A Modified Probability Neural Network Indoor Positioning Technique

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***Abstract*—This paper presents an indoor positioning technique using a modified probabilistic neural network (MPNN) scheme. It measures the received signal strength (RSS) between an object and stations, and then transforms the RSS into distances. A MPNN engine determines coordinate of the object with the input distances. The experiments are conducted in a realistic ZigBee sensor network. The proposed approach performs significantly better than triangulation technique when the RSS data are unstable. It can be efficiently applied to applications of location based service (LBS).**

Keywords- wireless sensor network; received signal strength; indoor positioning; modified probabilistic neural network.

I. INTRODUCTION

The global positioning system (GPS) is the most widely used satellite-based navigation and time transfer system for determining a position on the Earth's surface by comparing radio signals between several satellites [1]. The GPS provides accurate positioning functions using triangulation method [2] which finds a particular place on earth by the distances between the GPS hand-held receiver and the GPS satellites. Currently, GPS technique is applied for various electronic devices to enable location-based service, such as navigation, tourism, and military applications etc. However, GPS is a line-of-sight transmission method which cannot be used in indoor environment. Compare with outdoor orient GPS, in the indoor environment, the positioning system function also plays important role in many applications. Indoor positioning system (IPS) for related applications such as commercial, smart building, public safety, and military raises new challenges for positioning problem.

Furthermore, wireless technologies are available options for developing IPSs in the building, such as wireless local area network (WLAN) [3], wireless sensor network (WSN) [4], radio frequency identification (RFID) [5], Bluetooth [6], etc. Zigbee is one of the popular wireless sensor protocols. It takes full advantage of a powerful physical radio specified by IEEE 802.15.4 [7]. It has been designed to provide features such as low cost, low power consumption, simply implemented and high density of nodes per network. In addition, the IPS can implements a distributed computation algorithm that uses received signal strength indicator (RSSI) values from known reference nodes [7]. The most commonly used techniques for automatic location sensing are scene analysis, proximity, and triangulation [8][9]. Firstly, the scene analysis is a location sensing technique, which uses features of a scene observed to determine the location of the objects in the scene. Secondly, the proximity method [8] determines object's location when the object is near a reference node. Thirdly, the triangulation location sensing techniques calculates the object's position by geometric properties of triangles [10][11]. It determines 2-D position by lateration which requires distance measurement between the object and at least three non-collinear points. Basically, the IPSs always uses above techniques individually or in combination. To estimate the mobile position in WSN, the system needs to measure RSS values between object and known reference nodes. However, the RSS cannot be transformed to correctly distance. Frequency signals have transmission constraints in indoor environment that influences the accuracy of positioning systems. Normally, the IPSs affected by the RSS measurement errors. Moreover, the position of object cannot be calculated. Therefore, an algorithm which can determine correctly location of object with unreliable RSS is useful for establishing robust IPS.

This paper proposes a neural network approach to enhance to IPS estimation accuracy. Neural network is a fault tolerance design methodology which can be applied in developing both linear and non-linear systems. Hence, the proposed method is able to estimate an object's position with distorted RSS.

II. INDOOR POSITIONING PRINCIPLES & PROBLEMS

This section presents the principle of basically position estimation algorithm which using RSS and describes the positioning problem formulation.

A. Received Signal Strength

The RSS based positioning approach estimates the position from samples of RSS vectors which can be obtained from wireless sensors hardware. The functionality should be worked at least three non-collinear fixed sensor points. RSS based IPSs are propagation-loss equations which measure RSS values to build signal strength map in a local area. The map can be generated using any method to measure the distance between RSS devices. Radio propagation model with positioning algorithm is used to determine the object's position according to the RSS map [9]. Typically, The RSS values [12] are within the interval [-40 dBm, -95 dBm]. The industry standard always defines RSS value by 256 intervals.

B. Geometric Mathematical Algorithm

The relation structure diagram of undetermined object and wireless sensors is shown in Figure 1. The object's coordinate which can be estimate is defined to (x_O, y_O). Suppose A, B, and C are nodes of wireless sensors. The corresponding coordinates are (x_A, y_A), (x_B, y_B), and (x_C, y_C). The r_A, r_B, and r_C are the distance between object and sensors.

