

The Development of WLAN-based Indoor Positioning Systems for Aerospace Engineering Education Improvement Programs

S. J. WU, Chih-Chen YIH, and S. H. YEN
Department of Mechanical & Automation Engineering
I-SHOU University
1, Sec. 1, Hsueh-Cheng Rd., Ta-Hsu Hsiang,
Kaohsiung County, Taiwan 840
Tel: +886-7-657-7711 Ext. 3227, Fax: +886-7-657-8853
Email: wsj007@isu.edu.tw; ccyih@isu.edu.tw; shyen@isu.edu.tw

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ABSTRACT: *Aerospace engineering education improvement program sponsored by Advisor Office, Ministry of Education in Taiwan aims to improve the capability of undergraduate students to design and conduct experiments as well as to obtain hands-on experience in a variety of aerospace engineering such as flight dynamics, control, navigation, global positioning, and wireless communication. In a four-year aerospace engineering education improvement project (2001-2004), we establish a laboratory to develop WLAN-based indoor positioning systems.*

In general, it is difficult for undergraduate students to have the opportunities of obtaining hands-on experience on the surveillance/navigation of aerospace systems due to the highly complex features of the real systems. In order to simulate this surveillance/navigation scenario, we develop an indoor positioning system to explore ways of simulating next-generation GPS-aided surveillance/navigation systems. Indoor positioning also plays an essential role in the area of automation systems. There are many indoor positioning-related problems such as product tracking in the manufacturing process, navigation of mobile robots, real-time positioning and tracking of patients in hospitals, and sensor network consisting of various types of sensors. With the rapid growth of the Internet, more and more wireless local area network (WLAN) has been installed on campus, in company, and at home. This project develops an IEEE 802.11-based indoor positioning system. The main idea behind the proposed indoor positioning system is to calculate the position using the probabilistic model and measurement of received signal strength. The proposed methodology can position and track the mobile device by integrating the maximum-likelihood estimate of the position and measurement-based Artificial Neural Network-trained RF map. We develop positioning software and implement the positioning algorithm in an IEEE 802.11 WLAN to validate the proposed indoor positioning methods.

1 INTRODUCTION

Indoor positioning plays an essential role in the area of automation systems. There are many indoor positioning-related problems such as product tracking in the manufacturing process, navigation of mobile robots, real-time positioning and tracking of patients in hospitals, and sensor network consisting of various types of sensors [2, 12]. With the rapid growth of the Internet, more and more wireless local area network (WLAN) has been installed on campus, in company, and at home. This project develops an IEEE 802.11-based indoor positioning system (see Fig. 1). The main idea behind the proposed indoor positioning system is to calculate the position using the probabilistic model and measurement of received signal strength. The proposed methodology can position and track the mobile device by integrating the maximum-likelihood estimate of the position and measurement-based Artificial Neural Network-trained RF map. We develop positioning software and implement the positioning algorithm in an IEEE 802.11 WLAN to validate the proposed indoor positioning methods.

