

Design of an Intelligent Location Identification Scheme based on LANDMARC and BPNs

S. Chaisit, H.Y. Kung, and N.T. Phuong

Abstract—Radio frequency identification (RFID) applications have grown rapidly in many industries, especially in indoor location identification. The advantage of using received signal strength indicator (RSSI) values as an indoor location measurement method is a cost-effective approach without installing extra hardware. Because the accuracy of many positioning schemes using RSSI values is limited by interference factors and the environment, thus it is challenging to use RFID location techniques based on integrating positioning algorithm design. This study proposes the location estimation approach and analyzes a scheme relying on RSSI values to minimize location errors. In addition, this paper examines different factors that affect location accuracy by integrating the backpropagation neural network (BPN) with the LANDMARC algorithm in a training phase and an online phase. First, the training phase computes coordinates obtained from the LANDMARC algorithm, which uses RSSI values and the real coordinates of reference tags as training data for constructing an appropriate BPN architecture and training length. Second, in the online phase, the LANDMARC algorithm calculates the coordinates of tracking tags, which are then used as BPN inputs to obtain location estimates. The results show that the proposed scheme can estimate locations more accurately compared to LANDMARC without extra devices.

Keywords—BPNs, indoor location, location estimation, intelligent location identification.

I. INTRODUCTION

THE use of radio frequency identification (RFID) has been growing rapidly in various industrial applications, such as object tracking and location identification. Furthermore, RFID is applied to provide information on people, animals, and products in transit [1]. It is used for location positioning in many industries because it is simple to implement and maintain and is economical. Moreover, several applications require object location awareness. For example, workmen must consider the location detection of products stored in warehouses, and farmers must find tagged maintenance tools and equipment scattered throughout a plant. Location-aware computing has a significant potential to improve manual

S. Chaisit is Ph.D. student with Department of Tropical Agriculture and Cooperation, National Pingtung University of Science and Technology (NPUST), Neipu, Pingtung, Taiwan, ROC, and lecturer with Department of Information Technology, Rajamagala University of Technology Isan, Kalasin, Thailand. (e-mail: neng_smc@yahoo.com).

H.Y. Kung is Professor with the Department of Management Information Systems, National Pingtung University of Science and Technology (NPUST), Neipu, Pingtung, Taiwan, ROC. (e-mail: kung@mail.npust.edu.tw).

N.T. Phuong was master student with the Department of Management Information Systems, National Pingtung University of Science and Technology (NPUST), Neipu, Pingtung, Taiwan, ROC. She is now with Department of Network and Communications, Thai Nguyen University of Information and Communication Technology, Vietnam. (e-mail: phuongthimainguyen@gmail.com).

processes and to support important decision-making tasks in many fields, along with improving service quality, decreasing costs, and reducing risks.

Each indoor localization technology has different requirements and location accuracies. Among indoor localization technologies, RFID is becoming more attractive because of its relatively low cost of deployment and its suitability for indoor environments due to the no-contact, non-light-of-sight nature of RFID technology. Several applications of RFID localization have been proposed in [2] by using received signal strength indicator (RSSI) data.

An RFID localization system can also handle numerous production processes and frequent rearrangements of machinery and other technical equipments. However, multipath interference, a low probability of available line-of-sight paths, moving objects and reflecting surfaces, all these factors cause continuing problem in modeling radio propagation in indoor environments [3].

Certain radio communication characteristics can be converted to geometrical data, such as angle of arrival (AoA), time of arrival (ToA), time difference of arrival (TDoA), and RSSI [4]. Estimating location methods using RSSI data is the simplest and most economical among the four location mechanisms without additional devices and tools. RSSI data affects location accuracy influenced by multipath length, reflection, and fading effects. Although these issues are central for location estimation techniques using RSSI data, improved measurement algorithms can be controlled and exploited to reduce errors in accuracy.

The LANDMARC algorithm, a well-known localization system, minimizes the number of required RFID readers and increases location accuracy by using reference tags. The main function of LANDMARC system is to find the tracking tag's nearest neighbor's reference tags by comparing the signal strength of tracking tags with the reference tags detected by the reader [5]. However, LANDMARC performance depends mainly on the number and placement of RFID readers, as well as reference tags. Various localization methods have been introduced to improve the location accuracy of the LANDMARC method [3], [6].