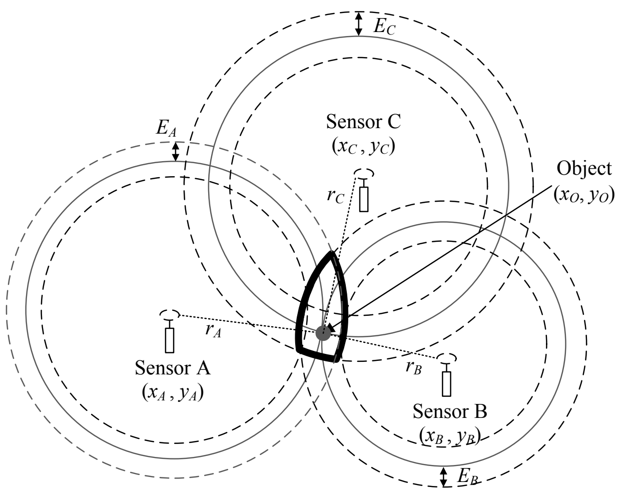

Figure 1. The relation structure diagram of unknown object and wireless sensors.

The geometric triangulation mathematical model can be applied to find the object's coordinate (x_O, y_O). The general Euclidean distance (r_A, r_B, r_C) solutions can be calculated by,

$$\begin{aligned} r_A &= \sqrt{(x_A - x_O)^2 + (y_A - y_O)^2} \\ r_B &= \sqrt{(x_B - x_O)^2 + (y_B - y_O)^2} \\ r_C &= \sqrt{(x_C - x_O)^2 + (y_C - y_O)^2} \end{aligned} \tag{1}$$

and then

$$\begin{aligned} (r_A)^2 - (r_B)^2 &= -2x_A x_O - 2y_A y_O - x_B^2 - y_B^2 \\ &\quad + 2x_B x_O + 2y_B y_O + x_A^2 + y_A^2 \\ (r_A)^2 - (r_C)^2 &= -2x_A x_O - 2y_A y_O - x_C^2 - y_C^2 \\ &\quad + 2x_C x_O + 2y_C y_O + x_A^2 + y_A^2 \end{aligned} . \tag{2}$$

Equation (2) can be represented as a matrix equation by

$$\begin{aligned} &\begin{bmatrix} (r_A)^2 - (r_B)^2 + \left(x_B^2 + y_B^2 - x_A^2 - y_A^2\right) \\ (r_A)^2 - (r_C)^2 + \left(x_C^2 + y_C^2 - x_A^2 - y_A^2\right) \end{bmatrix} = \\ &\begin{bmatrix} 2(x_B - x_A) & 2(y_B - y_A) \\ 2(x_C - x_A) & 2(y_C - y_A) \end{bmatrix} \begin{bmatrix} x_O \\ y_O \end{bmatrix}. \end{aligned} \tag{3}$$

Consider N sensors, the matrix is given as

$$\begin{aligned} &\begin{bmatrix} (r_1)^2 - (r_2)^2 + \left(x_2^2 + y_2^2 - x_1^2 - y_1^2\right) \\ (r_1)^2 - (r_3)^2 + \left(x_3^2 + y_3^2 - x_1^2 - y_1^2\right) \\ \vdots \\ (r_1)^2 - (r_N)^2 + \left(x_N^2 + y_N^2 - x_1^2 - y_1^2\right) \end{bmatrix} = \\ &\begin{bmatrix} 2(x_2 - x_1) & 2(y_2 - y_1) \\ 2(x_3 - x_1) & 2(y_3 - y_1) \\ \vdots & \vdots \\ 2(x_N - x_1) & 2(y_N - y_1) \end{bmatrix} \begin{bmatrix} x_O \\ y_O \end{bmatrix}. \end{aligned} \tag{4}$$

