ANN Indoor Position Determination Based on Area Correlation in WLAN Environment

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***Abstract*—Indoor position determination based on artificial neural network (ANN) with area correlation is proposed in this paper. For any pattern matching based algorithm in WLAN environment, the characteristics of received signal strength (RSS) or signal to noise ratio (SNR) to multiple access points (APs) are utilized to establish radio map in the off-line phase, and in the on-line phase, the actual two or three dimensional coordinates of mobile terminals (MTs) are estimated based on the comparison between the new recorded RSS or SNR and fingerprints stored in radio map. Although the feed-forward ANN with three layers is sufficient to approximate any continuous function to a desired accuracy and describe any mapping relationship between input and output values, the optimal types of input vectors for different actual complex indoor environments is difficult to be determined. So in this paper, the correlation between SNR from different APs and physical area is analyzed for the purpose of establishing multiple ANN subsystems for separate sub areas. Feasibility and effectiveness of this method is verified according to the experimental comparison with K-nearest neighbor (KNN), probability and ANN methods without area division.**

Keywords-WLAN; indoor location; ANN; correlation; radio map

I. INTRODUCTION

With the increasing interests of context-aware ubiquitous environments, WLAN based indoor location systems has get much more attention recently. Not just for military use, but also civil application, WiFi based location awareness applications include, but are not limited to, emergency service, tracking, exploration, guiding and escorting system, finder, positioning of entities in large warehouses [1].

Currently, any localization techniques can be classified into distance based and pattern matching based algorithms. For the distance based algorithm, such as global positioning system (GPS), cellular systems for outdoor environment and proximity detection (PD), time of arrival (TOA), time difference of arrival (TDOA) and angle of arrival (AOA) method for indoor location applications, because of the non line of sight (NLOS) multi-path effects induced by building geometry, human body absorption, dynamic nature of environments, requirements of special receiving equipments and interference of neighboring devices, the wide application of this method for indoor location has been restricted [2,3]. So, the pattern matching method has been researched and widely used, especially for WLAN based location technology, such as personal digital assistant (PDA) or notebook computer with wireless network card. Furthermore, there is large number of terminals in real living environments and non-registered 2.4GHz ISM band and free wireless license are utilized for 802.11 b/g protocol [4].

The life cycle of pattern matching method for any WLAN location awareness system can be separated into two distinct phases [5], the off-line phase and on-line phase which are also defined as calibration phase and estimation phase. In the off-line phase, the samples of the beacon signal strength at different referent points (RPs) are recorded for the purpose of establishing radio map, and in the on-line phase, the estimated coordinates of MTs are obtained by matching the RSS or SNR with the fingerprints pre-stored in the radio map [6].

Because of its ability of reducing time cost of the layout of indoor location system, saving storage cost of the radio map establishment and enhancing real-time capacity in the on-line phase [7-9], ANN method becomes one of the popular algorithms for indoor location system recently [10]. In this paper, multiple ANN subsystems are separately established for different location areas based on the correlation analysis.

The remainder of this paper is organized as follows. In section 2, mathematical model of ANN indoor location system is analyzed. In section 3, the establishment of radio map is proposed based on the avoidance of multi-mode phenomenon. In section 4, area correlation is discussed for the purpose of selecting the optimal input vectors for ANN system training based on the analysis of distance relativity between mean value of SNR and different spatial directions. In section 5, location performance of ANN based on area division is compared with ANN without division. Conclusions are presented in section 6.

II. MATHEMATIC DESCRIPTION OF ANN MODEL

A. Proposal of ANN Method for Indoor Location

Although the traditional methods based on fingerprinting architecture, such as nearest neighbor (NN), KNN and probability methods can provide high location accuracy and precision in some special conditions, the time cost and storage load for the WLAN signal acquisition and preprocessing are much larger and heavier, and also, the adaptability for different complex and dynamic indoor environmentd is terrible.