Artificial neural networks (ANNs) are inspired by biological neural networks and are information-processing systems that can acquire, store, and use experiential knowledge. ANNs can automatically learn the features of inputs and create appropriate outputs without requiring users to know the hidden processes within the network [7]. backpropagation neural networks (BPNs) use an error backpropagation training algorithm to adjust the weights. Studies by Battiti [7], Borenovic [8], and Lippmann [9]

introduced localization methods using BPNs to show the relationship between inputs (signal strengths) and outputs (positions).

The Marquardt–Levenberg algorithm, a standard nonlinear least squares optimization algorithm, incorporates a backpropagation algorithm for training the feedforward neural network. The Marquardt–Levenberg algorithm outperforms other techniques in networks limited to several hundred weights [10].

As the above reasons and principles, for reducing location errors, therefore, this study proposes to combine the LANDMARC method and BPNs, in addition to examining different factors that affect location accuracy by integrating BPNs with LANDMARC algorithm.

In this paper, the contents are organized as follows. Section 2 presents some related works which inform the information of indoor location methods using RSSI values and backpropagation neural networks (BPNs). Section 3, the proposed indoor localization scheme called IL- N^2 is explained how to locate the reference tag and tracking tag positions and operate the localization algorithm. Section 4 shows the experiment and results Section 4 shows the experiment and results which the first part describes to experimental design and then explains to the results of this study. Finally, section 5 is conclusion of this study which includes application and limitations.

II. RELATED WORK

A. Indoor Location Methods using RSSI Values

In the LANDMARC algorithm [11], the location results depend on three key issues. The first issue is the placement of the reference tags. The reference tag layout affects the location accuracy of an algorithm significantly. The second issue is determining the number of reference tags needed by a reference cell to obtain the most accurate estimate of the coordinates for each unknown tracking tag. When the coordinates of the k nearest reference tags are used to locate one unknown tag, the algorithm is called a k -nearest neighbor algorithm. The third issue is determining the weights of different neighbors. The weighting (w_i) factor can be chosen in several different manners, and w_i may have same the value between the k nearest reference tags $w_i=1/k$.

LANDMARC possesses three major advantages. First, it minimizes the number of RFID readers, which is relatively inexpensive. Second, it can accommodate environmental dynamics easily because its reference tags and target tags are in the same environment. This allows it to offset many environmental factors that contribute to variations in detected signals. Third, it is more flexible, more dynamic, and more accurate, compared to other localization methods. However, LANDMARC performance depends mainly on the number and placement of RFID readers, as well as reference tags.

Various localization methods have been introduced to improve the location accuracy of the LANDMARC method [3], [6], [12]. Because the relationship between RSSI values and distance is dynamic, reader-tag distances calculated by

RSSI increase location errors. The Jiang [3] localization system reduced the severity of this problem. One reference tag in the set is considered a tracking tag and its coordinates are estimated using LANDMARC. The coordinates of the tracking tag are computed using the coordinates obtained by LANDMARC minus the average error of all reference tag coordinates. The process is repeated until the tracking tag coordinates stabilize. The stable coordinates indicate the final position of the tracking tag.

The localization method proposed by Jin et al. [13] reportedly outperforms LANDMARC for efficiency, stability, and accuracy. Only reference tags that are simultaneously detected by at least three RFID readers are used as candidate tags for neighboring tags. A triangulation mechanism calculates the coordinates of the tracking tag and the k nearest neighbor tags. This approach yields the average error for the k nearest neighbor tags and finds the final coordinates of the tracking tag.

To reduce the number of RFID readers in a localization system, Bekkali [14] introduced a location estimation system that used only two RFID readers and a number of known–location tags (reference tags). The received signal strength was used to calculate the distance between RFID readers and tags. The distance between target tags and reference tags could also be computed. A multilateration algorithm was then used to calculate the locations of target tags, and Kalman filtering minimized location errors.

