Deep Learning-based Floor Prediction Using Cell Network Information

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ABSTRACT

Location services are one of the most used applications today on mobile devices. The vast majority of localization systems propose solutions for locating the user in a 2D single floor environment. However, accurate estimation of the user's floor level, in tall multi-story buildings, is a crucial basis for many applications, especially for emergency services.

This paper presents a fingerprinting-based system that provides a low-cost floor localization service using the ubiquitous cellular signals received by the user's cell phone. Specifically, a convolutional neural network is trained to map the sequential change of the received cellular signals to the corresponding floor. Evaluation using different Android phones shows that the proposed system can track the user floor with at least 95.9% accuracy in different scenarios. This demonstrates the superiority of the system compared to the state-of-the-art systems in all experiments.

CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing**; • **Computing methodologies** → **Neural networks**; • **Networks** → **Mobile networks**;

KEYWORDS

Cellular, indoor localization, deep learning, fingerprinting, floor estimation

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1 INTRODUCTION

Accurate floor localization is crucial when summoning an emergency service in a multi-story building. This information can greatly limit the area to be canvassed, ensuring a more prompt response.

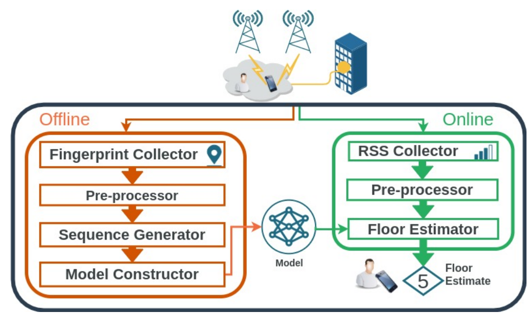

Figure 1: System Architecture

While GPS has been proved to be a powerful way for localization, it has some shortcomings such as battery consumption and limited ability to work indoors. This opened the door for a range of localization techniques that utilize sensing capabilities (e.g. using accelerometers, barometers, gyroscopes,.. etc.) [5] and wireless connectivity (e.g. WiFi) [1] of nowadays smartphones. However, these modalities can only be used if the user has a high-end phone; limiting the universal adoption of such techniques.

Recently, cellular-based localization systems have gained immense attention due to their associated advantages including pervasiveness, being supported by all mobile devices (even legacy ones), posing no additional power consumption concerns, and incurring no extra deployment cost. However, most of these systems, e.g. as [3] focus only on 2D localization.

The SkyLoc system [4] proposes a cellular-based floor identification solution by constructing fingerprints of the signals received at different floors in the building. Thereafter, it leverages a K-nearest neighbor classifier (KNN) to match the received cell measurements to the stored fingerprints and estimate. Collected fingerprint data undergo feature selection to improve the accuracy of the model by using the most representative set of cell towers and discarding irrelevant or noisy ones. However, performing feature selection manually is a challenge. Deep neural networks have been shown to define state-of-the-art performance in many problem domains due to their automatic and powerful feature extraction/representation ability. This motivates us to leverage them for floor estimation purposes.

2 RESEARCH CONTRIBUTION

In this paper, we propose a deep learning-based cellular floor localization system that can accurately determine a user's floor by exploiting cellular information received by her device. Our approach uses a sequence of received signal strength (RSS) scans captured by a user's cell phones from different cell towers in the area of interest

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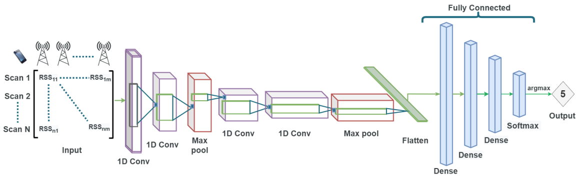

Figure 2: The employed network structure

to train a 1D convolutional neural network (CNN). A CNN model is employed to perform automatic feature extraction capturing the underlying changes of RSSs overtime and mapping them to the corresponding user's floor.

