

A Neural-Network-Based Indoor Positioning System by Using Sectored Antenna Array

Chih-Yung Chen, Yu-Ju Chen, Ya-Chen Weng, Rey-Chue Hwang*

Abstract—This paper presents the development of sectored antenna array and modified probabilistic neural network positioning algorithm for an indoor positioning system (IPS). Firstly, a new hexagonal IPS station is composed of six printed-circuit board Yagi-Uda antennas and Zigbee modules. It is designed to obtain the signals between an object and the station. Then, a modified probabilistic neural network (MPNN) is applied to estimate the accurate position of the object with the signal strength. From the experimental positioning results shown, the developed IPS system has the outperformance in an 8x8 square meters indoor scene. The proposed indoor positioning technique not only has a high positioning accuracy, but also is an effective solution to solve the difficult issue of positioning station deployment.

Index Terms—indoor positioning, Yagi-Uda antenna, modified probabilistic neural network, received signal strength.

I. INTRODUCTION

Due to the rapid developments of wireless communication technique and personal network [1-3], wireless technology has been widely applied into the application of indoor positioning system (IPS). So far, many wireless communication technologies such as wireless local area network (WLAN) [4-7], wireless sensor network (WSN) [8-9], radio frequency identification (RFID) [10-12], Bluetooth [13-14], Zigbee [15-16], etc. have been widely used in the sensing technique of IPS. In fact, the positioning algorithm also plays an important role in the application of IPS. It is the method used for determining the object's location. Nowadays, three algorithms, including triangulation, scene analysis and proximity, are mainly methods used for the object's position estimation [17-22]. In lots of positioning systems, the received signal strength (RSS) values sensed from the known reference nodes are used to calculate the coordinate of unknown objects. Thus, multiple wireless stations are required for RSS based IPSs with appropriate installation. Undoubtedly, such a condition would increase the difficulty of positioning environment deployment and the necessary equipment cost.

Cidronali et al [23] designed a new switched beam array

Chih-Yung Chen, Department of Computer and Communication, Shu-Te University, Kaohsiung City, Taiwan. R.O.C.,

Yu-Ju Chen, Department of Information Management, Cheng Shiu University, Kaohsiung City, Taiwan, R.O.C..

Ya-Chen Weng, Department of Computer and Communication, Shu-Te University, Kaohsiung City, Taiwan. R.O.C..

Rey-Chue Hwang, Department of Electrical Engineering, I-Shou University, Kaohsiung City, Taiwan, R.O.C.,

*Corresponding author

antenna which was used in wireless indoor positioning. The antenna is intended to augment a wireless devices operating as coordinator or base station, and its design has been optimized for installation on the ceiling of any large indoor space. Similar to [23], this research presents a novel indoor positioning scheme which is composed of array antennas and Zigbee modules. The information of signal angle and RSS are used to estimate the object's location.

In recent years, NN technique has been employed into the positioning applications [24-30] due to its powerful learning and mapping capabilities. In this research, PNN model was applied to perform the positioning work. The whole paper is organized as follows. The proposed indoor positioning system is presented in Section 2. Section 3 describes MPNN model for the positioning estimation. Section 4 presents the relevant experiments and results. At last, a conclusion is given in Section 5.

II. INDOOR POSITIONING SYSTEM

The proposed indoor positioning scheme is shown in Fig. 1. It is composed of the indoor positioning station and the embedded positioning device. The indoor positioning station consists of a six directional sectored antenna array, a module with six Zigbee sensors and a microcontroller for transmitting the RSS signals. The diagram of the sectored antenna array is presented in Fig. 2. The embedded positioning device consists of a MPNN model and an ARM-based system. It is used to perform the positioning work and then display the result on the screen of ARM system.

