Computer Networks 95 (2016) 51–61

Contents lists available at ScienceDirect

Computer Networks

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

An approach using support vector regression for mobile location in cellular networks

Robson D.A. Timoteo[a], Lizandro N. Silva[b,1], Daniel C. Cunha[a,*], George D.C. Cavalcanti[a]

[a] Centro de Informática da UFPE, Av. Jornalista Anibal Fernandes, s/n, 50740-560 Recife, PE, Brazil
[b] Telefonica-Vivo, Avenida Engenheiro Domingos Ferreira, 837, 51011-051 Recife, PE, Brazil

ARTICLE INFO

Article history:
Received 13 February 2015
Revised 10 December 2015
Accepted 15 December 2015
Available online 22 December 2015

Keywords:
Wireless communications
Positioning system
Fingerprinting techniques
Machine learning
Support vector regression

ABSTRACT

Wireless positioning systems have become very popular in recent years. One of the reasons is the fact that the use of a new paradigm named *Internet of Things* has been increasing in the scenario of wireless communications. Since a high demand for accurate positioning in wireless networks has become more intensive, especially for location-based services, the investigation of mobile positioning using radiolocalization techniques is an open research problem. Based on this context, we propose a fingerprinting approach using support vector regression to estimate the position of a mobile terminal in cellular networks. Simulation results indicate the proposed technique has a lower error distance prediction and is less sensitive to a Rayleigh distributed noise than the fingerprinting techniques based on COST-231 and ECC-33 propagation models.

1. Introduction

An extraordinary growth of wireless systems has been observed in recent years. The evolution and dissemination of mobile computing devices, such as tablets, smartphones, sensors and actuators, have motivated this development, primarily in the context of the *Internet of Things*, a new paradigm that is moving forward in the scenario of wireless telecommunications [1].

Considering that wireless information access is widely available, a high demand for accurate positioning in wireless networks has become more intensive, especially for location-based services [2,3]. For this purpose, the positioning techniques can be classified in indoor and outdoor. In case of indoor positioning, the main challenges are: (*i*) inefficiency of global positioning system (GPS)—one of the most traditional localization techniques [4]—inside buildings; (*ii*) different materials (glass, plaster, wood) are used to construct the buildings walls and each material has its specific attenuation values for radio frequency signals; (*iii*) multipath loss, i.e., propagation phenomenon that results in radio signals reaching the receiving antenna by two or more paths. For outdoor localization, GPS is a widely adopted technique that is in use for many years. However, GPS do not solve the outdoor positioning problem for large networks of very small and low power devices. Some factors, such as size, cost, and power constraints inhibit the use of GPS on all nodes. So, it is necessary to explore other alternatives, such as radiolocalization [5–9].

Mobile positioning using radiolocalization techniques can involve different parameters, such as time of arrival (ToA), angle of arrival (AoA), and received signal strength indicator (RSSI) measurements. Various proposals can be found in the literature, but these techniques tend to be

* Corresponding author. Tel.: +55 81 21268430; fax: +55 81 21268438.
E-mail addresses: rdat@cin.ufpe.br (R.D.A. Timoteo), lizandro.silva@telefonica.com (L.N. Silva), dcunha@cin.ufpe.br (D.C. Cunha), gdcc@cin.ufpe.br (G.D.C. Cavalcanti).
[1] Tel.: +55 81 981208194.

http://dx.doi.org/10.1016/j.comnet.2015.12.003

very inaccurate, in particular because of multipath and non-line-of-sight (NLoS) propagation [10–12]. For the purpose of obtaining a better precision, an interesting approach is to model the geolocalization problem of mobile terminals in wireless networks as a machine learning (ML) problem. ML is a data-driven approach that learns from data. So, based on past observations, ML algorithms aim to automatically extract information from data in order to make accurate predictions. For example, in [13], a least square-support vector machine algorithm is proposed to model the relationship between ToA measurements and the position of the user.