3 SYSTEM ARCHITECTURE

As shown in Figure 1, the proposed system works in two stages: a training offline stage and an online prediction stage. In the offline stage, a cellular fingerprint is constructed for the building of interest. This is accomplished using a *fingerprint collector* app deployed on cellular devices. The *pre-processor* module is used to convert fingerprint data to a format suitable for model training. The *sequence generator* then divides the fingerprint into sequences that capture the change in RSS through time. Finally the *model constructor* builds and trains a deep CNN model using the generated sequences.

In the online stage, an *RSS collector* app similar to the one used for the fingerprint is used to collect scans. These scans go through the same pre-processing steps and are assembled into a sequence. The *floor estimator* module then uses the built model to provide estimations of the current user's floor.

3.1 Fingerprint Collector

The goal of this step is to collect the necessary data for training the considered deep model. To do that, we deployed a mobile application on several devices to log RSSs from the cell towers in the area. On each floor of the building, RSS scans are collected through a free user walk and tagged by the floor ID.

3.2 Pre-processor

Each RSS scan includes cell information (cell tower ID and RSS) received from the detectable towers, typically seven or less [2]. Therefore, the number of detected towers varies across scans and thus hinders their direct feeding to the considered deep network. This module maps each scan to a unified RSS vector (i.e. same size) where each entry represents the RSS from a cell tower. RSS of non-heard cell towers is set to 0.

3.3 Sequence Generator

This module is used to prepare RSS sequences (i.e. history) required by the CNN model during the offline and online phases. Since all scans collected are timestamped, they can be regarded as a large trace. Sequence generation involves segmenting a user trace into fixed-length RSS sequences using a moving window such that each sequence overlaps with the preceding sequence, i.e. successive sequences are shifted by one timestep. Thereafter, each sequence is labelled with the floor of the last timestep in the sequence. The generated sequences are forwarded to the Model Constructor module for training a floor localization model.

Table 1: Comparison of prediction accuracy

Testbed	# Floors	# Towers	Carrier	SkyLoc[4]	Pr. System
Testbed 1	6	41	A	94.9%	**95.9%**
		18	B	87.5%	**96.31%**
Testbed 2	5	49	A	99.1%	**99.4%**

3.4 Model Constructor

Figure 2 shows the network structure of the proposed system. The system adopts a 1D CNN due to its ability to exploit temporal locality present in input sequences as well as its automatic feature extraction capabilities. The input layer is a fixed length sequence vector of multiple timesteps, each of which contains RSSs from the covering cell towers. The network is composed of two portions: an unsupervised feature extraction portion and a supervised classification portion. The automatic feature extraction is achieved through the use of 'filters', which are matrices that are convolved against successive local regions of the input sequence. These matrices are learnable and thus end up becoming optimal kernels for detecting optimal features (feature maps) to support the floor estimation task. The dimensions of the obtained feature maps are then reduced using a Max-pooling operation. All output feature maps are reformed into a single vector which is then passed to the supervised portion (the fully connected network) for classification purposes. The output layer consists of a number of neurons corresponding to the number of considered floors with a Softmax activation function.

3.5 Floor Estimator

During the online phase, a user is at an unknown floor receiving signals from the covering cell towers. These signals are captured at the current time instant, pre-processed and forwarded to the *Sequence Generator* module to compose the required sequence by leveraging prior readings. Consequently, this sequence is submitted to the trained CNN model to estimate the current user's floor.

4 EVALUATION

In this section, we compare the accuracy of our proposed system to the state-of-the-art floor localization system: SkyLoc [4]. Cellular data was collected over the course of two months from two different buildings; two carriers were used with the first building and one carrier with the second. Table 1 summarizes the results and shows that the proposed system outperforms SkyLoc [4] in all testbeds.This is because the proposed system considers the relationship between consequent cellular scans in the input sequence in addition to the powerful feature extraction capabilities of CNNs. The table also shows that the proposed system provides a consistent performance across different carriers (even with fewer towers in Carrier B). This confirms the reliability of the proposed system.

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