B. Backpropagation Neural Networks (BPNs)

BPNs have proven effective in many problems of interest among most ANNs. A BPN has a layered structure consisting of an input layer, one or more hidden layers, and an output layer. The hidden layers in the BPN architecture make it useful for many applications. Although BPNs are applicable in networks with any number of layers, BPNs require no more than three layers in complex decision regions [10]. BPNs use an error backpropagation training algorithm to adjust the weights. Studies by Battiti [7], Borenovic [8], and Lippmann [9] introduced localization methods using BPNs to show the relationship between inputs (signal strengths) and outputs (positions).

Since the backpropagation learning algorithm was first popularized, methods of accelerating convergence in the algorithm have been studied intensively. This research falls into two categories. The first category includes ideas such as varying the learning rate or using momentum. The second category consists of standard numerical optimization techniques, the most popular of which are conjugate gradient or quasi-Newtonian methods. Other approaches apply the nonlinear least squares method. The Marquardt–Levenberg algorithm, a standard nonlinear least squares optimization algorithm, incorporates a backpropagation algorithm for training the feedforward neural network. The Marquardt–Levenberg algorithm outperforms other techniques in networks limited to several hundred weights [10].

III. PROPOSED LOCALIZATION SCHEME

The proposed indoor localization scheme is called IL-N² using the intelligent technology, artificial neural network to enhance precisely object location. It locates target tag positions in a room by combining the LANDMARC scheme with BPNs. The inputs to the proposed localization system are RSSI values measured by RFID readers, and the outputs are target tag locations. First, LANDMARC uses measured RSSI values to calculate target tag coordinates. Because the relationship between RSSI and distance is dynamic, calculated coordinates are adjusted by a BPN to increase location accuracy. The final output is tracking tag coordinate with enhanced accuracy.

The two main parts of the system are the client and server. The client includes the RFID reader and tags. The RFID reader reads the Electronic Product Code (EPC) and RSSI of tags within range of the reader and transmits these data to the server. The localization program uses the client data to calculate tag locations. The client and server are connected through a wireless network.

This IL-N² scheme was designed for two phases to support the improvement of location estimation techniques. Fig. 1 shows the proposed system architecture. The two phases in the proposed localization approach are an offline phase and an online phase.

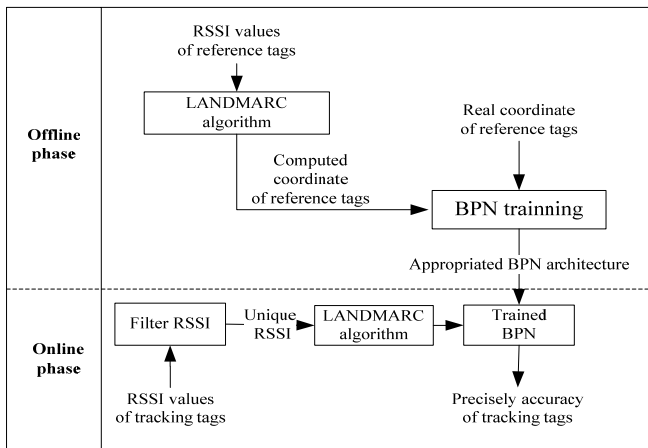


Fig. 1 The IL-N² scheme architecture

A. Offline Phase

This phase is a training phase in which the BPN analyzes the nonlinear relationship between coordinates by applying computed coordinates of the LANDMARC algorithm and by analyzing actual tag coordinates. Fig. 2, the BPN architecture obtained by this phase has two inputs and two outputs. The two inputs are the computed tag coordinates, and the two outputs are the more accurate tag coordinates. In the offline phase, the RFID reader is configured in continuous mode, and reference tags are divided into two groups. The m tags in the first group are called original reference tags and placed in a grid. The second group includes u randomly deployed tags used as reference-tracking tags, playing the roles of tracking tags. The offline phase includes three steps.