Previous works used different ML approaches to address wireless positioning prediction. Among these techniques, support vector regression (SVR) has been used successfully in indoor location fingerprinting [6–9]. Brunato and Battiti [7] compared five different algorithms: support vector machine (SVM), weighted and non-weighted *k*-nearest neighbors, Bayesian approach, and multi-layer perceptron. Their best results were obtained with SVR. In a recent work, Zou et al. [14] used online sequential extreme learning machine to indoor localization. Their proposal obtained better precision than *k*-nearest neighbors, fuzzy *k*-nearest neighbors, and batch extreme learning machine; however, they did not compare it with SVR. A comparison between extreme learning machine and SVR applied to the problem of range-free localization can be found in [6]. The authors concluded that extreme learning machine is also a good machine learning technique, however, it cannot be preferred to SVR.

In this work, we propose an ML approach using SVR to predict path loss in an urban outdoor environment. From these predictions, coverage maps are used to locate the position of a mobile terminal. Simulation results indicate that the SVR-based approach is a better alternative when compared to fingerprinting location techniques using COST-231 and ECC-33 propagation models. Besides, the proposed approach is less sensitive to a Rayleigh distributed noise than the two fingerprinting location methods considered. It is also important to remark that, to the best of our knowledge, this is the first work to address outdoor localization using ML.

The outline of the paper is as follows. In Section 2, we present the principles of fingerprinting location techniques, as well as some basic concepts about SVR. In Section 3, we propose a fingerprinting SVR-based algorithm to estimate the position of the mobile node based on the path loss predictions. Numerical results comparing the localization methods are shown in Section 4, and finally, conclusions are drawn in Section 5.

2. Basic background

This section provides sufficient background on fingerprinting location techniques and SVR.

2.1. Fingerprinting location techniques

Fingerprinting (FP) location techniques are a group of mobile station (MS) positioning methods that are accurate and suitable for NLoS environments and can be applied in any wireless network [15,16]. There is a huge variety of fingerprinting techniques, but as shown in [15], all share the same basic elements as follows: fingerprint, database, location server, search space reduction technique and pattern matching.

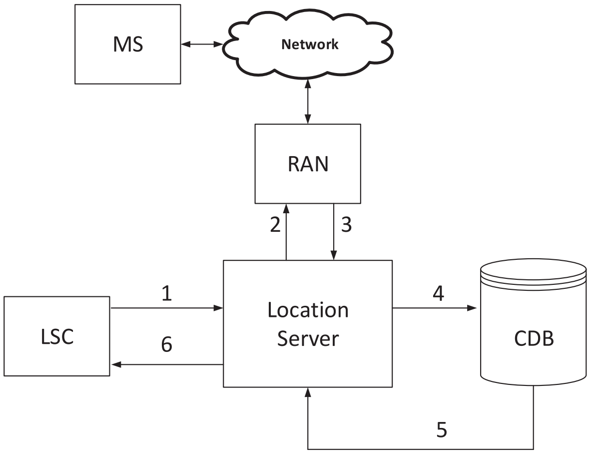

Fig. 1. Simplified diagram of a fingerprinting location (adapted from [15]).

Fingerprint is the vector with all features (observed values) which are used for pattern matching. Among the signal parameters commonly used as features, we can emphasize RSSI, AoA, ToA and time difference of arrival (TDoA) [16]. The database, also known as fingerprint correlation database (CDB), is built from collected field data and predictions made by radio propagation models, such as COST-231 [15]. Each fingerprint stored in the database is linked to a specific position. In this scenario, it is not feasible to make measurements at all positions. Therefore, propagation models are used to generalize the measurements. The location server is a network element that is responsible for receiving location requests, consulting the database and estimating the MS position.

Analyzing all fingerprints in such massive database can be very time-consuming which might not be feasible in practical applications. Therefore, fingerprinting location methods make use of some techniques to reduce the search space within the database. There is a wide range of alternatives, which can be used for reducing the search space, such as genetic algorithms (GA) [15], CDB filtering [15], and timing advanced-based approaches [17].

In order to estimate the MS position, the location server tries to match the measured fingerprint (from sought MS) to a fingerprint stored in the CDB. The key idea is to find the point in the CDB which has the highest similarity or correlation with the measured fingerprint.

Fig. 1 shows a simplified schematic diagram for a generic fingerprinting location technique. This diagram corresponds to a location service client (LSC) according to [18]. In step 1, the LSC sends a request to the location server. Then, the location server requests measurements from MS (target) through the radio access network (RAN). In step 3, RAN sends measurements to the location server. After receiving the measurements, the location server composes the fingerprint and, in step 4, it queries the CDB to