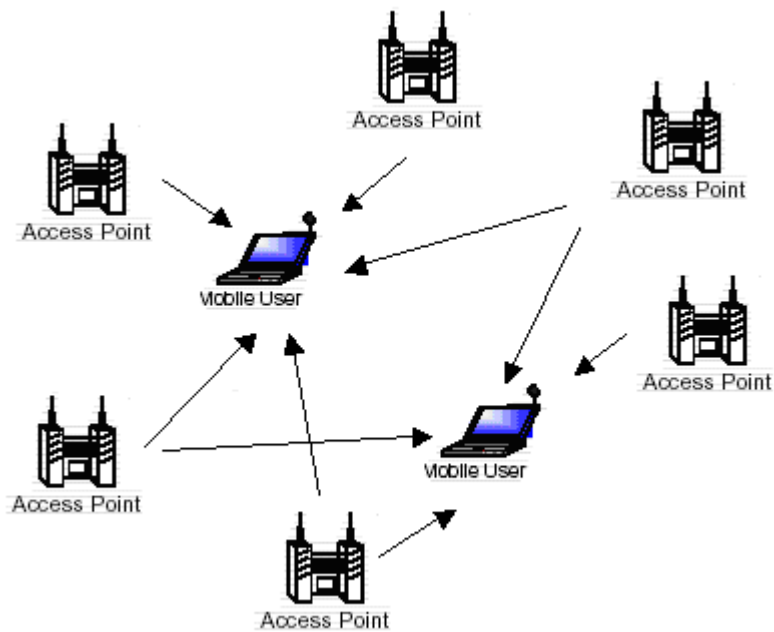


Fig. 1 Indoor wireless local area network (WLAN) positioning system

User's location is important because it can provide location-related information and service. Positioning system consists of indoor and outdoor types. Outdoor positioning systems include inertia positioning, wireless signal positioning, geographic feature positioning, satellite GPS positioning [3], and CDMA base station positioning. Indoor positioning systems comprise ultrasonic positioning, infrared positioning [4-5], laser range finder positioning, indoor radar positioning, and wireless signal positioning. Outdoor satellite GPS positioning has recently been applied to the area of flight navigation, military surveillance, and civilian vehicle navigation. Many commercial products have been developed and come into markets. For example, Microsoft windows XP operating system can support several commercial GPS interfacing cards. However, it is well-known that outdoor GPS positioning is not suitable for indoor environment due to the characteristics of indoor multi-path fading channels. Therefore, scientists and engineers are doing research for more accurate and low-cost indoor positioning.

IEEE 802.11-based local area network (WLAN) positioning system (e.g., RADAR system developed by Microsoft Research [1]) has many advantages. These advantages include the following: (1) no expensive hardware such as indoor radar or laser range finder is required; (2) the required WLAN interfacing cards and access points are low-cost; (3) software-based positioning can save the hardware cost and is easy to integrate with existing WLAN systems. Wireless signal positioning can be divided into received signal strength (RSS) and time of arrival (TOA). Because of the variations of indoor environment [6-10], the model of multi-path channel fading may not be easy to obtain. The proposed method uses RSS associated with artificial neural network (ANN) to calculate the positioning for accuracy improvement. Moreover, the system can exploit the rapid calculation capability of the ANN to track positions of dynamic objects.

Using 802.11 WLAN to estimate the user's position has attracted a lot of attentions from many researchers in recent years. Unlike the short-distance coverage of infrared or ultrasonic positioning, WLAN-based positioning can cover longer distance. Moreover, WLAN-based positioning system doesn't require additional hardware and can provide extra service for WLAN users. The research objective of this research is to provide a more accurate positioning without significantly increasing the calculation load.

For an indoor local area covered by several access points (APs), the proposed positioning system must collect AP signal strength (SS) at different positions and build a RF map through ANN training of the SS measurement. Then, by taking the SS at a different position, the proposed system can determine the user's location from the RF map. Researchers at University of Maryland at College Park use probabilistic model to reduce the search space of position estimation [14]. They developed Joint Clustering and Incremental Triangulation method which can reach 90% accuracy within 7 inches.

Moreover, Microsoft's RADAR system has a positioning accuracy of 1-3 meters. Commercial wireless positioning software such as Ekahau's Positioning Engine 2.1 can position objects with 1 meter accuracy. However, due to the variety of indoor environment (e.g., an office building and a shopping mall), further evaluation is necessary for the positioning accuracy of the above-mentioned systems.

2 METHODOLOGY

This project develops an IEEE 802.11-based indoor positioning system. The main idea behind the proposed indoor positioning system is to calculate the position using the probabilistic model and measurement of received signal strength. The proposed positioning method includes the following:

(1) Maximum likelihood position estimation [9, 11]

Probabilistic model:

Assuming m access points and n devices required for positioning, we can express the planar position parameters as follows:

$$\gamma = [x_1, y_1, x_2, y_2, \dots, x_n, y_n, x_{n+1}, y_{n+1}, \dots, x_{n+m}, y_{n+m}] \quad (1)$$

$$d_{i,j} = [(x_i - x_j)^2 + (y_i - y_j)^2]^{\frac{1}{2}} : \text{relative position between device } i \text{ and device } j.$$

The positioning is posed as the problem of calculating the positions of mobile devices $[x_1, y_1, x_2, y_2, \dots, x_n, y_n]$ from the known AP positions $[x_{n+1}, y_{n+1}, \dots, x_{n+m}, y_{n+m}]$.

$P_{i,j}$ is received signal power measured on device i (unit: milliwatts, emitted by device j). Assume that $P_{i,j}$ is log-normal distributed; then the random variable $P_{i,j} = 10 \log_{10} P_{i,j}$ is Gaussian distributed.

$$P_{i,j} (dBm) \sim N(\bar{P}_{i,j} (dBm), \sigma_{dB}^2) \quad (2)$$

$$\bar{P}_{i,j} (dBm) = P_0 (dBm) - 10n_p \log_{10} (d_{i,j} / d_0) \quad (3)$$

where $\bar{P}_{i,j} (dBm)$: mean power in decibel milliwatts

n_p : path loss exponent is a function of the environment

σ_{dB}^2 : variance of the shadowing

$P_0 (dBm)$: received power in decibel milliwatts at a reference distance ($d_0 = 1 m$) and can be calculated from the free path loss formula or measurement data.

