WiFi-based indoor location system on a mobile device for a university building using Bayesian filters

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Abstract
This work describes the implementation of an indoor location system on a mobile device for a faculty of the Universidad Nacional de Ingeniería, Peru. The proposed system makes use of WiFi signals and a Bayes filter to predict the location. The main advantage of the proposed method is that it does not require special hardware. The experimental results show 92.31% for position accuracy and a real-time response.

1. Introduction
Typical global positioning systems can obtain high accuracy in outdoor environments, but they obtain low position accuracy for inside buildings (Motte et al., 2011). This problem has attracted many researchers and is useful for applications like asset tracking, proximity marketing, immersive experiences, augmented reality, warehouse robots, and more.

At present, there exist many indoor location systems (Sakpere et al., 2017), including infrared (IR), ultrasonic, radio frequency identification (RFID), wireless local area networks (WLAN), Bluetooth, and others (Zafari et al., 2017; Brena et al., 2017). In (Dhital et al., 2010), a precise WiFi-based system using the Monte Carlo filter is presented, however, the system performs tracking for precise trajectories, which is not suitable for our work. In Cano et al. (2013), an indoor positioning system for smart buildings is proposed, but it makes use of RFID devices, which results in extra costs. In a recent work, Li et al. (2018) describes a novel system that uses machine learning, but the system is intended for centimeter level precision and relies on visible-light technology. In addition, indoor Google Maps provides guidance in buildings, but its accuracy is not enough, according to our experience.

In this work we developed a system for indoor location in the Faculty of Electrical and Electronics Engineering at the Universidad Nacional de Ingeniería, Peru. This system does not demand additional hardware or implementation of special electronic hardware.

2. Methodology
2.1. Overview
The proposed indoor location system operates in real-time and makes use of six pre installed WiFi access points (APs). This system is intended to work on Android devices with low computational resources and low power consumption. In order to accomplish the response time, computational demand and energy requirements, we use a simple but effective Bayes estimator.

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2.2. Data Recolection

As mentioned in the previous section, the environment is the Faculty of Electrical and Electronics Engineering at the Universidad Nacional de Ingeniería, Peru. So, first, the main areas are identified and the total environment is divided into regions larger than 2x2 meters and less than 5x5 meters. Figure 1 depicts such distribution. Notice that only the green regions (access areas to different main environments) will be used for indoor location since these regions helps to find the desired main environment for visitors purposes.

![Regions at the first floor](image1)

(a) Regions at the first floor

![Regions at the second floor](image2)

(b) Regions at the second floor

Figure 1: Distributions of regions.

2.3. Pre-processing

The captured data are organized in one RSSI table per region. Then, the dataset is randomly shuffled and divided for training/testing. Several papers related to indoor location and based on RSSI measurement, assume its Gaussian probability density function (PDF) (Chruszczyk, 2017; Kaji and Kawaguchi, 2012). This is excused by relation to PDF of radio-receiver’s noise or together with the influence of average white Gaussian noise (AWGN) radio-channel which is generally modelled by a normal PDF. Figure 2 shows the original histograms and the cleaned histograms. Then, one AP table for each access point is constructed, which is the union of the clean histograms of regions with the same AP.

![APs histograms at region R001](image3)

Figure 2: Sample of original and cleaned histograms
2.4. Bayesian Filter

As formulated in (1), the AP tables generated in previous subsection are used to calculate the $P_{(A|B)}/P_{(B)}$ relationship. So, by a series of iterations, the prior value $P(A)$ is updated with the current estimated posterior value $P_{(A|B)}$ at the end of each iteration. The implementation of the Bayes-based estimator is shown in the Algorithm 1.

$$P_{(A|B)} = \frac{P_{(B|A)}P(A)}{P(B)}$$  \hfill (1)

Algorithm 1: Bayes Algorithm

N = # of regions, R = # of routers, $W_r = AP$ table for router r

procedure Bayes Estimator (w1, w2, ..., wR)

while probability < 95% do

% Performing Bayes

for r from 1 to R do

posterior$W_r = \text{norm}(\text{prior}W_r \times W_r[:, w_r])$

prob$_r = \text{max}(\text{posterior}W_r)$

pred$_r = \text{where}(\text{posterior}W_r == \text{prob}_r)$

end

% Finding the highest probability

probability = max(prob$_{1,2,...,R}$)

r$_{best} = \text{where}(\text{prob}_{1,2,...,R} == \text{probability})$

prediction = pred$_{r_{best}}$

% Assigning the new prior

for r from 1 to R do

prior$W_r = \text{posterior}W_r_{r_{best}}$

end

Return prediction, probability

end

end procedure

3. Experimental Results

To evaluate the performance of the indoor localization system, the Bayes estimator algorithm is carried out in the testing dataset. The results were summarized in a confusion matrix, which is a specific table layout that allows us to easily visualize the performance, see Figure 3. There, each column represents prediction and each row represents real values. In addition, the overall accuracy of our Bayes prediction algorithm is 92.31%. The application for indoor localization was tested on a Samsung J2 Android device (Android version 6.0.1). Then, we tested the app in different positions at different regions, and verified if the developed localization system works properly.

As expected, we verified that the system correctly predicted the locations for almost all positions inside different regions. Some results are shown in Figure 3. As we can see, the
in different regions.

\[
\begin{array}{cccccccccccc}
\text{R01} & \text{R02} & \text{R03} & \text{R04} & \text{R05} & \text{R06} & \text{R07} & \text{R08} & \text{R09} & \text{R10} & \text{R11} & \text{R12} & \text{R13} \\
0.97 & 0.94 & 0.94 & 0.91 & 0.89 & 0.95 & 0.94 & 0.96 & 0.96 & 0.97 & 0.92 & 0.94 \\
0.03 & 0.06 & 0.06 & 0.02 & 0.02 & 0.05 & 0.06 & 0.04 & 0.04 & 0.02 & 0.01 & 0.03 \\
0.01 & 0.01 & 0.02 & 0.07 & 0.06 & 0.01 & 0.02 & 0.01 & 0.01 & 0.02 & 0.01 & 0.02 \\
0.01 & 0.01 & 0.01 & 0.03 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\
0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\
0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\
0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\
0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\
0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\
0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\
0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01 \\
\end{array}
\]

(a) Result at region 5

Figure 3: Confusion matrix

(b) Result at region 9

Figure 4: Online results on an Android device at first and second floor.

4. Conclusion

In this paper, we introduced the implementation of a WiFi-based indoor location system to guide persons a faculty of the Universidad Nacional de Ingeniería, Peru. In order to achieve a high position accuracy with a fast response time using low computational resources, we make use of a simple but effective Bayes estimator. In fact, the experiments show promising results, obtaining an accuracy of 92.31% and a response time of around 20 milliseconds. In addition, the proposed methodology could be used for similar localization tasks such as asset tracking, immersive experiences, augmented reality, controlling robots and more.
References