Matrices $\overline{\mathrm{A}}$ and $\overline{\mathrm{B}}$ are defined as

$$\overline{\mathrm{A}} = \begin{bmatrix} 2(x_2 - x_1) & 2(y_2 - y_1) \\ 2(x_3 - x_1) & 2(y_3 - y_1) \\ \vdots & \vdots \\ 2(x_N - x_1) & 2(y_N - y_1) \end{bmatrix}$$

and (5)

$$\overline{\mathrm{B}} = \begin{bmatrix} (r_1)^2 - (r_2)^2 + \left(x_2^2 + y_2^2 - x_1^2 - y_1^2\right) \\ (r_1)^2 - (r_3)^2 + \left(x_3^2 + y_3^2 - x_1^2 - y_1^2\right) \\ \vdots \\ (r_1)^2 - (r_N)^2 + \left(x_N^2 + y_N^2 - x_1^2 - y_1^2\right) \end{bmatrix}.$$

Hence, the object's coordinate can be calculated by

$$\begin{bmatrix} x_O \\ y_O \end{bmatrix} = \left(\overline{\mathrm{A}}^{\mathrm{T}}\overline{\mathrm{A}}\right)^{-1} * \left(\overline{\mathrm{A}}^{\mathrm{T}}\overline{\mathrm{B}}\right). \tag{6}$$

Finally, solve (6), the object's coordinate (x_O, y_O) can be obtained.

III. Problem Statements

As mentioned above, geometric mathematical method is usually effective in determining the coordinate of unknown object. However, the radio frequency based positioning has limitations in real environment, such as multi-path, diffraction, and reflection etc. Generally, the environment effects within buildings are strongly influenced by the structures and used wall materials. Those effects will cause fault RSS measurement. It raises the challenge in designing an IPS. Due to the uncertain RSS, triangulation mathematical model positioning techniques cannot accurately determine the position of object. Therefore, a more robust approach with fault tolerance ability is required for IPS problem.

IV. Modified Probabilistic Neural Network Indoor Positioning System

Probabilistic neural network (PNN) is a supervised neural network proposed by Specht [13]. It is a classification method based on established statistical principles and Bayes decision rule. Basically, PNN network has four layers including input layer, hidden layer, summation layer, and decision layer.

In the classification problems, PNN network provides its efficiency and reliable easiness. All input vectors can be mapped into the same output phase state vector. However, for the function approximation cases, PNN could not be used where there is more than one local region in the input vector space. To solve this limitation, the modified probabilistic neural network (MPNN) was initially proposed by Zaknich [14]. It involved uniquely identifying only those vectors in local hypercube regions of the input vector space that mapped to given quantized outputs. In this study, MPNN is used to estimate the coordinate of object.

The modified probabilistic neural network used to be the indoor positioning system is named MPNN-IPS in this paper. The general MPNN architecture is shown in Figure 2.

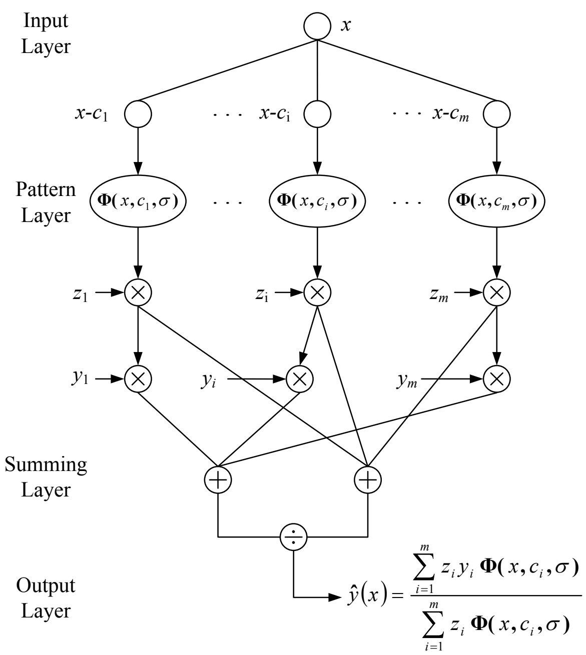

Figure 2. MPNN Architecture

The architecture of MPNN consists of input layer, pattern layer and summing layer. The algorithm of MPNN is described as follows. Firstly, a set of class vectors $\mathbf{C}$ i.e., IPS training data, is given by

$$\mathbf{C} = \{c_1, c_2, \ldots, c_m\} \tag{7}$$

where m is the number of class vectors $\mathbf{C}$.