The probability density function $P_{i,j}$ is

$$f_{P|\gamma} (P_{i,j} | \gamma) = \frac{10 / \log 10}{\sqrt{2\pi\sigma_{dB}^2}} \frac{1}{P_{i,j}} \exp \left[-\frac{b}{8} \left(\log \frac{d_{i,j}^2}{\tilde{d}_{i,j}^2} \right)^2 \right] \quad (4)$$

$$b = \left(\frac{10n_p}{\sigma_{dB} \log 10} \right)^2$$

$$\tilde{d}_{i,j} = d_0 \left(\frac{P_0}{P_{i,j}} \right)^{1/n_p}$$

where $\tilde{d}_{i,j}$ is the MLE of $d_{i,j}$ (given received power $P_{i,j}$).

The log of joint conditional pdf is

$$l(P|\gamma) = \sum_{i=1}^{m+n} \sum_{\substack{j \in H(i) \\ j < i}} l_{i,j} \quad (5)$$

$$l_{i,j} = \log f_{P|\gamma} (P_{i,j} | \gamma_i, \gamma_j)$$

Maximum Likelihood Position Estimator can be found as follows:

$$\hat{\theta}_{\bar{R}} = \arg \min_{\{z_i\}} \sum_{i=1}^{m+n} \sum_{\substack{j \in H(i) \\ j < i}} \left(\ln \frac{\tilde{d}_{i,j}^2}{d^2(z_i, z_j)} \right) \quad (6)$$

Estimation Bounds:

For any unbiased estimator $\hat{\theta}$, the Cramer-Rao bound (CRB) is:

$$\text{cov}(\hat{\theta}) \geq F_{\theta}^{-1} \quad (7)$$

$$\theta = [x_1, x_2, \dots, x_n, y_1, y_2, \dots, y_n]$$

$$\theta_x = [x_1, x_2, \dots, x_n], \theta_y = [y_1, y_2, \dots, y_n]$$

where Fisher information matrix (FIM) is defined as follows:

$$F_{\theta} = -E \nabla_{\theta} (\nabla_{\theta} l(P|\gamma))^T \quad (8)$$

$$F_R = \begin{bmatrix} F_{R_{xx}} & F_{R_{xy}} \\ F_{R_{xy}}^T & F_{R_{yy}} \end{bmatrix}$$

(2) Integration of MLE and ANN position estimation

The proposed scheme measures the RSS (Received Signal Strength) and SNR (Signal to Noise Ratio) between access points and mobile devices. We use probabilistic model and ANN (Artificial Neural Network) to calculate the position of mobile device. The real-time and parallel calculation capabilities of dynamically driven recurrent networks [13] are exploited to track positions of mobile devices. Although we can derive the probabilistic model of the RSS, MLE, and estimation error bounds, the measurement is critical in the determination of the mobile device position. Because of the moment of mobile device, this project uses ANN to train the measurement data to build a RF map.

3 SYSTEM IMPLEMENTATION

We develop positioning software and implement the position algorithm in an IEEE 802.11 WLAN to validate the proposed indoor positioning methods.

(1) Implementation steps

1. Develop Windows GUI to read SS/SNR through Windows XP/Windows DDK (Developer's Device Kit) and calculate the positions of mobile devices using probabilistic model.
2. Measure signal strength, derive a distance-signal strength equation, and compare it with probabilistic model.
3. Develop Windows XP /Windows CE positioning software and GUI
4. Set up experimental wireless network, measure SS/SNR, and train the measurement data using ANN model (see Fig. 2).
5. Conduct positioning experiments, use experimental data to refine the positioning algorithm, and compare it with other positioning software.

(2) Indoor positioning system architecture (see Fig. 3)

Hardware: PDA, Notebook PC, Desktop PC.

Operating System: Windows XP, Windows CE Pocket 2003.

Positioning Algorithm: Probabilistic Model and ANN-trained Positioning.

GUI: Visual C++ .NET (Windows XP), Embedded Visual C++ 4.0 (Windows CE Pocket 2003)

Device driver: Wireless Cards, Access Points.

