Implementation of an Indoor Location System for Mobile-Based Museum Guidance

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Abstract. In this work we proposed an indoor location system that makes use of a mobile phone and WiFi signal levels to determine the location of a person in the museum "Eduardo de Habich" at the Universidad Nacional de Ingeniería, Peru. Therefore, by determining the location, additional information such as recommendations, multimedia, an more could be shown to each user in order to have a better user experience. The main advantage with similar indoor location systems such as Beacons or RFID technology is that the proposed system does not require additional hardware as it only uses pre-installed WiFi hotspots. The experimental tests show promising results, achieving a location accuracy of 93.61%, which is useful for similar navigation tasks.

Keywords: Indoor location system · WiFi signal · Bayesian filter · Mobile phone · User experience

1 Introduction

Current navigation systems like Global Positioning System (GPS) or Global Navigation Satellite System (GLONASS) offer high accuracy in outdoor environments, but in indoor areas they provide low position accuracy [1]. For this reason, the implementation of indoor location systems has attracted the interest of researchers due to the demand for these systems in several real applications like immersive experiences, asset tracking, proximity marketing, indoor navigation, controlling robots in a warehouse, augmented reality, and more.

Up to date, there exist several approaches for indoor location systems [2] such as radio frequency identification (RFID), wireless local area networks (WLAN), Bluetooth among others [3,4]. Regarding WiFi based indoor location systems, in [5] a precise WiFi-based indoor location system using Monte Carlo (MC) filter is proposed, however, the system is intended for tracking trajectories with a high precision, which it is not suitable for our project since the divided regions are not so smalls. In [6], an indoor positioning system for smart buildings is used, but the system makes use of RFID technology, which results in additional costs. In a more recent work, [7] describes a novel system that uses machine learning techniques,

J. A. Lossio-Ventura et al. (Eds.): SIMBig 2019, CCIS 1070, pp. 69–75, 2020.
https://doi.org/10.1007/978-3-030-46140-9_7

nevertheless the system is intended for centimeter level location and relies on visible-light technology. In another recent work [8], an easy and understandable method is proposed in order to improve IoT localization in smart buildings across heterogeneous devices via a Markov-Chain model, however the system achieves a localization accuracy of 87.2% for a hexagonal region of 3.5 m cell radius. In addition, indoor Google Maps [9] provides guidance in buildings, but its accuracy is not enough, according to our experience.

In this paper, a system for indoor location for museum guidance is proposed, which is intended for the museum "Eduardo de Habich" at the Universidad Nacional de Ingeniería, Peru. In contrast with indoor location systems that relies on external devices like RFID hardware or Bluetooth beacons (which result in additional costs), the proposed system does not require additional equipment. In this way, making use of a mobile phone and pre installed access points, our indoor location system is able to provide a good position accuracy and the information related to its location.

2 Proposed Method

2.1 Overview

The presented system performs interior localization of museum visitors in real-time on a mobile phone using WiFi signal. This system works on devices with low computational resources. With the purpose to achieve response time and power computational requirements, a simple but effective estimator is employed, which is a Bayes recursive estimator (also called Bayes filter).

The proposed methodology has two phases: offline phase and online phase. At online phase, WiFi levels are captured several times per region, obtaining an RSSI table per region, later the RSSI data is divided into training and testing datasets for performance evaluation, then the normalized histograms are calculated and cleaned via Gaussian curve, finally the localization system is evaluated. At online phase, the Bayesian filter is implemented in an Android mobile device.

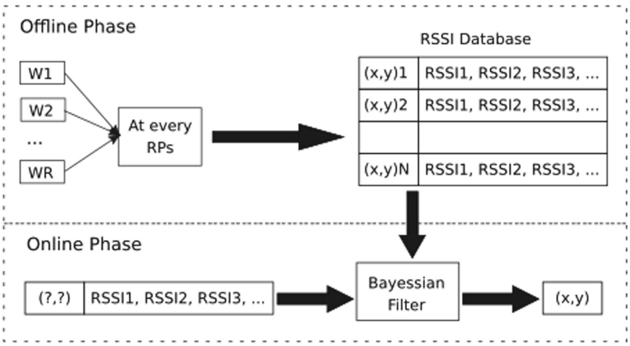


Fig. 1. Diagram for the proposed indoor location system

This filter uses the captured WiFi levels and the cleaned RSSI database to predict the most likely region. Figure 1 shows the diagram of our methodology.

2.2 Data Recolection

First, the main areas of the museum "Eduardo de Habich" at the Universidad Nacional de Ingeniería are identified and divided into regions larger than 2×2 m and less than 5×5 m. Figure 2 shows such a distribution.