So, in order to balance the location performance and cost of system establishment, ANN based location method is proposed, which can be trained in the off-line phase by a large number of input training samples (SNR from different APs). After the

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training, the weights and biases are modified in order to make the ANN system satisfy proper mapping relationship between inputs (SNR) and corresponding outputs (position coordinates) and adapt to new recorded signal samples which also means great generalization ability.

B. Three Layer Feed-forward ANN Model

In this paper, the three layer feed-forward ANN shown in Fig.1 is selected as the initial ANN topological structure and back propagation method (BP) is utilized to minimize location error based on the optimization of weights and biases.

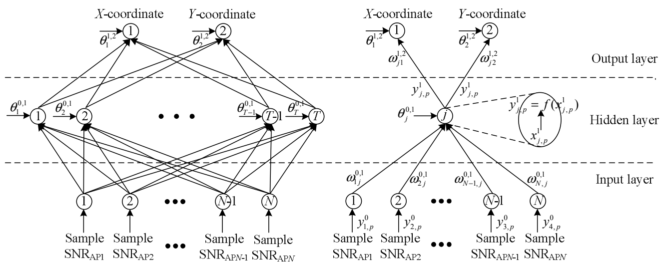


Figure 1. Topological structure of ANN for indoor location system

Where,

- $\omega_{ij}^{l-1,l}$ denotes the connection weight from layer l-1 to l;
- $x_{j,p}^{l}$ (l=1, 2) denotes the output value of perceptron j in layer l for sample p;
- $y_{j,p}^{l}$ (l=0, 1) denotes the input value from perceptron j in layer l for sample p.

Input layer, hidden layer and output layer are separately denoted as layer 0, 1 and 2. Sigmoid function $f(\cdot)$ is used as the transition function of each perceptron. Following relationship shown in Eq.(1) should also be satisfied for each perceptron.

$$\begin{cases} x_{j,p}^{l} = \sum_{j=1}^{N(l-1)} \omega_{ij}^{l-1,l} y_{j,p}^{l-1} - \theta_{j}^{l-1,l}, \quad l=1,\ 2 \\ y_{j,p}^{l} = f(x_{j,p}^{l}) = \dfrac{1}{1+\exp(-x_{j,p}^{l})}, \quad 0 < f(x_{j,p}^{l}) < 1 \\ N(l) = \begin{cases} N, & l=0 \\ T, & l=1 \end{cases}, \quad j = \begin{cases} 1,\cdots,T, & l=1 \\ 1\ or\ 2, & l=2 \end{cases} \end{cases} \tag{1}$$

Based on the iterative modification of weights and biases, ANN based indoor location system is optimized for purpose of acquiring minimal training error E_{train} defined in Eq.(2).

$$E_{train} = \frac{1}{2}\sum_{p}^{P}\left\|\boldsymbol{Y}_{p}^{2} - \boldsymbol{Z}_{p}\right\|^{2} = \frac{1}{2}\sum_{p=1}^{P}\sum_{j=1}^{2}(y_{j,p}^{2} - z_{j,p})^{2} \tag{2}$$

Where,

- P denotes the number of training samples.
- $z_{1,p}$ and $z_{2,p}$ separately denote the expected x and y coordinates in training phase.
- $y_{1,p}^{2}$ and $y_{2,p}^{2}$ separately denote the output x and y coordinates.

BP iterative process for the acquirement of optimal weights and biases is shown by Eq.(3).

$$\begin{cases} \omega_{ij}^{l-1,l}(k+1) = \omega_{ij}^{l-1,l}(k) - \dfrac{\alpha \partial E_{train}}{\partial \omega_{ij}^{l-1,l}(k)} = \omega_{ij}^{l-1,l}(k) - \alpha\sum_{p=1}^{P}\delta_{j,p}^{l}(k) y_{j,p}^{l-1}(k) \\ \theta_{j}^{l-1,l}(k+1) = \theta_{j}^{l-1,l}(k) - \beta\sum_{p=1}^{P}\delta_{j,p}^{l}(k) y_{j,p}^{l-1}(k) \\ \delta_{j,p}^{l}(k) = \begin{cases} f'[x_{j,p}^{l}(k)]\sum_{m=1}^{2}\delta_{m,p}^{l+1}(k)\omega_{jm}^{l,l+1}(k), & l=1 \\ [y_{j,p}^{l}(k) - z_{j,p}]f'[x_{j,p}^{l}(k)], & l=2 \end{cases} \\ i = \begin{cases} 1,\cdots,N, & l=1 \\ 1,\cdots,T, & l=2 \end{cases}, \quad j = \begin{cases} 1,\cdots,T, & l=1 \\ 1\ or\ 2, & l=2 \end{cases}, \quad k \le K_{iter} \end{cases} \tag{3}$$

