Computer Networks 120 (2017) 43–55

Contents lists available at ScienceDirect

Computer Networks

journal homepage: www.elsevier.com/locate/comnet

Robust, cost-effective and scalable localization in large indoor areas

Tong Guan*, Le Fang, Wen Dong, Dimitrios Koutsonikolas, Geoffrey Challen, Chunming Qiao

Computer Science and Engineering, the State University of New York at Buffalo, Buffalo, New York

ARTICLE INFO

Article history:
Received 24 March 2016
Revised 18 November 2016
Accepted 7 April 2017
Available online 8 April 2017

Keywords:
Indoor localization
Large indoor areas
RSS
Fingerprinting
Cost-effective

ABSTRACT

Indoor location information plays a fundamental role in supporting various interesting location-aware indoor applications. Widely deployed WiFi networks make it feasible to perform indoor localization by first establishing a received signal strength (RSS) map covering the whole area based on a signal propagation model, then determining a location from an online RSS measurement given the RSS map. However, challenges remain in practical deployments, due to inaccurately estimated RSS values in the RSS map and an insufficient number of access points (APs) in large indoor areas. To address these challenges, we develop a robust, cost-effective and scalable localization system (REAL). Our approach adaptively searches for the best model parameters with limited training resources. In addition, REAL utilizes a probabilistic approach for location searching by considering errors from the signal propagation model. It also exploits information regarding unobserved APs at a given location and an optimal clustering method. We systematically evaluate the accuracy of the propagation model with different configurations. Our intensive real-world experimental results demonstrate that REAL achieves considerable localization accuracy at a very low training cost. In addition, the comparisons over two large indoor environments show that REAL consistently outperforms other state-of-the-art systems and can be effectively applied to various real-world scenarios.

© 2017 Published by Elsevier B.V.

1. Introduction

Indoor location information is a fundamental part of mobile and ubiquitous computing, supporting a variety of interesting applications such as location-aware advertisements for shoppers and indoor navigation for the blind. Although the satellite-based global positioning system (GPS) provides efficient and scalable services to mobile users in outdoor cases, it is not suitable for establishing indoor location because the signal is attenuated, reflected, and scattered by complicated indoor environments. Therefore, how to design and implement a scalable and cost-effective indoor localization system has been extensively studied over the last decade.

Positioning algorithms can be coarsely classified into two categories: trilateration and fingerprinting. The basic idea of trilateration is to estimate the position of an object by measuring its distance from at least three known reference points. However, the accuracy achieved through trilateration is unacceptable without deploying extra infrastructure such as ultra wideband (UWB) signals. In this paper, we focus on the fingerprinting approach to avoid such overhead. Fingerprinting usually contains two phases: an offline training phase of collecting features (e.g., a vector of RSS measurements from various APs) at known locations to establish an RSS map; and an online localization phase of estimating a location based on the RSS map and an online RSS measurement.

Despite considerable progress in this area, many challenges remain—particularly for deployments spanning large areas. More specifically, most validation experiments are either carried out in small areas [1,2] or done under the assumptions that more than three reference base stations can be seen at all locations [3]. In contrast, data collected in our building shows that at 20% of the locations, the number of distinct physical WiFi APs seen by a device is lower than three. It is even worse for a Bluetooth network deployed in the same area with similar density: more than three Bluetooth beacons are only seen at 45% of measured locations due to a shorter communication range.

Another major challenge is the laborious and time-consuming effort required in the calibration and training phase. The weaknesses of such schemes are two-fold: first, it is almost impossible for deployment in large indoor environments at a scale of over thousand square meters; second, the resulting accuracy is not worth considering such expensive pre-deployment cost. Recently, a large amount of literature [2–7] has proposed reducing the training effort by predicting RSS values with propagation models instead of taking measurements manually. Although complicated models have been proposed and extra hardware are used, the RSS mod-

* Corresponding author.
E-mail addresses: tongguan@buffalo.edu, tongguan2009@gmail.com (T. Guan), lefang@buffalo.edu (L. Fang), wendong@buffalo.edu (W. Dong), dimitrio@buffalo.edu (D. Koutsonikolas), challen@buffalo.edu (G. Challen), qiao@buffalo.edu (C. Qiao).

http://dx.doi.org/10.1016/j.comnet.2017.04.032
1389-1286/© 2017 Published by Elsevier B.V.

eling error still cannot be eliminated completely. As a result, inaccurately predicted RSS values are used in the location searching phase and the error introduced from the modeling itself is not well considered.

Finally, traditional schemes take two directions in the online location searching phase: they either convert RSS to distance and then utilize triangulation to locate the client [3]; or they employ a K-nearest neighbor (KNN) alike algorithm to estimate the location [1,8]. Although a clustering method is utilized in [2], but these results are not satisfactory since they do not consider the modeling error and no prior studies have investigated the optimal cluster size.