Then, the WiFi information such as SSID, MAC and RSSI are recollected via a custom application in Java for Android devices. Therefore, 150 samples in each region (at different times during three non consecutive days/nights) are captured. Later, no stable APs and far APs are filtered, so, only the best APs are selected for the final dataset.

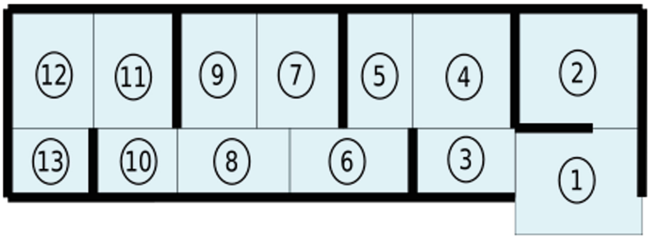


Fig. 2. Division of the museum into regions

2.3 Pre-processing

In this step, the samples are randomly shuffled, and divided in 80% for training and 20% for testing in order to evaluate the performance of our estimator. Then, the normalized histograms are extracted from the training dataset (for each AP and region). However, this original training database is composed of noisy samples which are affected by reflections and scattering (see Fig. 3).

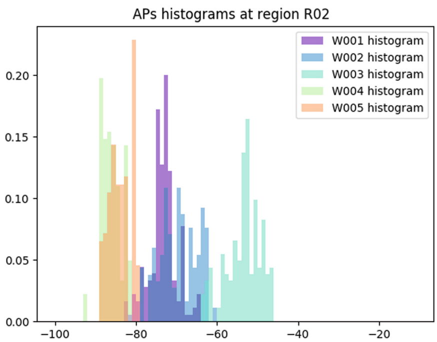


Fig. 3. Sample of the original histograms

Many papers related to RSSI based indoor location assume its Gaussian probability density function (PDF) [10,11]. This is justified by the relation to PDF of radio-receiver's noise or together to influence of average white Gaussian noise radio-channel which is modelled by a Gaussian PDF. Therefore, original histograms are cleaned by approximating each one to a Gaussian PDF. In Eq. (1), the formulation of a Gaussian PDF is shown, which is defined by two parameters: μ (mean) and σ (standard deviation).

$$f(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{1}$$

Figure 4 depicts one sample of the original and cleaned histograms, which are presented as continuous Gaussian curves. As we can see, this new normal distribution fills the missing values of the original RSSI histogram and readjust the noisy values which were disturbed by strong reflections and scattering.

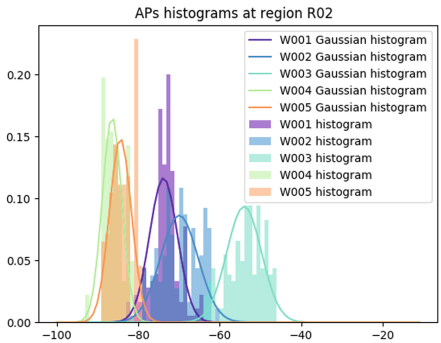


Fig. 4. Sample of the original and cleaned histograms

Finally, construction of one AP table for each access point is performed. In this way, the AP table will be made up of the union of the Gaussian histograms of different regions with the same AP. Table 1 show its structure.

Table 1. AP table for access point j (Wj)

Region	Gaussian histograms
Region 1	Wj Gaussian histogram at Region 1
Region 2	Wj Gaussian histogram at Region 2
	...
Region N	Wj Gaussian histogram at Region N

2.4 Bayesian Filter

In order to achieve response time and computational requirements, a straightforward and effective estimator is used, it is based on the Bayes recursive estimator [12]. This is able to infer the posterior using sensed and prior knowledge (see Eq. (2)). Being A the event we want the probability, and B the new evidence that is related to A. Therefore, the posterior $P_{(A|B)}$ is calculated by the likelihood $P_{(B|A)}$ (probability of observing the new evidence) and the prior $P_{(A)}$ (probability of our hypothesis without any additional prior information). $P_{(B)}$ is the marginal likelihood, which is the total probability of observing the evidence.

$$P_{(A|B)} = \frac{P_{(B|A)}P_{(A)}}{P_{(B)}} \tag{2}$$

Algorithm 1 describes the implementation of the Bayes-based estimator. This takes the AP tables and current WiFi measurement as inputs, and return the estimated region and its probability. Thereby, the algorithm recursively calculates the probability of the posterior region (line 11), then the probability (line 12) and predicted region (line 13) are calculated. The Algorithm 1 was implemented in Python for evaluation of performance of the Bayes estimator, and implemented in Java for real-time inference on an Android mobile phone.

