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Design protocol and performance analysis of indoor fingerprinting positioning systems

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ABSTRACT

Location fingerprinting is a technique widely suggested for indoor positioning. Given specific positioning requirements, this paper provides methods for setting up the network elements such that those requirements can be met by the location fingerprinting method. In particular, the paper aims to optimize indoor fingerprinting systems such that the positioning performance gets close to the optimal performance indicated by the lower bound of the system. The Weiss–Weinstein bound (WWB) and Extended Ziv–Zakai bound (EZZB) are suggested for indoor environments, as they are shown to have superior predictive performance for this application. The effects of the number and geometry of access points (APs), the number and spatial arrangement of reference points (RPs), and the number of signal strength samples taken per location are presented, both through simulations and analytical lower bound estimates. The impact of the path-loss exponent, the standard deviation of the signal strength measurement, and size of the operating area are also investigated. These theoretical/simulation estimates are also assessed using experimental data. By utilizing these tools, a system designer is able to set appropriate parameters to optimize the compromise between positional accuracy and the costs associated with the setting up of the fingerprinting measurements database.

1. Introduction

With increasing user demands on Location-based Services (LBS) and Social Networking Services (SNS), indoor positioning has become more crucial. Because of the general failure of Global Positioning System (GPS) indoors, non-satellite-based technologies, therefore, are important for indoor localization [1]. In general, the techniques used for localization indoors and outdoors are basically the same. Localization techniques that can be used indoors usually are based on triangulation (time of arrival (TOA), time difference of arrival (TDOA), Angle of Arrival (AOA)), proximity, dead reckoning, and fingerprinting using received signal strength (RSS) measurements [2]. Note that every positioning technique has its own pros and cons, so they should be chosen considering the requirements that a specific application should meet.

Wireless Local Area Networks (WLAN) have widely been employed for indoor location fingerprinting technique which is one of the suggested methods for indoor positioning [3–5]. This technique requires a survey of Radio Frequency (RF) signal strength vectors to be made ahead of the system's use for localization. Fingerprinting can be considered as an estimator which employs the RSS measurements to calculate the most likely position of the user. It has two stages: 'training' and 'positioning'. It stores the location-dependent characteristics of a signal collected at Reference Points (RPs) in a database in the training stage, and in the positioning stage, estimation algorithms are applied to estimate the position of the user based on the fingerprint of the user and the database.

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The main advantage of location fingerprinting is its capability of alleviating some of the problems related to multipath and Non-Line of Sight (NLOS) propagation in an indoor environment [6]. In addition, it requires no addition infrastructure hardware as Wi-Fi access points (APs) are widely deployed indoors, and every mobile device is equipped with a Wi-Fi receiver. However, there are challenges for location fingerprinting. The main drawback is the required time, data storage, and human efforts to deploy the training stage in the area of operation. Although different ways suggested in [7,8] to reduce the labor effort of the training stage, it is not always possible to carry out this stage of fingerprinting when the rapid deployment is required; so other techniques can be used instead such as TOA discussed in [9,10]. Furthermore, there are temporal variation for Wi-Fi fingerprints caused by human presence and orientation as well as to the presence of small objects in a room [11]. While in [4] recording the fingerprints for different body orientation is suggested so that the effect of orientation remains minimal, the fingerprinting procedure becomes time-consuming and labor-intensive.

The fingerprinting estimation methods can be implemented in various ways from a mathematical point of view. They are based on deterministic [4] or probabilistic [12] algorithms which have been used in Wi-Fi [6], FM radio [13], and mobile phone [6] networks. The measurements of the RSS values at one location can vary considerably due to the environmental uncertainties that might cause fluctuations in the RSS data. Therefore, in deterministic fingerprinting the average value is stored for post processing. Nearest Neighbor (NN), K-Nearest Neighbor (KNN), and K-Weighted Nearest Neighbor (KWNN) methods are the most popular deterministic fingerprinting methods [4]. However, in probabilistic methods, the RSS measurements are considered as a random variable at one point. The Maximum Likelihood Estimate (MLE), Minimum Mean Square Error (MMSE), and histogram methods are all probabilistic.

