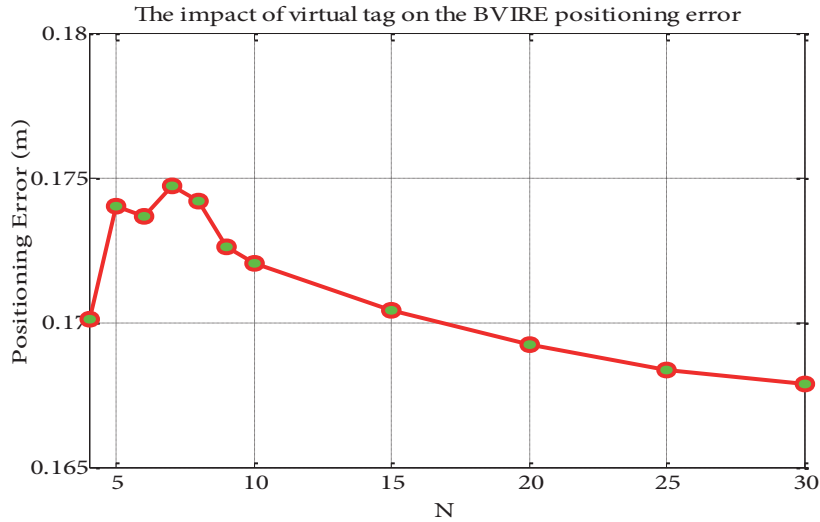


Figure 9. The impact of N on the BVIRE positioning error.

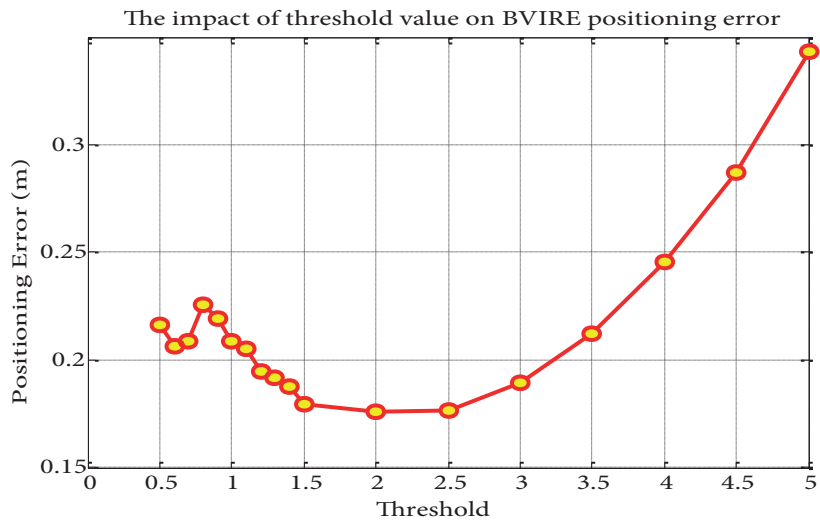


Figure 10. The impact of the threshold value on the accuracy of the positioning.

20% and 13.6% reductions compared with the LANDMARC and VIRE algorithms, respectively. Therefore, depending on the comparison results of the three algorithms, our BVIRE algorithm has the minimum geometric positional relationship, which in turn leads to a high accuracy in the positioning system.

7. Conclusion

The accuracy of the localization system on the overall and the boundary areas suffers strictly from the multipath circumstance, circumferential elements, and the costly increasing in the number of tags. Therefore, this paper presented an improved BVIRE algorithm for an indoor RFID-based localization method based on a linear regression model of the boundary virtual reference tags' signal strength to solve the mentioned issues. According to our results, we have enhanced our BVIRE algorithm by utilizing RFID techniques to further improve the positioning precision for locating the tracking object and to effectively remove the large number of

tags, which gives a higher precision in the obtained results. The contributions of this paper comprise a location's computation of the target object based on the algorithm of RFID object location identification. It has been implemented using RFID readers of an adaptable limit and active tags. The proposed BVIRE algorithm keeps out the virtual tags in an effective way to minimize the amount of reference tags and to evaluate the location of target object. The error of the evaluated location has been greatly minimized by 90.25% and 13.26% compared to PinPoint and VIRE methods, respectively. Our proposed BVIRE algorithm shows more precision in target localization as it is adapted to the dynamic environment. Since the BVIRE's prediction model is easily derived from the information of reference tags, its remodelling has a higher efficiency and better performance compared with similar approaches, where the CDF's error of BVIRE has been reduced to 68.679% and 38.765% compared with PinPoint and VIRE algorithms, respectively. Also, its GDOP has been improved by 20% compared to the LANDMARC algorithm. In addition, when the distance of the tags is specified by 1 m, the average error in the localization accuracy of BVIRE is minimized to 0.31 m. As a result, our proposed method has a better performance and accuracy in several evaluation indicators. For future work, we will improve the latency of our system and apply it to three-dimensional positioning.