Algorithm 1. Bayes Estimator Algorithm

1: $N = number\ of\ regions$; $R = number\ of\ routers$
2: $W_r = AP\ table\ for\ router\ r$
3: **procedure** BAYESESTIMATOR($w_1, w_2, ..., w_R$)
4:     # Start with uniform distribution
5:     $priorW_{1,2,..,R} = [1/N; 1/N; ...; 1/N]_{Nx1}$
6:     $probability = (100/N)\%$
7:     **while** probability $< 95\%$ **do**
8:         # Perform Bayes
9:         **for** r from 1 to R **do**
10:             $posteriorW_r = norm(priorW_r \times W_r[:, w_r])$
11:             $prob_r = max(posteriorW_r)$
12:             $pred_r = where(posteriorW_r == prob_r)$
13:         **end for**
14:         # Find the highest probability
15:         $probability = max(prob_{1,2,..,R})$
16:         $r\_best = where(prob_{1,2,..,R} == probability)$
17:         $prediction = pred_{r\_best}$
18:         # Update the new prior
19:         **for** r from 1 to R **do**
20:             $priorW_r = posteriorW_{r\_best}$
21:         **end for**
22:     **end while**
23:     Return $prediction, probability$
24: **end procedure**

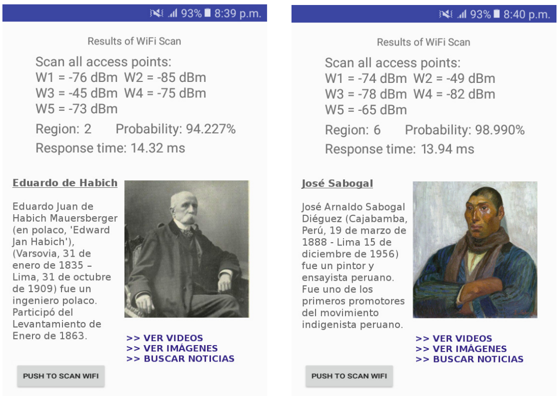
3 Experimental Results

In order to obtain the performance and another metrics for the indoor localization system, we evaluated it on the testing dataset. The results are defined by the overall accuracy and the confusion matrix (see Fig. 5). This matrix for the proposed system shows a high accuracy for the diagonal values and low accuracy for the others, it means that the system has a high accuracy per class/region. Also, the accuracy of the indoor location system is about 93.61%.

	R01	R02	R03	R04	R05	R06	R07	R08	R09	R10	R11	R12	R13
R01	0.95	0	0	0	0.01	0.02	0	0	0	0.01	0	0.01	0
R02	0	0.91	0	0	0.02	0.01	0	0.02	0	0	0	0.04	0.01
R03	0.01	0	0.95	0	0.01	0	0	0	0.03	0	0.01	0	0
R04	0	0	0	0.94	0	0.01	0.02	0	0.01	0	0	0.02	0
R05	0	0.04	0	0.03	0.9	0	0	0.02	0	0.01	0	0.01	0
R06	0.01	0	0.01	0	0	0.92	0	0.01	0.03	0	0.02	0.01	0
R07	0	0	0	0.02	0	0	0.94	0	0.01	0.01	0	0	0.03
R08	0.01	0	0.01	0	0.02	0	0	0.92	0	0.02	0	0.02	0
R09	0	0	0.01	0.01	0.01	0	0.01	0	0.93	0	0.01	0.01	0
R10	0.01	0.02	0	0	0.01	0	0	0	0	0.96	0	0	0
R11	0	0.02	0	0	0.02	0	0	0.01	0.01	0	0.94	0	0
R12	0	0.01	0	0.02	0	0	0.01	0	0	0	0	0.95	0.01
R13	0	0.01	0.01	0	0	0.01	0	0	0	0.01	0	0	0.96

Fig. 5. Confusion matrix for the proposed system

For the evaluation of the system, our Android application was tested on a Samsung J2 with Android 6.0.1. This is conducted in different regions and for several positions. As expected, the system correctly predicted the locations in all regions. Figure 6 shows some results of this test. As we can see, our system correctly predict the location with a probability above 94%.



(a) Result at region 2 (b) Result at region 6

Fig. 6. Online results on an Android mobile phone

4 Conclusions

This paper introduced the implementation of a WiFi based indoor location system to guide visitors at the museum "Eduardo de Habich" at the Universidad Nacional de Ingeniería, Peru. With the aim to accomplish a high positioning accuracy, a fast response time and low computational power consumption, the proposed system makes use of a simple and effective Bayes recursive estimator. Experiments show promising results, obtaining an accuracy of 93.61% and a response time of 14 ms. Thus, the proposed methodology is not limited to this work, but can also be applied to similar localization tasks such as robot control, immersive experiences, asset tracking, augmented reality, among others.

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