Although many aspects of the fingerprinting positioning systems are well studied and widely discussed, there is a lack of analytical models at the fingerprinting system design level [14]. Thus, given specific positioning requirements, there is not a well studied model and clear design tools as to how set up the system elements such that those requirements are met. For instance, given a level of accuracy performance or error probability for a positioning system, there is no smart protocol to guide decisions on the system configuration parameters such as the optimum number and the location of the RPs, the minimum required number of APs, and the arrangement of the whole fingerprinting system. This lack can, therefore, potentially cause wasted time, energy, and money when developing a system to meet particular requirements. On the other hand, by deploying analytical methods and considering the theoretical lower bounds on positioning error, the system designer would be able to evaluate the performance of the system ahead of time and optimize the system parameters while the system requirements are met. Knowing the lower limit of the achievable localization error helps the designer to have an informed insight into whether or not further improvements are achievable [15]. Various system configurations can also be evaluated to achieve the potential location accuracy during the trade-off between cost and accuracy. Although estimation of the positioning errors also help improve the network parameters [16], lower bound calculations also are of significance in the positioning systems (and in many other system designs procedures) as they expresses a lower bound on the variance of estimators of a deterministic parameter. It is known that one of the goals of the statistical theory is to describe how well we can estimate parameters of interest in principle for any given model.

The accuracy of an indoor fingerprinting positioning system depends mostly on the estimation method used to locate the user. However, no estimator can achieve a better performance than the value that the lower bound on Root Mean Square Error (RMSE) determines [15]. In other words, the RMSE of any estimators corresponding to the lower bound, indicates how good the estimators are, and how much further improvement is possible for the localization estimator as it approaches to the optimal performance.

Various lower bounds are proposed and are used to evaluate the estimation performance of different systems. The lower bounds developed in estimation theory can be categorized into two main categories. First, the non-Bayesian bounds for cases where the location of the test point(TP) is deterministic and second, Bayesian bounds for cases that the location of the TP is based on a random distribution [17]. Some of the common deterministic lower bounds include the Cramer–Rao (CR) [18] and the Barankin bounds [19] and some of the common Bayesian bounds include the Bayesian Cramer–Rao bound (BCRB) [17], the Weiss–Weinstein bound (WWB) [20,21], and the Ziv–Zakai bound (ZZB) [22] with their improvements. In this paper we discuss the bounds that are more related to our work, for our proposed positioning system.

In estimation theory, the Cramer–Rao bound (CRB) as a general evaluation tool for localization accuracy is the most common lower bound on the variance of any unbiased estimator [23]. There are many studies to calculate CRB for their localization systems [24–26]. However, CRB does not always provide the actual lower bound of the estimator since it assumes the estimator is unbiased while most of the localization techniques are biased [27]. For instance, the matching algorithms are considered biased since there are a restricted number of RPs they can match to. Furthermore, the CRB does not employ the known prior information about the distribution of the location of the user or measurements taken in the past [27,15]. It also does not provide any information about the number of the RPs in the fingerprinting system.

The BCRB is an extension of the CRB, and combines the prior information with the CRB and results in a new bound on the MSE that does not have any limitation for biased estimators. However, due to some discontinuities in the joint probability density function caused by NLOS propagation effects, the required conditions for the BCRB are not met, so it is not a perfectly valid and reliable lower bound for use in indoor environments [28]. In this paper we utilize more general and robust lower bounds such as the WWB and the Extended Ziv–Zakai bound (EZZB) [29] that could alleviate these problems for the indoor localization case [15].

Authors in [26] calculated the CRB of localization using Signal Strength Difference (SSD) as the location fingerprint.