Ad Hoc Networks 12 (2014) 100–114

Contents lists available at SciVerse ScienceDirect

Ad Hoc Networks

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

Low-dimensional signal-strength fingerprint-based positioning in wireless LANs

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A R T I C L E   I N F O

Article history:
Received 3 June 2011
Received in revised form 2 November 2011
Accepted 6 December 2011
Available online 24 December 2011

Keywords:
Compressive sensing
Sparse representation
Multivariate Gaussian model
Kullback–Leibler divergence
RSSI measurements
Localization

A B S T R A C T

Accurate location awareness is of paramount importance in most ubiquitous and pervasive computing applications. Numerous solutions for indoor localization based on IEEE802.11, bluetooth, ultrasonic and vision technologies have been proposed. This paper introduces a suite of novel indoor positioning techniques utilizing signal-strength (SS) fingerprints collected from access points (APs). Our first approach employs a statistical representation of the received SS measurements by means of a multivariate Gaussian model by considering a discretized grid-like form of the indoor environment and by computing probability distribution signatures at each cell of the grid. At run time, the system compares the signature at the unknown position with the signature of each cell by using the Kullback–Leibler Divergence (KLD) between their corresponding probability densities. Our second approach applies compressive sensing (CS) to perform sparsity-based accurate indoor localization, while reducing significantly the amount of information transmitted from a wireless device, possessing limited power, storage, and processing capabilities, to a central server. The performance evaluation which was conducted at the premises of a research laboratory and an aquarium under real-life conditions, reveals that the proposed statistical fingerprinting and CS-based localization techniques achieve a substantial localization accuracy.

1. Introduction

Location-sensing has been impelled by the emergence of location-based services in the transportation industry, emergency situations for disaster relief, the entertainment industry, and assistive technologies in the medical community. Location-sensing systems can be classified according to their dependency on and/or use of (a) specialized infrastructure and hardware, (b) signal modalities, (c) training, (d) methodology and/or use of models for estimating distances, orientation, and position, (e) the coordination system (absolute or relative), scale, and location description, (f) localized or remote computation, their mechanisms for device identification, classification, and recognition, and their accuracy and precision requirements. The distance can be estimated using time-of-arrival (*e.g.*, GPS, PinPoint [1]) or signal-strength measurements, if the velocity of the signal and a signal attenuation model for the environment can be accurately estimated, respectively. Positioning systems may employ different modalities, such as, IEEE802.11 (*e.g.*, Radar [2,3], Ubisense, Ekahau [4]), infrared (*e.g.*, Active Badge [5]), ultrasonic (*e.g.*, Cricket [6,7], Active

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1570-8705/$ - see front matter © 2012 Published by Elsevier B.V.
doi:10.1016/j.adhoc.2011.12.006

Bat), Bluetooth [3,8–11], 4G [12], vision (*e.g., EasyLiving* project), and physical contact with pressure (*e.g., Smart Floor*), touch sensors or capacitive detectors. They may also combine multiple modalities to improve the localization, such as optical, acoustic and motion attributes (*e.g.,* SurroundSense [13]).

The popularity of IEEE802.11 infrastructures, their low deployment cost, and the advantages of using them for both communication and positioning, make them an attractive choice. Most of the signal-strength based localization systems can be classified into the following two categories, namely *signature- or map*-based and *distance-prediction*-based techniques. The first type creates a signal-strength signature or map of the physical space during a training phase and compares it with the signature generated at runtime (at the unknown position) [2,14,15]. To build such signatures, signal-strength data is gathered from beacons received from APs. During a training phase, such measurements are collected at various predefined positions (of the map) and signatures are generated that associate the corresponding positions of the physical space with statistical measurements based on signal-strength values acquired at those positions. Such maps can be formed with data from different sources or signal modalities to improve location-sensing [3,6]. The distance-prediction-based techniques use the signal-strength values and radio-propagation models to predict the distance of a wireless client from an AP (or any landmark) or even between two wireless clients (peers) with estimated position (such as CLS [16]). In situations where a deployment of a wireless infrastructure may not be feasible, positioning mechanisms may exploit cooperation by enabling devices to share positioning estimates [1,16–22]. A survey of positioning systems can be found in [23].

In this paper, first we build on our earlier work on CLS [16,20], which generates statistical-based fingerprints using the *received signal-strength* (RSSI) measurements from an IEEE802.11 infrastructure. The vast majority of current fingerprint positioning methods does not take into account the interdependencies among the RSSI measurements at a certain position from the various APs. These interdependencies provide important information about the geometry of the environment and can be quantified using the second-order spatial correlations among the measurements. Hence, the employment of multi-dimensional distributions is expected to provide a more accurate representation of the RSSI signatures, leading to improved positioning performance. Simple models whose second-order statistics can be accurately and easily estimated could be used in practice. In particular, a multivariate Gaussian-based approach is employed to take into consideration the statistics of the RSSI measurements not only from each distinct AP but also the interplay (covariance) of measurements collected from pairs of APs. The signature comparison and position estimation is based on the Kullback–Leibler divergence (KLD): the cell corresponding to the minimum KLD is reported as the estimated position. This approach is generalized by applying it iteratively in different spatial scales.

The difficult to predict nature of the RSSI measurements, due to the impact of transient phenomena on the RSSI values, impels for extensive training, which increases the overhead of the fingerprint-based positioning systems: a larger training set and more sophisticated algorithms are often employed to capture the dynamic complex nature of the RSSI measurements. On the other hand, the inherent sparse nature of the localization of a mobile device in the physical space (since it can be placed at a single position of a discretized grid-like form of the environment) motivates the use of the recently introduced theory of *compressive sensing* (CS) [24,25] for target localization [26]. CS states that signals which are sparse in a suitable transform basis can be recovered from a highly reduced number of incoherent random projections. Hence, the CS-based approach comes as an evolution to the traditional methods dominated by the well-established Nyquist–Shannon sampling theory, and consequently it could be exploited in the design of efficient localization systems characterized by limited resources.

In a recent work [27], a CS-based indoor localization method was introduced based on RSSI measurements. In particular, the location estimation algorithm is carried out on the mobile device by using the average RSSI values in order to construct the transform basis. The sparsity-based CS localization algorithm proposed in this paper differs from the work in [27] in several aspects. In contrast to [27], where the estimation is performed by the wireless device with the potentially limited resources, in our proposed algorithm the computational burden can be assigned to a central node (fusion center), where increased storage and processing resources are available. Unlike in [27] that uses the average RSSI values, the proposed CS approach is applied directly on the raw RSSI measurements, thus exploiting their time-varying behavior. Then, the estimation of the unknown position is performed by solving a constraint optimization problem for reconstructing a sparse vector with its coordinates being “1” or “0” depending on whether the mobile device is placed or not at the corresponding cell.

This paper makes the following contributions:

1. It proposes and evaluates a novel fingerprinting approach that exploits the spatial correlations of signal-strength measurements collected from various wireless APs based on a *multivariate Gaussian* model.
2. It introduces a novel localization approach that applies *compressive sensing* (CS), which can achieve an increased accuracy in the position estimation, while reducing the communication overhead required for the exchange of measurements, and thus, becoming more appropriate for energy-constrained devices.
3. It performs a comparative performance analysis of various signal-strength fingerprinting methods in the premises of a research laboratory and an aquarium under different conditions.

The paper is organized as follows: Section 2 presents recently introduced statistical signal-strength signature techniques, along with the proposed statistical approach based on the use of multivariate Gaussian distributions for modelling the statistics of the RSSI measurements. In Section 3, the main principles of CS are introduced and the proposed CS-based localization method is analyzed in detail. Section 4