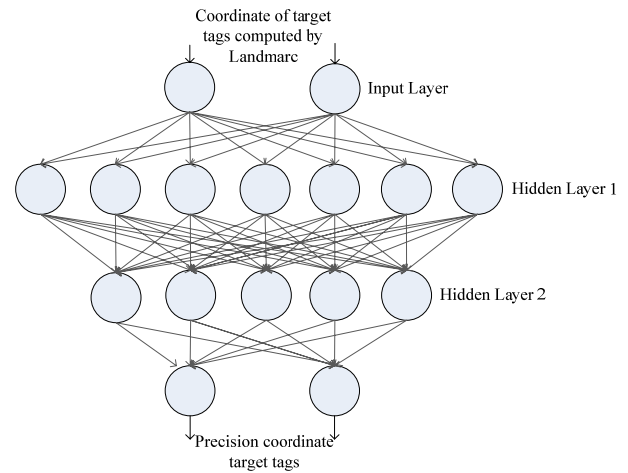


Fig. 2 The multi-layer perceptron configuration

Step 1: RFID readers detect tags and transmit their RSSI values to the server. Even tags detected by a stationary reader vary over time, and RSSI values of detected tags are also unstable. The proposed approach therefore improves localization accuracy by collecting RSSI data at 10 points in time. Each collection period is 3 s long. The final RSSI values sent to the server are average RSSI values of the 10 data collections.

Step 2: LANDMARC uses final RSSI values to calculate coordinates of reference-tracking tags. The computed and actual coordinates of reference-tracking tags are stored in a database. The LANDMARC algorithm is shown in [7].

Step 3: The BPN is trained to use the actual coordinates of the reference-tracking tags from the database constructed in step 2.

Training algorithm:

- 1) Begin
- 2) Initialize weights and learning rate
- 3) Submit all input patterns and compute network outputs
- 4) Compute errors and sum of squares of errors
- 5) Calculate Jacobian matrix
- 6) Compute ∇x
- 7) Recompute sum square of errors ($V(x)_{new}$) with $x=x+\nabla x$
- 8) Compare sum square of errors
- If $V(x) < V_{min}$ then end process
- Else if $V(x) > (V(x)_{new})$ then $\mu/\beta, x=x+\nabla x$
- $\mu=\mu.\beta$
- Go back to 5)
- End if
- End if
- 9) End

Fig. 3 Training algorithm

The BPN training process is explained in Fig. 3. Inputs are computed coordinates and outputs are estimated coordinates. These outputs are compared with the reference tags' real coordinates (target outputs) to determine the location errors. The Levenberg-Martquardt backpropagation algorithm is used

to train the neural network. The process is repeated until the location error is minimized.

B. Online Phase

Based on the BPN trained in the offline phase, a real-time location system is established. In this phase, the same experimental setup is used in the offline phase, except that the reference-tracking tags are replaced with tracking tags. The RFID reader and m reference tags are placed in a grid, and u tracking tags are randomly placed. The localization process includes three steps.

Step 1: As in the offline phase, RFID readers gather the EPC and RSSI values of tags and transmit final RSSI values of detected tags to the server.

Step 2: On the server, the LANDMARC algorithm calculates the coordinates of target tags.

Step 3: The trained BPN uses the coordinates of target tags to minimize location errors. The system outputs are target tag coordinates.

IV. EXPERIMENT AND RESULTS

A. Experiment Architecture

The performance of the IL- N^2 location estimation system was evaluated. Fig. 3 shows the experiment environment, including the landmark layout of reference tags.

The experiment was conducted to examine 3 main affected factors of the location accuracy that were density of reference tags, location of the reader, and the comparison of the location approach between the proposed scheme and traditional LANDMARC schemes. The different distances between reference tags were set with 10, 20, and 30 centimeters for vertical distance, and 5 centimeters increased of horizontal distance for each experimentally test. For example, the vertical distance between reference tags was 10 centimeters and the horizontal distance was 15 centimeters of reference tag of the horizontal distance. A RFID reader was used at five locations, L_i , 24 passive original reference tags, and seven tracking tags.

In the experiment, the reader measured the RSSI of received signal from both reference tags and tracking tags, and then sent to the server via a wireless network.

In the training phase, seven reference-tracking tags with identified locations were deployed. The locations of the seven tracking tags were recomputed using the LANDMARC algorithm. The LANDMARC scheme computed coordinates for approximately 100 tracking tags over a 16-h period with the original reference tags, the reference-tracking tags, and the reader in their original locations, as shown in Fig. 4.

On the server, the real locations of the reference-tracking tags were recorded in the database. The computed and actual coordinates for the reference-tracking tags were then used as training data in the BPN system. The BPN was retrained whenever the Root Mean Square (RMS) error after the iteration exceeded 0.1. The training process stopped when the RMS error was reduced to a value smaller than 0.1.