In this paper, we extended our work published in [9], a low-cost and robust indoor localization system called REAL. REAL searches for RSS propagation model parameters and uses them to build an RSS map, even with only a few training locations for a large indoor environment. In addition, REAL exploits a robust location searching process by considering the model error through a probabilistic approach, the information on "unobserved" APs, and a novel density-based clustering method. We extended our previous work by conducting intensive evaluations and thorough comparisons with state-of-the-art systems in terms of both model calibration and localization error. Specifically, the major novelties and contributions of this work are:

- We evaluated the accuracy of the propagation model with different configurations systematically and developed an adaptive approach for the model calibration process given different amount of training resources. Base on comprehensive evaluations, we show that our approach can achieve relatively high RSS prediction accuracy and outperform state-of-the-art systems under various scenarios.
- We evaluated the effectiveness of our system in two large real-world indoor environments, the 3750 m^2 3rd floor of Davis Hall and the 7360 m^2 1st floor of Student Union at University at Buffalo. We conducted intensive experiments over both WiFi and Bluetooth networks in these sites. Our evaluation results show that REAL consistently outperforms other state-of-the-art systems in these two sites regardless of the amount of training resources and the coverage of transmitters.

The rest of the paper is organized as follows. In Section 2, we provide the background about RSS mapping techniques. In Section 3, we introduce our localization system REAL, and its mapping technique and improved location searching algorithm. We present our performance evaluation in a real building in Section 4. Finally, we conclude our work in Section 5.

2. Related works

Trilateration techniques depend on an accurate estimation of distance, however, estimating distance by utilizing RSS in 802.11 networks is quite inaccurate due to multipath, refraction or shadow fading. The work in [10] has shown that, for only 69% of the time, distance estimation with WiFi RSS in a typical indoor environment falls between 2/3 and 3/2 of the actual distance. The large ranging error will greatly affect the accuracy of trilateration solutions. In order to acquire accurate ranging information, research has focused on deploying additional infrastructure or extra hardware to estimate distances. UbiSense [11] and the work in [12] relied on UWB signals to calculate distance by estimating the time of arrival (TOA) of the direct signal path. Although remarkable performance has been achieved, the complexity and specific hardware requirement make such systems impractical to deploy.

As a pioneering work, RADAR [1] proposed an alternative approach called fingerprinting. Instead of relying on inaccurate distance estimation, fingerprinting systems record the RSS from several reference points in range and store them in a database (also known as RSS radio map) along with the known location coordinates. Early fingerprinting systems are implemented utilizing a variety of radio frequency (RF) signals such as infrared signals (Active Badge [13] and EIRIS [14]), and ultrasound signals (such as Cricket [15] and the work in [16]). Although such research has shown promising results, they are impractical and expensive to deploy nowadays, due to the growing smartphone market and parallel massive deployment of 802.11 networks. Therefore, our discussion only focuses on effective and practical indoor localization systems based on WiFi infrastructure in the scope of this paper.

Based on RADAR, Horus improved the location searching result by assigning each candidate in the fingerprint database a probabilistic weight based on the online query. However, making measurements manually with a resolution of 1.5 m (in a 68 by 26 m space) is tedious for deployment in large indoor areas. In order to reduce the pre-deployment effort, many researchers have exploited a signal propagation model—such that the RSS has a linear relationship with the log-distance between the signal transmitter and receiver—to reduce the calibration effort [2–7,17]. TIX [17] modified APs to measure the RSS from neighboring APs, and linear interpolation was then applied to establish the RSS map, which requires the knowledge of AP transmission power and modification of commercial APs. The authors in [4,5] deployed sniffers to adaptively tune the propagation parameters in real time. Despite such a huge amount of effort in finding the most accurate propagation model, the modeling error can not be eliminated completely. Therefore, especially for deploying localization system in large indoor environments, the real challenge lies in searching for the best location from the inaccurate predicted RSS map.

In terms of location searching, one typical comparison metric is the mean square error (MSE) between RSS measurement vectors. Intuitively, a smaller distance in the RSS vector space indicates a shorter distance between their corresponding location in the real world. The authors in [1,8,18] utilized KNN alike approaches—the client's location is estimated as the center or the weighted average of top k nearest neighbors. ARIADNE proposed a clustering approach that groups locations based on MSE—the center of the cluster with the largest size is returned as the final result. However, ARIADNE does not consider the uncertainty of estimated RSS values from the constructed map, which is introduced from inaccurate propagation models. More importantly, their evaluation are carried out in a small indoor space, with a strong assumption that more than three APs can be detected anywhere. However, practically, one usually observes only fewer than three APS, which creates the ambiguity where multiple locations have similar MSEs compared to the online RSS measurement. Although [19] solved this problem with the assistance of peers and acoustic ranging, the problem remains if no helping device is in close proximity.

To summarize, although considerable improvements have been achieved regarding indoor localization over 802.11 networks, none has achieved an impressive performance for large indoor cases while preserving acceptable accuracy, low pre-deployment cost, and robustness at the same time. Our goal is to design an indoor localization system that overcomes these shortcomings through a set of key features: a) low complexity and cost, the system does not require additional infrastructure, reconfiguration of the existing 802.11 networks, or installation of any other hardware (such as UWB) on commercial-off-the-shelf (COTS) devices such as smartphones, tablets or laptops, b) robustness, the system is adaptive to environmental changes such as movement of furniture or people, c) scalability, the system is easily adaptable to even larger areas and works under infrastructure using similar radio signals such as Bluetooth and ZigBee, d) accuracy, the system offers excellent performance compared with existing ap-

Download English Version:

https://daneshyari.com/en/article/4954667

Download Persian Version:

https://daneshyari.com/article/4954667

Daneshyari.com