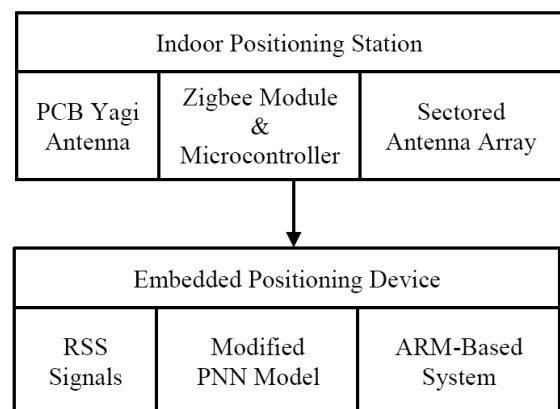


Fig. 1 The proposed indoor positioning scheme.

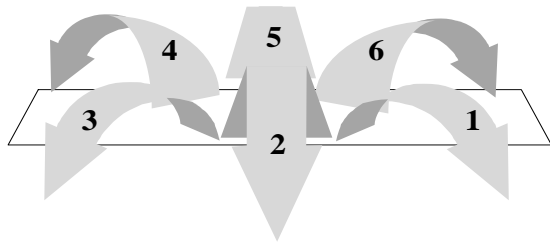


Fig. 2 The diagram of sectored antenna array.

In this research, the specified sectored antenna array used for developing the indoor positioning system. This array is composed of six printed-circuit board (PCB) Yagi-Uda antennas with hexagonal arrangement which can provide 360 degrees coverage. Thus, in our approach, only one station is demanded for IPS and all component parts are small for installation.

The Yagi-Uda antenna is one of the most successful radio frequency directional antenna. It has the characteristics of gain and directivity so that it is able to receive or transmit radio in a specific direction. Fig. 3 shows the figures of Yagi-Uda antenna and its radiation pattern [31].

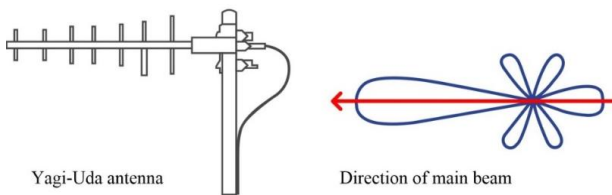


Fig. 3 Yagi-Uda antenna and radiation patterns.

Generally, the size of Yagi-Uda antenna is too large to be used in the real indoor positioning application. However, the PCB Yagi antenna has been proven that it is an economical and effective antenna with directional radiation property for the practical using in indoor positioning work. Fig. 4 shows an example of Yagi-Uda antenna applied to Zigbee wireless sensor network module under the bandwidth of 2.4 GHz condition. And, Fig.5 is the measured radiation patterns on different azimuth directions of PCB antenna.

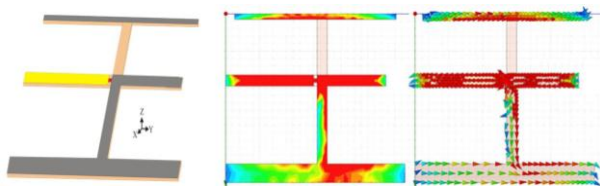


Fig. 4 The simulation results of PCB Yagi-Uda antenna.

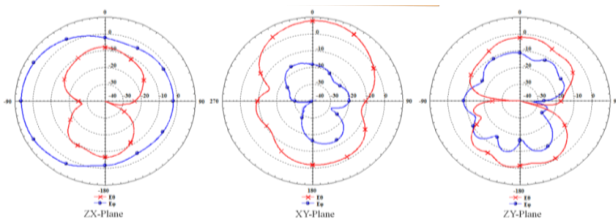


Fig. 5 The measured radiation patterns of PCB antenna on zx, xy and zy directions.

Fig. 6 presents the implemented IPS station which has a microcontroller, six Zigbee wireless module and six PCB antennas.

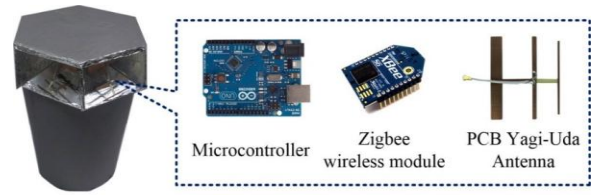


Fig. 6 The proposed hexagonal IPS station.