References

- [1] Dardari D, Falletti E, Luise M. *Satellite and Terrestrial Radio Positioning Techniques*. 1st ed. San Diego, CA, USA: Elsevier Academic Press, 2012.
- [2] Hui L, Darabi H, Banerjee P, Jing L. Survey of wireless indoor positioning techniques and systems. *IEEE T Syst Man Cyb* 2007; 37: 1067-1080.
- [3] Lionel M, Yunhao L, Yiu CL, Abhishek P. LANDMARC indoor location sensing using active RFID. In: *IEEE 2003 Pervasive Computing and Communications Conference*; 26 March 2003; Fort Worth, Texas. USA.. pp. 407-415.
- [4] Jie Y, Qiang Y, Lionel N. Adaptive temporal radio maps for indoor location estimation. In: *IEEE 2005 Pervasive Computing and Communications Conference*; 8-12 March 2005; Kauai Island. pp. 85-94.
- [5] Want R. An introduction to RFID technology. *IEEE Pervasive Computing* 2006; 5: 25-33.
- [6] Yiyang Z, Yunhao L, Lionel M. VIRE active RFID-based localization using virtual reference elimination. In: *IEEE 2007 Parallel Processing Conference*; 10-14 September 2007; Xi'an, China. pp. 56-61.
- [7] Bolic M, Simplot D, Stojmenovic I. *RFID Systems Research Trends and Challenges*. 1st ed. Oxford, OX, UK: Wiley, 2010.
- [8] Dardari D, Conti A, Lien J, Win M. The effect of cooperation on localization systems using UWB experimental data. *EURASIP J Adv Sig Pr* 2008; 1: 1-11.
- [9] Bahl P, Padmanabhan N. RADAR an in-building RF-based user location and tracking system. In: *IEEE 2000 Proceedings of IEEE Computer and Communications Conference*; 2000; 26-30 March 2000; Tel Aviv, Israel. pp. 775-784.
- [10] Kiran J, Steven H, Sachin K. PinPoint localizing interfering radios. In: *USENIX 2013 Networked Systems Design and Implementation Conference*; 2-5 April 2013; Chicago, IL, USA: USENIX. pp. 241-254.
- [11] Tuchler M, Schwarz V, Huber A. Location accuracy of an UWB localization system in a multi-path environment. In: *IEEE 2005 Ultrawideband Conference*; 5-8 September 2005; Zurich, Switzerland. pp. 414-419.
- [12] Bahl P, Padmanabhan VN, Balachandran A. A software system for locating mobile users: design, evaluation, and lessons. *J MSTR-TR* 2001; 4: 1-12.
- [13] Youssef M, Rieger C, Shankar U, Agrawala A, Youssef A. Pinpoint an asynchronous time-based location determination system. In: *Proceedings of ACM MobiSys Conference*; 19-22 June 2006; Uppsala, Sweden: ACM. pp. 165-176.

- [14] Attia M, Moussa A, Zhao X, El-Sheimy N. Assisting personal positioning in indoor environments using map matching. *Archives of Photogrammetry, Cartography and Remote Sensing* 2011; 22: 39-49.
- [15] Stallings W. *Wireless Communication and Networks*. 2nd ed. Upper Saddle River, NJ, USA: Pearson Hall Education, 2004.
- [16] Zhang J, LuoJun Y, Wang Y. Improved wireless sensor network localization algorithm. *Journal of Computer Engineering* 2009; 35: 133-135.
- [17] Zirari S, Canalda P, Spies F. Modelling and emulation of an extended GDOP for hybrid and combined positioning system. In: *ENC-GNSS 2009 Global Navigation Satellite European Navigation Conference*; 3-6 May 2009; Naples, Campania. Italy: ENC-GNSS. pp. 35-44.
- [18] Yuan S, Wymeersch H, Win M. Fundamental limits of wideband localization–part II. *IEEE T Inform Theory* 2010; 56: 4981-5000.
- [19] Mironovova M, Havlis H. Calculation of GDOP coefficient. *Journal of the Society for Technical Communication* 2011; 5: 978-980.