Robust 3D Indoor Positioning System Based on Radio Map Using Bayesian Network

Abdulraqeb Alhammadi[1], Saddam Alraih[2], Fazirulhisyam Hashim[1], and Mohd. Fadlee A. Rasid[1]

[1]Faculty of Engineering, University of Putra Malaysia, Serdang, Selangor, Malaysia
[2]Faculty of Engineering, University of National Malaysia, Bangi, Selangor, Malaysia
Corresponding Author: e-mail-abdulraqeb@ieee.org

Abstract—Indoor positioning remains a serious issue due to the difficulty in attaining sufficient accuracy within an indoor environment using tracking technology of low complexity. Currently, most positioning systems do not embed the off-the-shelf (OTS) system which allows mobile devices to estimate location without using any additional hardware. In this paper, we propose a robust 3D indoor positioning system that is suitable for an indoor IoT application. This system based on Bayesian network that depends on Wi-Fi signals strength. It was experimentally tested in a building with pre-deployed access points (APs). The experimental results indicate that localization accuracy of the proposed system is high with the use of a small-sized radio map.

Index Terms—Bayesian network, positioning, fingerprinting

I. INTRODUCTION

CURRENTLY, positioning systems are a compelling research area since they are part of the internet of things (IoT) technology. The global position system (GPS) is commonly used in outdoor environments, usually with an unobstructed line of sight (LOS) from the receiver to the satellite. However, it does not operate well in indoor environments due to the multi-path effect and non-line-of-sight (NLOS) between the transmitter and receiver. In recent years, indoor positioning issues have received tremendous research attention due to the widespread usage of wireless local area networks (WLAN) in most indoor environments such as shopping malls, hospitals, universities, etc. The well-known RADAR is the first indoor positioning system using the k-nearest neighbors (KNN) algorithm [1]. However, this system and other proposed systems are still suffering from poor accuracy and high complexity. Several researchers and developers proposed various techniques and algorithms to achieve high accuracy and good localization systems. However, these algorithms depend on the quality of received signal strength indicator (RSSI) which directly affects system accuracy [2]. Several different indoor localization technologies have been developed based on RSSI such as Wi-Fi, ultrasound signal, ZigBee, and ultrawide band (UWB) [3]. One indoor localization system that depends on the probabilistic approach is the Bayesian network. Bayesian estimation is a statistical inference which employs prior knowledge to provide posterior probability distribution for unknown information. Madigan et al [4] introduced a 2-D Bayesian system based on the probabilistic approach which applies Gibbs sampling to generate samples from posterior distribution to predict user location based on maximuma posteriori. In our previous works [5] and [6], we proposed indoor localization system based on 2-D of access points (APs) and Mobile device. There are several 3-D indoor localization systems based on Bayesian estimation. Xu et al. [7] estimated the target location in a 3-D space using RFID reference tags and readers. Hitalo et al.[8] proposed a localization system based on the radio frequency (RF) fingerprinting technique. This system employs Bayes inference to locate a target in 3-D indoor environments. Nevertheless, most proposed systems are computationally expensive; the numbers of reference points (RPs) are too large. Some even require additional hardware support associated with mobile devices. This paper proposes the off-the-shelf (OTS) 3-D Bayesian graphical model (3D-BGM) based on the RF fingerprinting technique to predict user location with high accuracy and less RPs. The major contributions of this paper can be summarized as follows:

1) Performs long-time analysis of RSS data to investigate its effect on the localization system.
2) Proposes the 3-D Bayesian network based on RF fingerprinting technique.
3) Validates the analytical results with the 2-D Madigan model.

The rest of the paper is organized as follows. Section 2 describes the proposed model and pattern recognition process. Section 3 represents the experimental design and data collection. Section 4 outlines the experimental results, and finally, Section 5 concludes the current work.

II. SYSTEM MODEL

A. Proposed 3D Bayesian Graphical Model (3D-BGM)

The proposed Bayesian model is based on what was introduced by Madigan which only supports the 2D environment. The recommended model is an advanced version of Madigans' model as it was designed to support 3D indoor localization system. Five main nodes were used to develop the proposed model: APs nodes (x_i, y_i, z_i), estimated nodes $(X_j, Y_j Z_j)$, inter-site distance (ISD) node D_{ij}, RSSI node S_{ij}, and initial values nodes. Figure 1 presents the developed 3D-BGM based on the RF fingerprinting technique.