III. MPNN MODEL

In this research, MPNN was applied to estimate the coordinates of object and it was initially proposed by Zaknich **Error! Reference source not found.** The architecture of MPNN is shown in Fig. 7. It has one input layer, one pattern layer, one summing layer and one output layer. The detailed MPNN algorithm is described as follows. Suppose a set of class vector \mathbf{C} i.e. IPS training data is given by

$$\mathbf{C} = \{(c_1, y_1), (c_2, y_2), \dots, (c_m, y_m)\} \quad (1)$$

where m is the number of class vector \mathbf{C} . Each c_i contains six RSS signals of antenna array and y_i is the corresponding output of class c_i . Thus, for each input x , the probability density function (PDF) of MPNN is defined as

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

where σ is the smoothing parameter of Gaussian function. Then, the output \hat{y} i.e. the coordinate of object can be obtained by

$$\hat{y}(x) = \frac{\sum_{i=1}^m z_i y_i \Phi(x, c_i, \sigma)}{\sum_{i=1}^m z_i \Phi(x, c_i, \sigma)} \quad (3)$$

where z_i is the number of the number of x associated with c_i .

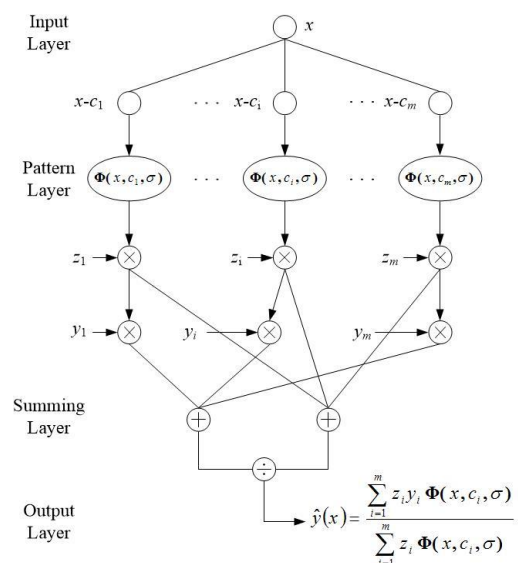


Fig. 7 The architecture of MPNN.

IV. POSITIONING EXPERIMENTS

In this research, an 8x8 square meters indoor field as shown in Fig. 8 is used for the experiments. In order to test the indoor positioning system developed, 288 and 440 positions (features) within the intervals of 0.5 meter and 0.4 meter were measured twice at different time periods. The first 288 and 440 position data are used for MPNN training and the second 288 and 440 position data are used for MPNN test. Besides, another two position data, 392 and 704 positions are randomly measured with the intervals of 0.5 meter and 0.4 meter. Both two data sets are used for MPNN positioning tests either.

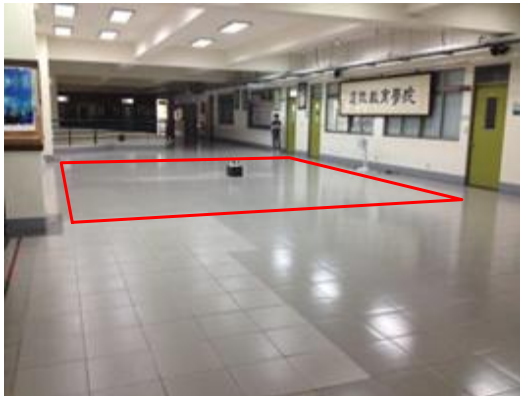


Fig. 8 The indoor experiment field.

Table 1 lists the statistic errors of 288 and 440 positional estimations by MPNN with 288 points training. The mean absolute error (MAE) and standard deviation (Std.) of errors are used to indicate the positioning condition. Table 2 lists the statistic errors of 288 and 440 positional estimations by MPNN with 440 points training.

Table 1. The statistic errors of 288 and 440 positional estimations by MPNN with 288 points training.