Device API: Windows DDK (Developer's Device Kit)

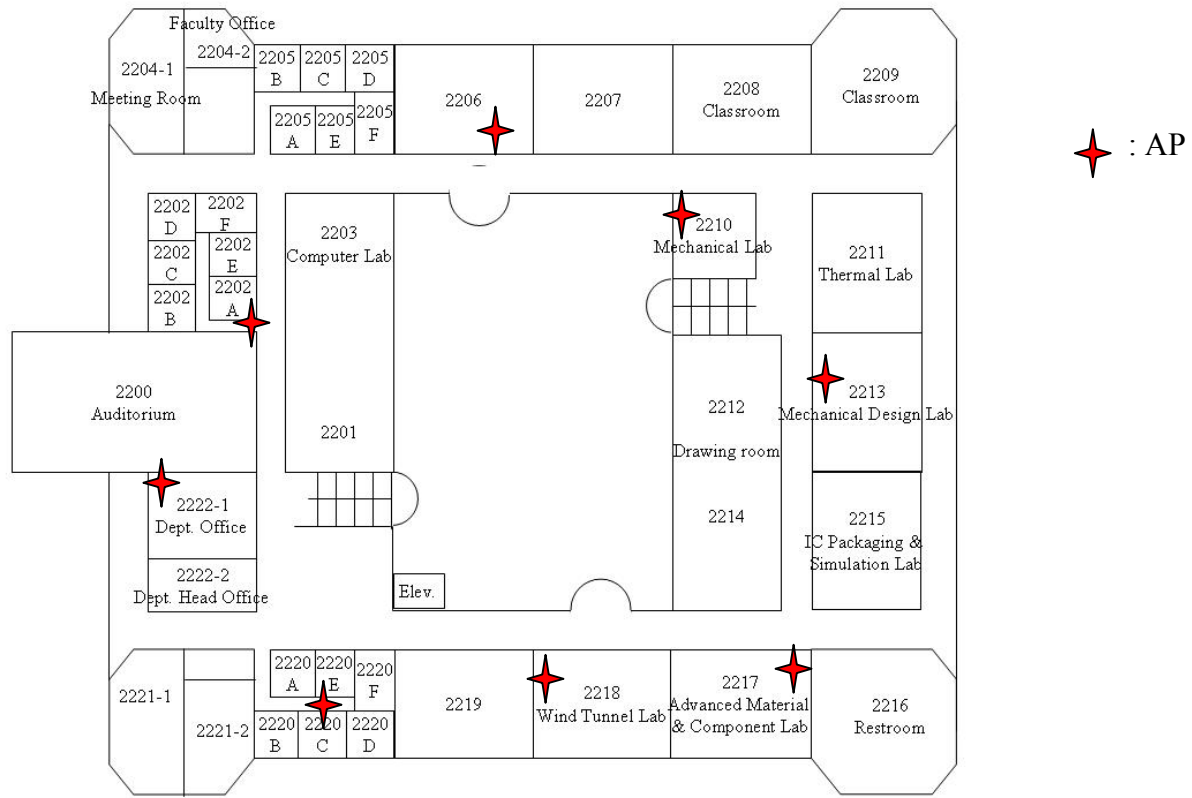


Fig. 2 Locations of Access Points.

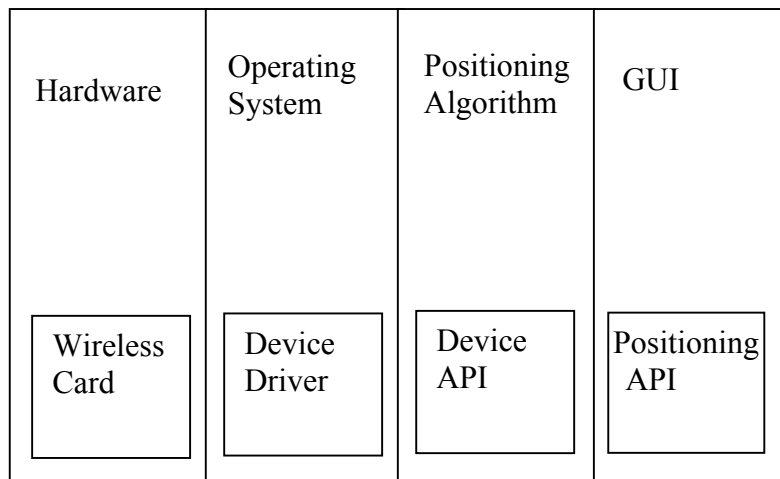


Fig. 3 802.11-based WLAN indoor positioning system architecture.

The photos of the classroom setup can be seen in Figs. 4 and 5.



Fig. 4 In class experiment lecture.



Fig. 5 Laboratory instrumentation setup.

4 CONCLUSION

An IEEE 802.11-based indoor positioning system is developed in this project. The main objective of the proposed indoor positioning system is to calculate the position using the probabilistic model and measurement of received signal strength. The proposed methodology can position and track the mobile device by integrating the maximum-likelihood estimate of the position and measurement-based Artificial Neural Network-trained RF map. We develop positioning software and implement the position algorithm in an IEEE 802.11 WLAN to validate the proposed indoor positioning methods.

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