For each input value x (i.e., distance data of object transformed from RSS set), a corresponding scalar output y_i which is the most mapping class c_i.

The output vector is

$$\mathbf{y} = \{y_1, y_2, \ldots, y_m\} \tag{8}$$

where m is the number of classes.

The probability density function of MPNN is defined as

$$\Phi(x, c_i, \sigma) = \exp\left(-\frac{(x-c_i)^T (x-c_i)}{2\sigma^2}\right) \tag{9}$$

where σ is the smoothing parameter of Gaussian function.

Finally, the output $\hat{y}$ i.e., coordinate of object can be obtained by

$$\hat{y}(x) = \frac{\sum_{i=1}^{m} z_i y_i \, \Phi(x, c_i, \sigma)}{\sum_{i=1}^{m} z_i \, \Phi(x, c_i, \sigma)} \tag{10}$$

where z_i is the number of samples in class vector c_i.

V. Experimental Result

To evaluate the performance of proposed system, this section presents the experimental results of the indoor positioning system based on the proposed MPNN IPS. The platform used in this study is a ZigBee/IEEE 802.15.4 development module [12]. This module includes an 8-bit CPU core which is an enhanced version of the industry standard 8051 core. The test region is deployed using four ZigBee wireless sensors and one estimated object device in the indoor environment. For testing the performance of proposed system, 196 data (features) were measured within an interval of 0.4 meter in an area of 6 square meters (m^2) as shown in Figure 3. Each feature is a RSS vector $R_i = [r_1, r_2, r_3, \ldots r_N]$ that measured from each of the N base stations with wireless single receiver. In this study, N is defined as 4.

The distribution of triangulation method estimates result as shown in Figure 4. The triangulation method calculated result is imprecise, and some coordinates of result are outside the test area. Figure 5 shows the distribution of the proposed approach estimated results. It demonstrates that the error of MPNN method evaluating result is less than the triangulation method. Moreover, all coordinates of result nodes are inside the test area. The simulation results are summarized in Table 1. It describes the estimation error and standard deviation for comparing the performance between triangulation method and the proposed IPS. The experiments describe the MPNN method is valid for IPS problem. Besides, MPNN provides better performance and stable estimation than triangulation method.

Table I. The estimation results comparison of triangulation and MPNN method.

unit (m)	Triangulation	MPNN
Absolute Mean Error	1.692095	1.2282
Stander Deviation	0.911634	0.770026

VI. Conclusions and Future Work

In the indoor environment, the RSS based positioning techniques estimates imprecision result by interference from multi-path, diffraction, and reflection effects. Therefore, this paper proposed a new MPNN IPS to determine the location of object when the measured distances are distorted. The demonstrate shows that the MPNN performed better than triangulation method. Besides, the determination results of MPNN are more stable. The proposed approach is advanced to establish as hardware or embedded system. The future studies will put more emphasis on RSS propagation-loss equations and positioning antenna design for measuring accuracy distances between the wireless devices.

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References

[1] P. K. Engee, "The global positioning system: Signals, measurements and performance," Int. J. Wireless Inf. Netw., vol. 1, no. 2, pp. 83–105, 1994.

[2] H. Liu, H. Darabi, P. Banerjee, and J. Liu. "Survey of wireless indoor positioning techniques and systems," IEEE Trans. on Systems, Man, and Cybernetics, vol. 37, no. 6, pp.1067-1077, 2007.

[3] A. Kotanen, M. Hannikainen, H. Leppakoski, and T. D. Hamalainen, "Positioning With IEEE 802.11b Wireless LAN", 14th IEEE Proceedings on Personal, Indoor and Mobile Radio Communications, vol. 3, pp.2218- 2222, 2003.

[4] Y. Ohta, M. Sugano, and M. Murata, "Autonomous Localization Method in Wireless Sensor Networks," Third IEEE International Conference on PerCom 2005 Workshops, 2005, pp.379 – 384.