Where,

- α and β separately denote learning rate of weights $\omega_{ij}^{l-1,l}$ and biases $\theta_{j}^{l-1,l}$.
- K_{iter} denotes the maximum iteration number.

III. AREA DIVISION METHOD

A. Relativity Analysis between Distance and RSS

For the purpose of establish optimal ANN-based location subsystems for different divided target area, the relativity between distance and RSS received from different APs should be analyzed firstly. The room 1211 is selected as the test environment because of its regular shape and excellent coverage performance by AP1, 2, 3, 8 and 9. Layout of experimental environment is shown in Fig.2.

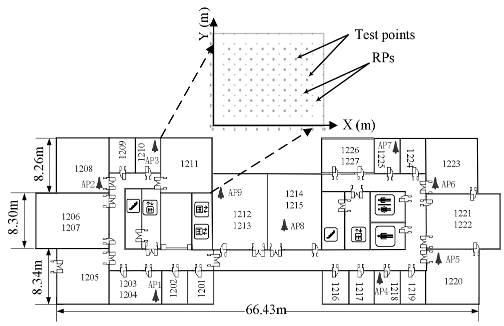


Figure 2. Layout of experimental environment

And the mean values from different APs and X or Y coordinates correlation coefficients $R_{k,X,j}$ and $R_{k,i,Y}$ are calculated by Eq.(4).

$$\begin{cases} R_{k,X,j} = \dfrac{\sum_{i=1}^{9}(M_{k,i,j} - \overline{M_{k,i,j}})(i-\bar{i})}{\sqrt{\sum_{i=1}^{9}(M_{k,i,j} - \overline{M_{k,i,j}})^{2}\sum_{i=1}^{9}(i-\bar{i})^{2}}} \\ R_{k,i,Y} = \dfrac{\sum_{j=1}^{8}(M_{k,i,j} - \overline{M_{k,i,j}})(j-\bar{j})}{\sqrt{\sum_{j=1}^{8}(M_{k,i,j} - \overline{M_{k,i,j}})^{2}\sum_{j=1}^{8}(j-\bar{j})^{2}}} \end{cases} \tag{4}$$

Where, $M_{k,i,j}$ denotes the mean value of RSS from APk at RP (i,

j). $\overline{M_{k,i,j}}$ denotes the mean value of $M_{k,i,j}$. And the correlation coefficients in target location area are shown in Table 1 and 2.

TABLE I. CORRELATION COEFFICIENT IN *X* DIRECTION

	$R_{1,X,j}$	$R_{2,X,j}$	$R_{3,X,j}$	$R_{8,X,j}$	$R_{9,X,j}$
j=1	-0.736	-0.869	-0.452	0.556	0.020
j=2	-0.208	-0.338	-0.618	0.147	-0.046
j=3	0.238	-0.267	-0.390	0.251	0.560
j=4	0.139	0.598	0.280	0.013	-0.099
j=5	0.832	0.406	0.197	-0.490	-0.562
j=6	0.671	0.802	-0.816	-0.292	-0.569
j=7	0.422	0.960	-0.516	-0.758	-0.558
j=8	0.667	0.958	-0.004	-0.025	-0.150