σ	288 points		440 points	
	MAE (cm)	Std. (cm)	MAE (cm)	Std. (cm)
$\sigma=0.1$	105.109	69.258	110.168	75.7654
$\sigma=0.09$	89.8082	61.5673	98.9441	68.9892
$\sigma=0.08$	75.4257	53.6842	89.2857	62.5117
$\sigma=0.07$	62.025	45.6867	81.6179	56.716
$\sigma=0.06$	48.701	38.331	75.2754	54.064
$\sigma=0.05$	34.6977	32.2786	71.5156	55.0467
$\sigma=0.04$	21.244	26.3896	71.7191	59.4848
$\sigma=0.03$	10.253	18.4068	76.0491	66.5151
$\sigma=0.02$	3.35754	11.1216	82.351	75.8395
$\sigma=0.01$	2.01998	12.1287	87.7202	79.7835
Avg.	45.26411	36.88525	84.46461	65.47159

Std.: Standard deviation

Table 2. The statistic errors of 288 and 440 positional estimations by MPNN with 440 points training.

σ	288 points		440 points	
	MAE (cm)	Std. (cm)	MAE (cm)	Std. (cm)
$\sigma=0.1$	114.443	77.3033	108.025	75.3758
$\sigma=0.09$	100.455	70.4024	94.5683	67.6896
$\sigma=0.08$	87.612	63.4382	81.6917	59.917
$\sigma=0.07$	76.8114	56.4131	69.0089	52.4475
$\sigma=0.06$	68.3944	50.0595	55.557	45.3722
$\sigma=0.05$	62.3424	45.9681	40.3179	37.8829
$\sigma=0.04$	59.2948	45.8955	24.0687	28.2314
$\sigma=0.03$	63.1633	49.0358	9.78353	15.7917
$\sigma=0.02$	70.7702	55.8473	2.22647	8.56119
$\sigma=0.01$	77.6275	59.9527	0.864431	7.62743
Avg.	78.0914	57.43159	48.61119	39.88967

Std.: Standard deviation

From the results of Table 1 and Table 2 shown, it can be clearly found that MPNN could have quite well positioning accuracy when the object's position is exactly on the points of MPNN's training. The best MAEs of 288 points test and 440 points test could reach to 2.01998 cm ($\sigma=0.01$) and 0.864431cm ($\sigma=0.01$), respectively. But, for MPNN model with 288 points training, its best test MAE to 440 points is 71.5156 cm ($\sigma=0.05$). Similarly, for MPNN model with 440 points training, its best test MAE to 288 points is 59.2948 cm ($\sigma=0.04$). In fact, such a situation is predictable. It is because of MPNN model is viewed a classifier which is used to estimate the object's position in accordance with the features (RSS signals) sensed. Thus, we believe that the positioning accuracy could be greatly improved if MPNN has mass and enough training data.

ACKNOWLEDGMENT

This research was supported by the Ministry of Science and Technology, Taiwan, ROC under Contracts No. MOST-104-2221-E-366-004, No. MOST-104-2632-E-366-001 and No. MOST-103-222-E-214-050.

REFERENCES

- [1] Y. Y. Gu, A. Lo, I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," *IEEE Communications Surveys & Tutorials*, vol. 11, no. 1, pp. 13-32, 2009.
- [2] H. Liu, H. Darabi, P. Banerjee, 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] G. W. Shi, Y. Ming, "Survey of indoor positioning systems based on ultra-wideband (UWB) technology," *Lecture Notes in Electrical Engineering, Wireless Communications, Networking and Applications, Proceedings of WCNA 2014*, vol. 348, pp. 1269-1278, 2016.
- [4] A. Kotanen, M. Hannikainen, H. Leppakoski, T. D. Hamalainen, "Positioning with IEEE 802.11b wireless LAN," *In the Proceedings of 14th IEEE Proceedings on Personal, Indoor and Mobile Radio Communications*, Beijing, China, pp. 2218-2222, 2003.