The proposed Bayesian graphical model displays four stages of the represented nodes, defined as follows:
First stage: The user location predicted at any point is bound by the testbed dimension which is considered as a uniform distribution. It is defined as:
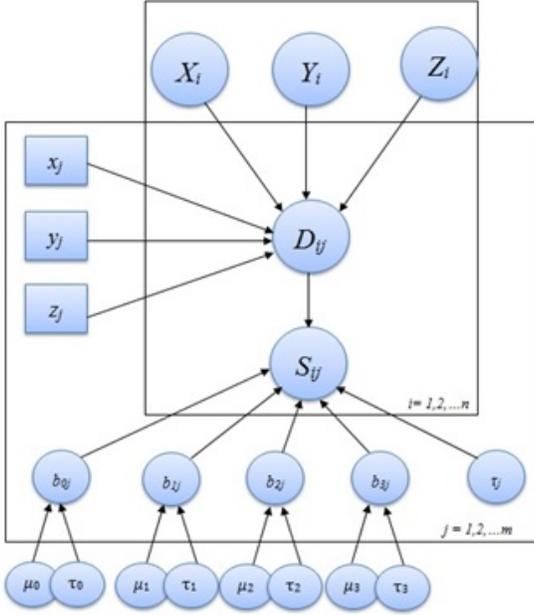
Fig. 1. Proposed 3D Bayesian graphical model

$$X_i \sim U(0, l) \tag{1}$$

$$Y_i \sim U(0, w) \tag{2}$$

$$Z_i \sim U(0, h) \tag{3}$$

where (l, w, h) are the length, width, and height of the testbed dimension, respectively, and user locations (X_i, Yi, Z_i) can be estimated at any point i^{th} bound by the testbed dimension.
Second stage: The distance of the predicted samples of un-known locations in the testbed can be given by the Euclidean distance:

$$D_{ij} = \log\left(1 + \sqrt{(X_i - X_j)^2 + (Y_i - y_j)^2 + (Z_i - z_j)^2}\right) \tag{4}$$

where D_{ij} represents the distance between AP coordinates (x_j, yj, z_j) and user locations (X_i, Yi, Z_i), where the value of 1 is added to avoid the invalid argument of the log function.
Third stage: RSS was defined as a normal distribution that has the mean and variance equal to the regression model of independent variables (b_{i0}, b_{i1}) and (τ_{b0}, τ_{b1}), respectively.

$$S_{ij} \sim N(b_{i0} + b_{i1} \log D_{ij}, \tau_i) \tag{5}$$

$$b_{i0} \sim N(b_0 + \tau_{b0})$$
$$b_0 \sim N(0.001), \tau_{b0} \sim \gamma(0.001, 0.001)$$
$$b_{i1} \sim N(b_1 + \tau_{b1})$$
$$b_1 \sim N(0.001), \tau_{b1} \sim \gamma(0.001, 0.001)$$

The RSSI is measured at user location i^{th} and AP location j^{th}, and S_{ij} is the normal distribution $S_{ij} \sim N(\mu, \tau)$. The regression model is assigned as the mean of the normal distribution of S_{ij}. The regression model consists of four initial parameters $(b_0, b_1, b_2, b_3$ and one independent variable D_{ij}.
Fourth stage: Initial parameters are the normal distribution

$b_{vj} \sim (\mu v)$ that carry any arbitrary values used to start the burning-in generating samples only in the initial stage, and they are defined as follows:

$$b_{i0} \sim (\mu_0, 0), b_{1j} \sim (\mu_1, 1), b_{v0} \sim N(\mu_v, \tau_v),$$
$$v = 1, 2, ..., 5.v \sim (0.001)$$
$$\tau_v \sim (0.001, 0.001)$$

B. RF Fingerprinting Technique

The proposed 3D-BGM is a device-free localization system that does not require any additional equipment to be used besides the available APs and mobile device. Figure 3 displays the process of the RF fingerprinting technique which consists of two phases described as follows:
Offline phase: This phase is also called the data collection phase which is responsible for collecting samples of RSSI fingerprints (known as RPs) using a mobile device that supports Wi-Fi technology. The user stands with a device at the location of interest within the testbed and collects RSSI samples from all available APs in time t_m where $m = 1, 2, .M$. The collected RPs associated with RSSI can be given as follows:

$$\rho_i = [\Phi_i, \chi]$$
$$\Phi_i = (x_i, yi, z_i) \forall_i = 1, 2, 3, ..., N$$
$$\chi = (\chi_1, ..., \chi_N) \begin{bmatrix} \chi_1^1 & \cdots & \chi_N^1 \\ \vdots & \ddots & \vdots \\ \chi_1^K & \cdots & \chi_N^K \end{bmatrix} \tag{6}$$