TABLE II. CORRELATION COEFFICIENT IN *Y* DIRECTION

	$R_{1,i,Y}$	$R_{2,i,Y}$	$R_{3,i,Y}$	$R_{8,i,Y}$	$R_{9,i,Y}$
i=1	-0.861	-0.822	-0.176	-0.417	0.084
i=2	-0.665	-0.887	-0.089	-0.743	0.442
i=3	-0.868	-0.953	0.451	-0.869	0.416
i=4	-0.813	-0.923	0.245	-0.412	0.308
i=5	-0.807	-0.859	0.432	-0.095	-0.195
i=6	-0.129	-0.903	-0.233	-0.194	-0.100
i=7	0.486	-0.053	0.107	-0.470	-0.215
i=8	-0.618	-0.272	0.127	-0.494	-0.177
i=9	-0.629	-0.781	-0.166	-0.821	-0.749

B. *Area Division Based on Distance Relativity*

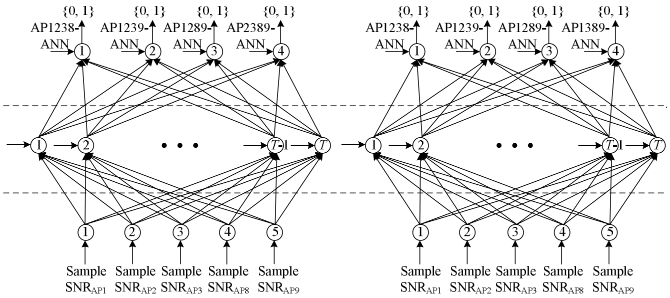
In order to improve location accuracy and reduce time cost for ANN training, the AP with least distance relativity for different directions is deleted based on Table 1 and 2 in order to establish 4 inputs ANN with the mean value of RSS. And after the deletion of AP, the target location area is divided into 5 separated areas with different types of ANN (AP1238-ANN, AP1239-ANN, AP1289-ANN, AP1389-ANN and AP2389-ANN) which are shown in Table 3.

TABLE III. AREA DIVISION BY DISTANCE RELATIVITY

	Y coordinates for X direction	*X coordinates for Y direction*
AP1238-ANN	A, B	1, 3, 6
AP1239-ANN	D, F	5
AP1289-ANN	E, H	2, 4, 8, 9
AP1389-ANN	Null	7
AP2389-ANN	C, G	Null

Where, the *X* direction with different *Y* coordinates are described by A, B, …, H. And the *Y* direction with different *X* coordinates are described by 1, 2, …, 9.

Based on area division method, five ANNs for different area are established with proper input vectors, but one of the significant problems is the identification of new recorded RSS distribution by pre-stored database. And in this paper, the ANN-based clustering method is utilized with a three layer feed-forward ANN shown in Fig.3.



(a) Area division in *X* direction (b) Area division in *Y* direction

Figure 3. ANN structure for clustering method

For the input vector with coordinates belonging to a special ANN, the corresponding target output value for this ANN is set value 1 and the other output value is defined as 0 for the ANN training process. Based on the area division, the target location area is divided with different ANN-based location subsystems. In this paper, there are 8 subsystems with different directions and AP groups shown in Table 3.

IV. EXPERIMENTS AND ANALYSIS

A. *Experimental Setup*

Layout of the experimental environment is shown in Fig.2 and dimensions are 66.43×24.9m^2 and height is 3m with 19 laboratories, 1 meeting room and 1 table tennis room. The walls are made of the bricks with large windows in aluminum frames and doors are made of metal.

The locations of APs are denoted by AP1, AP2, …, AP9 and these APs are fixed at the height of 2m above the floor. The APs are D-link DWL-2100AP that supports 802.11g standard with data rates up to 54 Mbps and RSS measurements are recorded by a laptop computer with Intel PRO/Wireless 3945ABG Network Connection wireless card positioned 1.2m above the floor.

The measurements of RPs are performed for 72 points (locations) which are 1m apart from each other and the test points (56 points in all) are selected in the middle of 4 neighboring RPs shown in Fig.2. Where, 360 SNR samples per RP are recorded in the off-line phase (360×72 training samples) for the ANN training.