- [5] Y. B. Xu, M. Zhou, L. Ma, "Hybrid FCM/ANN indoor location method in WLAN environment," *In the Proceedings of IEEE Youth Conference on Information, Computing and Telecommunications*, Beijing, China, pp. 475–478, 2009.
- [6] V. Honkavirta, T. Perala, S. Ali-Loytty, R. Piche, "A comparative survey of WLAN location fingerprinting methods," *In the Proceedings of 6th Workshop on Positioning, Navigation and Communication (WPNC'09)*, Hannover, Germany, pp. 243–251, 2009.
- [7] M. Y. Umair, K. V. Ramana, D. K. Yang, "An enhanced K-Nearest Neighbor algorithm for indoor positioning systems in a WLAN," *2014 IEEE Computers, Communications and Its Applications*, pp. 19–23, January 20, 2014.
- [8] K. F. S. Wong, I. W. Tsang, V. Cheung, S. H. G. Chan, J. T. Kwok, "Position estimation for wireless sensor networks," *In the Proceedings of IEEE Global Telecommunications Conference*, MO, USA, pp. 2772–2776, 2005.
- [9] S. Aomumpai, K. Kondee, C. Prommak, K. Kaemarungsi, "Optimal placement of reference nodes for wireless indoor positioning systems," *11th International Conference on Electrical Engineering, Electronics, Computer, Telecommunications and Information Technology*. Paper no. 6839894, 2014.
- [10] P. Bahl V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," *In the Proceedings of INFOCOM 2000, Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies*, Tel Aviv, Israel, pp. 775–784, 2000.
- [11] H. D. Chon, S. Jun, H. Jung, S. W. An, "Using RFID for accurate positioning," *Journal of Global Positioning Systems*, vol. 3, pp. 32–39, 2004.
- [12] H. L. Ding, W. W. Y. Ng, P. P. K. Chan, D. L. Wu, X. L. Chen, D. S. Yeung, "RFID indoor positioning using RBFNN with L-GEM," *In the Proceedings of IEEE 2010 International Conference on Machine Learning and Cybernetics*, Qingdao, China, pp. 1147–1152, 2010.
- [13] A. K. M. M. Hossain, W. S. Soh, "A comprehensive study of Bluetooth signal parameters for localization," *In the Proceedings of 18th Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC'07)*, Athens, Greece, pp. 1–5, 2007.
- [14] F. Subhan, H. Hasbullah, A. Rozyyev, S. T. Bakhsh, "Indoor positioning in Bluetooth networks using fingerprinting and lateration approach," *In the Proceedings of 2011 International Conference on Information Science and Applications (ICISA)*, Jeju Island, Korea, pp. 1–9, 2001.
- [15] W. P. Chen, X. F. Meng, "A cooperative localization scheme for Zigbee-based wireless sensor networks," *In the Proceedings of 14th IEEE International Conference on Networks*, Singapore, pp. 1–5, 2006.
- [16] G. Goncalo, S. Helena, "Indoor location system using ZigBee technology," *In the Proceedings of Third International Conference on Sensor Technologies and Applications*, Athens/Glyfada, Greece, pp. 152–157, 2009.
- [17] B. Kim, W. Bong, Y. C. Kim, "Indoor localization for Wi-Fi devices by cross-monitoring AP and weighted triangulation," *In the Proceedings of IEEE Consumer Communications and Networking Conference (CCNC)*, NV, U.S.A., pp. 933–936, 2011.
- [18] Y. Mo, Z. Z. Zhang, Y. Lu, G. Agha, "A novel technique for human traffic based radio map updating in Wi-Fi indoor positioning systems," *KSII Transactions on Internet and Information Systems*, vol. 9, no. 5, pp. 1881–1903, 2015.
- [19] X. F. Jiang, C. J. Mike Liang, K. F. Chen, B. Zhang, J. Hsu, J. Liu, B. Cao, F. Zhao, "Design and evaluation of a wireless magnetic-based proximity detection platform for indoor applications," *In the Proceedings of 11th ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN/SPOTS)*, Beijing, China, pp. 221–231, 2012.
- [20] J. Hightower, G. Borriello, "Location sensing techniques," *Technical Report UW CSE 2001-07-30*, Department of Computer Science and Engineering, University of Washington, 2001.