The processes of positioning calculation are described in the part of proposed localization scheme.

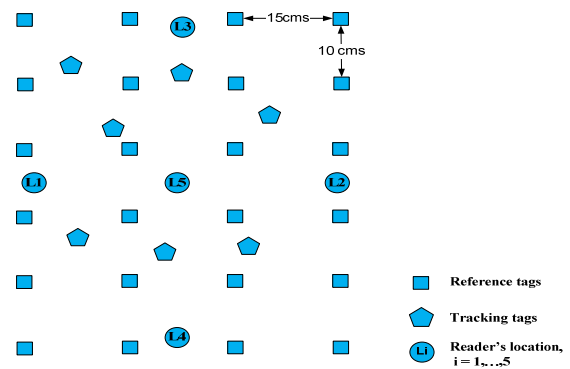


Fig. 4 Experimental environment design

The estimation error rate (EER) defined as the formula:

$$EER = (x_c - x_r) + (y_c - y_r)/2 \quad (1)$$

Where as (x_r, y_r) represent the actual coordinates of reference tags and (x_c, y_c) donates the computed coordinates of tracking tags.

The enhancing rate is the comparison the location accuracy from the proposed approach (IL- N^2) versus location accuracy from the LANDMARC as was defined as the formula of the improvement efficiency rate (IER) below;

$$IER = \frac{EER (IR - N^2) - EER (Landmarc)}{EER (Landmarc)} \cdot 100 \quad (2)$$

B. Results and Analysis

In the online phase, a series of experiments were conducted using different numbers of tracking tags in different situations. The performance of the IL- N^2 system was quantified by calculating the estimation error rate (EER) of a comparison of the actual coordinates and the computed target tag coordinates. After computing the estimation error rate for each tracking tag, the average estimation error for all tracking tags was calculated. The experiments were repeated as needed and the analysis was done using statistical technique.

Distance between reference tags. One problem in both LANDMARC and IL- N^2 is the distance between reference tags because accuracy is correlated with reference tag density. Therefore, increasing reference tag density certainly assists improve the accuracy of IL- N^2 . To determine the appropriate distance between reference tags, the estimation error rates were compared for varying distances between reference tags. The localization process was experimentally repeated with different distances between reference tags, including 10, 20, and 30 cm. Fig. 5 shows the comparison of the estimation error rate for different densities of reference tags. The estimation error rate increases as distance between reference tags increases. For all reference tag densities, the IL- N^2 approach outperformed LANDMARC.

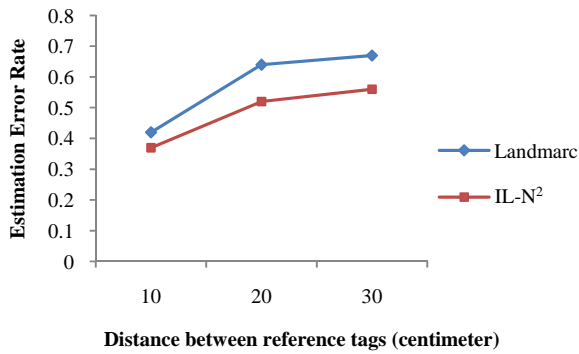


Fig. 5 Comparison between different distances of reference tags based on EER

Effects of Reader Location. Reader location is another key factor in system localization accuracy. Experiments to identify the read locations with the lowest estimation error rates showed that the reader should be placed at the center of the environment to obtain the lowest error. Fig. 6 shows the estimation error rate for the five reader locations.