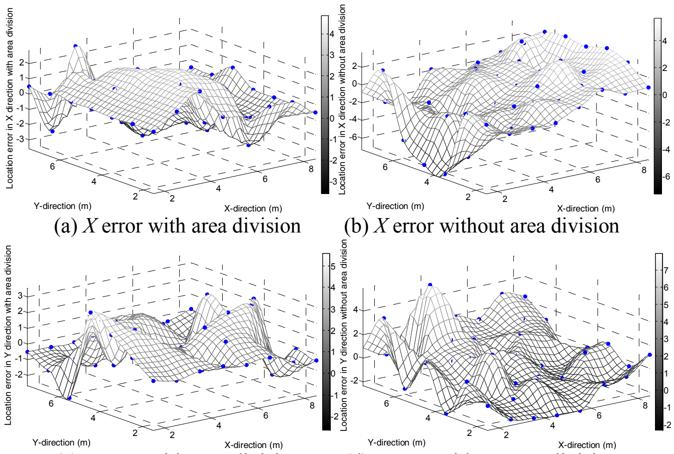
B. *Analysis of Experimental Results*

There two steps for the purpose of coordinate estimation.

- Determination of subsystem. Based on new recorded RSS in the on-line phase and clustering method, the optimal ANN-based location subsystem is selected with the largest membership degree

- Coordinate estimation. Utilizing the optimal ANN-based subsystems to estimate coordinates of MTs.

Location performance at the test points dotted in Fig.2 is shown in the following figures.



(a) *X* error with area division (b) *X* error without area division

(c) *Y* error with area division (d) *Y* error without area division

Figure 4. Location error for different directions

The location error in *X*-direction E_x and *Y*-direction E_y shown in Fig.4 are calculated by Eq.(5).

$$\begin{cases} E_x = z_{1,p} - y_{1,p}^2 \\ E_y = z_{2,p} - y_{2,p}^2 \end{cases} \tag{5}$$

In order to analyze the feasibility and effectiveness of ANN method with area division, comparison of location error for the 56 test points with the ANN-based location system without area division is shown in Fig.5.

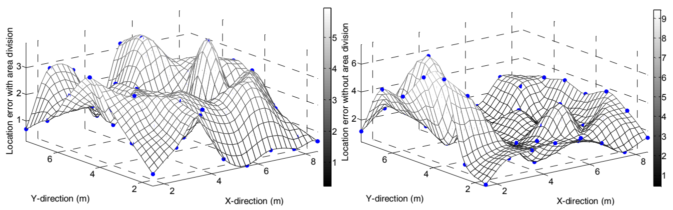


Figure 5. Comparison of location error for different ANN methods

The probability of accumulated error for different ANN-based location systems is shown in Fig.6.

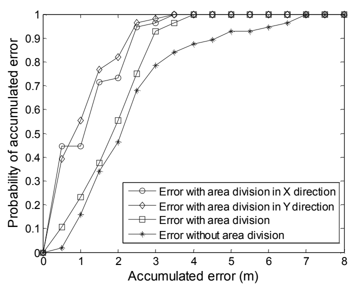


Figure 6. Probability of accumulated location error

Where, the location error *E* is calculated by Eq.(6).

$$E = \sqrt{E_x^{\ 2} + E_y^{\ 2}} \tag{6}$$

Based on Fig.6, the probability of location error which is less than a special value (from 0 to 8 meters) can be acquired and three conclusions are discussed as following.

- Location error of ANN method with area division is limited to 4m and probability of error which is less than 3 meters is 92.86% which can completely satisfy the application requirements.

- Location performance is significantly improved by area division for the ANN-based location system.

V. Conclusion

In this paper, based on the advantages of no extra location equipments and convenient terminals, the three layer feed-forward ANN model with area division for WLAN indoor location system is investigated. And also, clustering method is proposed for the purpose of selecting the optimal APs as the input vectors for ANN-based location system. Because based on this method, the target location area is divided into separate directions, and for each direction, the APs with best distance relativity is used to estimate the coordinates. In addition, the 92.86% location accuracy in 3 meters completely satisfies the application for ANN-based location system with area division.

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