- [21] K. Kaemarungsi, P. Krishnamurthy, "Properties of indoor received signal strength for WLAN location fingerprinting," *In the Proceedings of 1st Annual International Conference on Mobile and Ubiquitous Systems: Networking and Services (MobiQuitous '04)*, MA, USA, pp. 14–23, 2004.
- [22] D. Focken, R. Stiefelhagen, "Towards vision-based 3-D people tracking in a smart room," *In the Proceedings of 4th IEEE Intl Conference on Multimodal Interfaces*, PA, USA, pp. 400–405, 2002.
- [23] A. Cidronali, S. Maddio, G. Giorgetti, G. Manes, "Analysis and performance of a smart antenna for 2.45-GHz single-anchor indoor positioning," *IEEE Trans. Microw. Theory Tech.*, vol. 58, no. 1, pp. 21–31, 2010.
- [24] A. Zaknich, "Introduction to the modified probabilistic neural network for general signal processing applications," *IEEE Transactions on Signal Processing*, vol. 46, no. 7, pp. 1980–1990, 1998.
- [25] R. C. Chen, Y. H. Lin, "Using ZigBee sensor network with artificial neural network for indoor location," *In the Proceedings of Eighth International Conference on Natural Computation*, Chongqing, China, pp. 290–294, 2012.
- [26] M. Altini, D. Brunelli, E. Farella, L. Benini, "Bluetooth indoor localization with multiple neural networks," *In the Proceedings of 5th IEEE International Symposium on Wireless Pervasive Computing (ISWPC)*, Modena, Italy, pp. 295–300, 2010.
- [27] Y. S. Lin, R. C. Chen, Y. C. Lin, "An indoor location identification system based on neural network and genetic algorithm," *In the Proceedings of 3rd International Conference on Awareness Science and Technology (iCAST)*, Dalian, China, pp. 193–198, 2011.
- [28] H. Mohammad, A. F. Ozan, A. N. Ali, P. Aveh, "Neural network assisted identification of the absence of direct path in indoor localization," *In the Proceedings of IEEE Global Telecommunications Conference*, Washington, DC, USA, pp. 387–392, 2007.
- [29] S. H. Fang, T. N. Lin, "Indoor location system based on discriminant-adaptive neural network in IEEE 802.11 environments," *IEEE Transactions on Neural Networks*, vol. 19, no. 11, pp. 1973–1978, 2008.
- [30] C. Laoudias, D. G. Eliades, P. Kemppi, C. G. Panayiotou, M. M. Polycarpou, "Indoor localization using neural networks with location fingerprints," *Lecture Notes in Computer Science - 19th International Conference on Artificial Neural Networks*, Limassol, Cyprus, vol. 5769, no. 2, pp. 954–963, 2009.
- [31] Antennas and Propagation.
<http://www.radio-electronics.com/info/antennas/yagi/yagi.php>

Chih-Yung Chen received his PhD degree in Electrical Engineering from I-Shou University, Kaohsiung, Taiwan, in year 2007. Currently, he is an assistant professor of Computer and Communication Department, Shu-Te University, Kaohsiung City, Taiwan. His research interests include the areas of data base, programming design, hardware design and artificial intelligence.

Yu-Ju Chen currently is an assistant professor of Information Management Department at Cheng Shiu University. Her research interests include the areas of artificial intelligence, fuzzy theory and information management. She has published more than 90 papers in various journals and conferences.

Ya-Chen Weng was a master student of Computer and Communication Department, Shu-Te University, Kaohsiung, Taiwan. His research interests include the areas of artificial intelligence, fuzzy theory and signal processing.

Rey-Chue Hwang received his PhD degree in Electrical Engineering from Southern Methodist University, Dallas, TX, in 1993. Currently, he is a full professor of Electrical Engineering Department, I-Shou University, Taiwan, R.O.C. Dr. Hwang has published more than 250 papers in various journals and conferences in the areas of artificial intelligence system, signal processing and fuzzy control. He is now a Fellow of IET and a senior member of IEEE. He chartered the IEEE CIS Chapter, Tainan Section and served as the co-chair and chair from year 2004 to year 2009.