where Φ_i represents RPs in Cartesian coordinates at any point in the experimental testbed, N is the number of collected RPs stored in the radio map at different locations in the area of interest, χ denotes the collected samples of RSSI at each RP with $\chi_i = [\chi_i^1, ..., \chi_N^K]$ and $\chi_i^1 = \frac{\Sigma_{m=1}^M t_m}{M}$, and K represents the number of available APs in the testbed area. The average values of RSSI from each AP at different locations are used to construct the radio map.
Online phase: This phase is responsible for receiving samples of RSS from available APs and comparing them with collected data in the radio map constructed during the offline phase to estimate the unknown location. The mobile device receives θ online RSS observations which contain the current RSS from each AP $\theta = [\theta_i, ..., \theta_j]$ at any unknown location. Subsequently, these current RSS are compared to the radio map using the fingerprinting technique. Finally, the mobile location is estimated by deducing its coordinates from among the best matches on the radio map.

III. EXPERIMENTAL DESIGN

A. Data Collection

The performance of the proposed model was evaluated by conducting an experiment in an indoor environment with a dimension area of 50×22 m^2.Four APs were used to collect RSS fingerprints along the corridor which contained 50 RPs from each AP as shown in Figure 3.The dots with black color represent the RPs along the corridor. In this work, 30
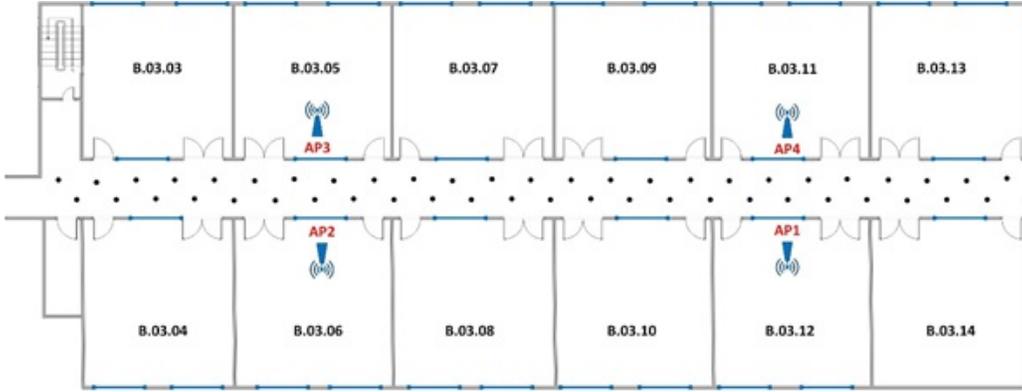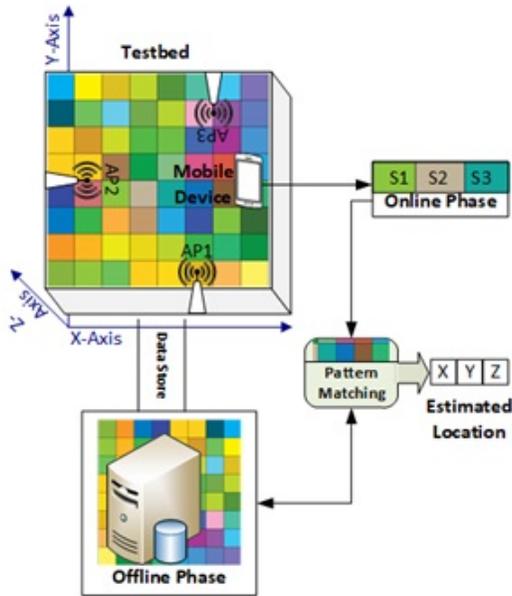
Fig. 2. Experimental testbed

Fig. 3. RF fingerprinting process

TABLE I
PARAMETER SETTING OF THE INFERENCE LOCATION

Parameter	Setting
Burn-in samples	1000
Updates (No. of iterations)	100000
Refresh	100
Thin	1
Estimated Nodes	X,Y,Z

portion of a Markov chain sample. This discarding helps to ignore the effect of initial values on the posterior inference.

C. Localization Error

The system accuracy measures the overall performance of the proposed algorithm or models for the location prediction. It depends on the calculated localization error E_i of each training point in the system. The localization error can be given by the Euclidean distance:

$$E_i = \sqrt{(O_x - \hat{O}_x)^2 + (O_y - \hat{O}_y)^2 + (O_z - \hat{O}_z)^2} \qquad (7)$$

where (O_x, O_y, O_z) and $(\hat{O}_x, \hat{O}_y, \hat{O}_y)$ are the actual and predicted locations for the mobile device of ith RPs, respectively. The overall system accuracy ψ refers to the average of the overall localization error which can be expressed by the following equation:

$$\psi = \frac{\sum_{i=1}^{N} E_i}{N} * 100 \qquad (8)$$

IV. RESULTS AND DISCUSSION

Figure 4 shows the boxplot of the standard deviation of RSS for the collected datasets at different times (with a gap of 3 years). It can be observed that AP4 has the lowest effect on RSS with a median of 2.51; the median of AP1, AP2, and AP3 are 3.76, 5.15, and 3.72, respectively. The deviation in the RSS reading during the long gap duration is due to the multipath and attenuation caused by changes in the testbed structure and the movements of people which led to fluctuating signal strengths at different times. Therefore, the radio map should be updated within a short time frame to avoid high localization error.
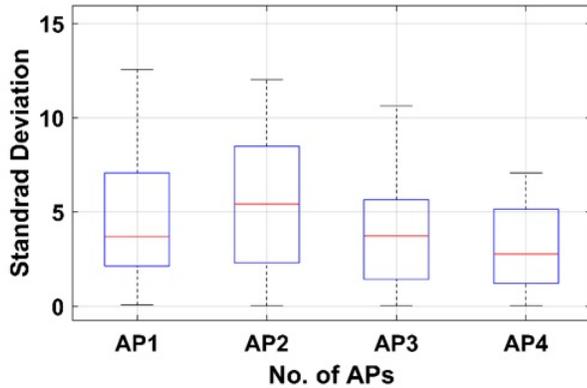
samples were collected in 360-degree rotation for each RP and AP along the corridor. Two experiments were performed in different time durations at the same location of the testbed, with the same number of Aps and the same mobile device. The gap between these two experiments was three years. This was to study the effects of RSS properties and how they can impact system accuracy over a long period of time. The data collection process for different time durations can be found in the previous paper [9].

B. User Location

User location is determined based on the Bayesian network using the OpenBUGS software [10]. This software is capable of generating a large number of samples using the Gibbs sampler. The generated samples for the unknown location depend on the convergence level, which means that increasing number of iterations yield no significant results. Table I presents the settings of OpenBUGS software for the inference location. The burn-in samples were used to discard the initial

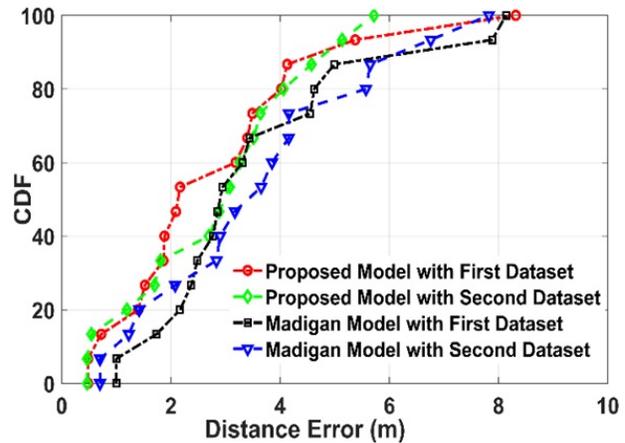Fig. 4. Effect of RSS over different time durations

Fig. 6. Comparison between 3D-BGM and Madigan model

on the RF fingerprinting technique uses available APs already deployed in the environment to estimate user location without any additional external devices. The proposed 3D-BGM has achieved an overall localization accuracy of 2.9 meters using only four APs with a small number of RPs compared to the first Bayesian model. In future, 3D-BGM will be further enhanced by considering a multi-story building rather than a single floor unit. This will be implemented by adding a new parameter to the proposed 3D-BGM called floor attenuation factor.

Fig. 5. Effect of the number of training points on the distance error

Figure 5 presents the effect of the number of training points employed to test the proposed 3D-BGM and Madigan model using first and second RSS datasets. Four sets of training points (Set1= 6, Set2 =9, Set3=12, Set4=15) were investigated using both RSS datasets for each model. It can be seen that the localization system achieves higher accuracy when the training points are increased for both models. Furthermore, the proposed 3D-BGM and Madigan model using the second RSS dataset reduced the average distance error compared to the first dataset. However, the proposed model outperformed the Madigan model for all datasets.

Figure 6 displays the rate of localization error for different types of datasets using the 2D-Madigan model and the proposed 3D-BGM. It was apparent that 3D-BGM outperformed the Madigan model for the first and second datasets. The overall average localization accuracies for the proposed 3D-BGM and Madigan model were 2.9 and 3.8 meters, respectively. Moreover, 3D-BGM achieved high accuracy using only four APs with a small number of RPs compared to the Madigan model.

V. CONCLUSION

This paper presented the design, analysis, and evaluation of 3D-BGM for indoor localization system. 3D-BGM based

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