[5] H. D. Chon, S. Jun, H. Jung, and S. W. An, "Using RFID for Accurate Positioning" Journal of Global Positioning Systems, vol. 3, no.1-2, pp.32-39, 2004.

[6] A. E. S. Salazar, "Positioning Bluetooth and Wi-Fi systems," *IEEE Trans. on Consumer Electronics*, vol. 50, pp. 151-157, 2004.

[7] http://www.zigbee.org/

[8] J. Hightower and G. Borriello, "Location sensing techniques," Technical Report UW CSE 2001-07-30, Department of Computer Science and Engineering, University of Washington, 2001.

[9] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," IEEE INFOCOM 2000, vol. 2, pp. 775-784, 2000.

[10] http://www.cs.washington.edu/research/portolano/papers/UW-CSE-01-07-01.pdf.

[11] J. R. Beveridge, C. Graves, and C. E. Lesher, "Local Search as a Tool for Horizon Line Matching," Technical Report CS-96-109, Colorado State University, 1996.

[12] https://www.silabs.com/products/mcu/zigbeemcu/Pages/default.aspx.

[13] D. F. Specht, "Probabilistic neural network for classification, map, or associative memory," Proc. of the IEEE International Conference on Neural Network, vol. 1, pp. 525-532, 1988.

[14] A. Zaknich, "Introduction to the modified probabilistic neural network for general signal processing applications," IEEE Trans. on Signal Processing, vol. 46, no. 7, pp. 1980-1990, 1998.

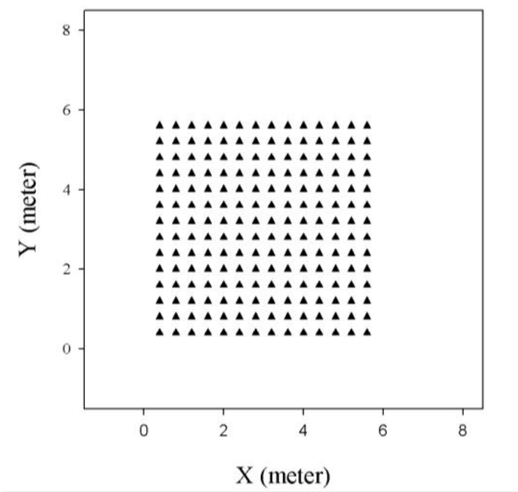

Figure 3. Distribution of 196 test nodes

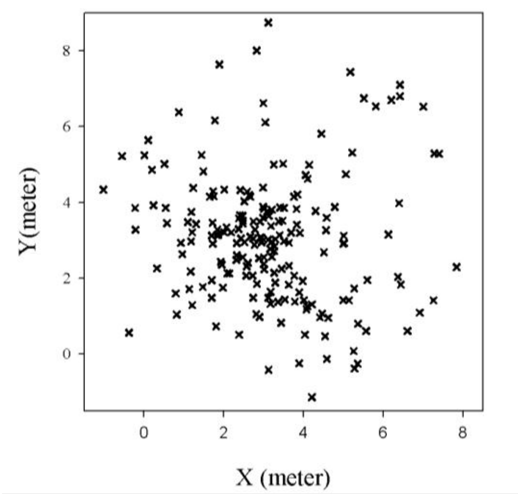

Figure 4. Distribution of triangulation method result.

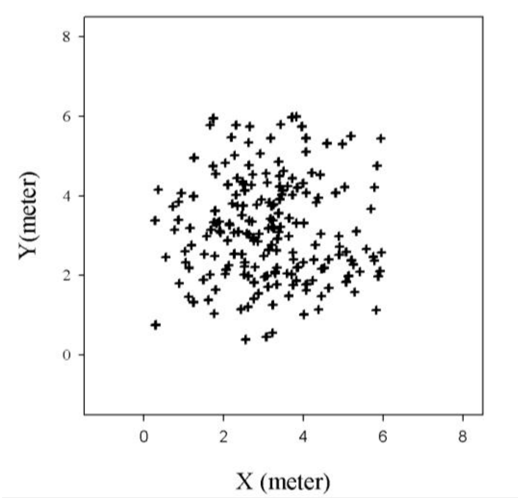

Figure 5. Distribution of MPNN method result.