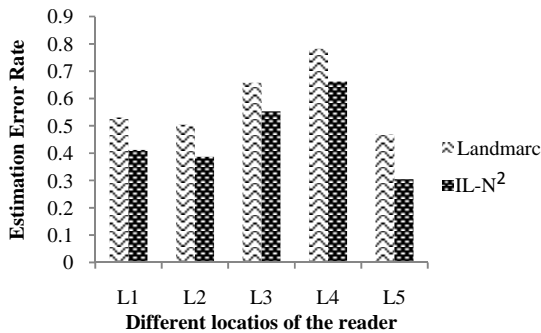


Fig. 6 Comparison of difference reader's locations based on EER

Comparison between IL-N² and LANDMARC. To measure the performance improvement obtained using the IL-N² approach, estimation error rates were compared between IL-N² and traditional LANDMARC. Fig. 7 shows that in both methods the error rate increased in conjunction with the number of tracking tags. However, the proposed method achieved a lower minimum error rate with a higher speed than the LANDMARC method. Performance enhancement was achieved by training the BPN in the offline phase. The advantage of BPN is its capability to reveal nonlinear relationships between computed and actual tag coordinates. After repeating the procedure for another 16 h with the same placement, the estimation error rate changed in different small values, but the IL-N² still achieved superior localization performance to LANDMARC approximately.

The enhancing efficiency rate is a percentage indicating the performance difference between IL-N² and LANDMARC. Table I illustrates that IL-N² outperforms LANDMARC by an average of 32 percent. Therefore, the proposed method is 32 percent more accurate compared to LANDMARC.

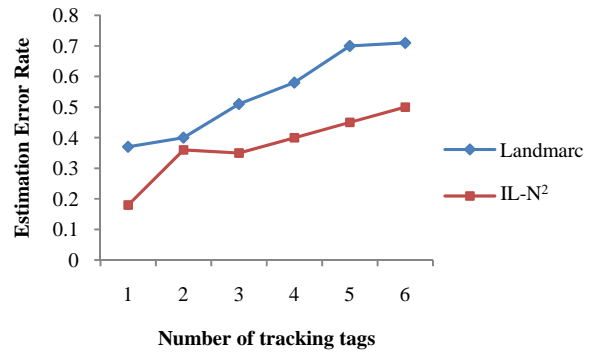


Fig. 7 Comparison of LANDMARC and IL-N² based on EER

It is also noted that the number of tracking tag reading simultaneously resulted to the location accuracy in different values, in particular when the number of tracking are equal one and two tracking tag. On the other hand, when the number of tracking tag is equal 3 or more, the difference of the calculated location accuracy differs only slightly. However, in the overall result of the experiment can be found that the effectiveness of IL-N².was increased to 32 per cent.

TABLE I
 ENHANCING RATE OF IL-N² VERSUS LANDMARC ALGORITHM

Number of tracking tag	Improving Efficiency Rate (%)
1	46.3
2	10.2
3	33.3
4	29.5
5	36.0
6	30.6

V. CONCLUSION

The localization scheme (IL-N²) uses LANDMARC combined with BPNs to optimize location accuracy. The two-phase scheme includes an offline phase and an online phase. The offline phase first uses LANDMARC to obtain coordinates of reference-tracking tags. Computed and real coordinates of these reference-tracking tags are stored in a database. The computed and real coordinates of reference tags are then trained using a BPN training process. Completion of a trained BPN architecture in the online phase reduces location errors. In the online phase, LANDMARC uses the RSSI values to estimate tracking tag coordinates. Performance comparisons show that the proposed system is more accurate compared to LANDMARC without extra devices and addition costs. Besides, the reader location should be located at the central of the land mark layout, including the density of the reference tag should be related to the spaces.

As the results, the design of an intelligent location identification scheme (the IL-N²) and the experiment in laboratory were found that the positions of all experimental objects were precisely calculated. The results of this study can be applied for searching very small or important objects, kept in tiny or difficult finding areas, such as valuable books, significant documents on shelves, high-valued drugs in sealed box, and etc. Moreover, these results support that the location

identification scheme using RSSI is the inspiration to enhance the location scheme with algorithm design and economical technique. Finally, it should be widely utilized in various objects' location identification because of its many advantages; i.e. its accuracy and minimal error, including low cost of deployment.

Although, the results of the experiment was summarized that the design of the position estimating approach resulted to the estimated location accuracy, this study still found some limitations. The first, there was only a reader for using in the performance. Moreover, there was only one type of passive tag qualified to the close distance of RSSI values.

To determine the most appropriate distance between the reference tag and the density of the reference tag that is exactly how it should be? and to determine the number of reference tag to suit various size area that should be how many for each area, are important issues and needed to be find out and further research in the future for the real region implementation.

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