A Deep Learning based Approach for Indoor Localization

A short review for "CSI-based fingerprinting for indoor localization: A deep learning approach"

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X. Wang, L. Gao, S. Mao, and S. Pandey, "CSI-based fingerprinting for indoor localization: A deep learning approach," IEEE Transactions on Vehicular Technology, vol.66, no.1, pp.763—776, Jan. 2017. DOI: 10.1109/TVT.2016.2545523.

Location is important information for many mobile applications, for example, navigation and tracking. Since most mobile users are indoors, indoor localization is of great interest. Accurate indoor localization can enable traditional and new applications such as navigation in a stadium or exhibition hall, location-based advertisement, access control to wireless networks or information based on location, and even faster beamforming/beam tracking in 5G mmWave networks. Although having been studied for decades, there is still a great need for accurate and robust solutions for complex indoor environments.

Among various indoor localization techniques, WiFi based fingerprinting has many advantages. For example, it does not require access to GPS or cellular base stations, and WiFi access is ubiquitous in many indoor environments. There is also no need for accurate propagation models as in ranging based schemes. In such schemes, survey data is collected for chosen positions in the off-line phase. During the on-line phase, a mobile device records its realtime WiFi signal and compares it with stored survey data, to find the best match and determine its location [1]. Many existing schemes are based on received signal strength (RSS), which only represent coarse channel information [2]. The new trend is to move from RSS to channel state information (CSI), which represents fine-grained channel information and is now available for several WiFi cards [3]. The challenge is how to effectively process the much larger CSI data for accurate indoor localization in realtime.

In this paper, the authors propose a novel deep-learning-based fingerprinting scheme, termed DeepFi, to address the challenge [4]. The deep-learning-based scheme can fully exploit the rich features of WiFi CSI data and obtain the optimal weights as fingerprints [5]. The authors also incorporate a greedy learning algorithm to reduce computational complexity. In particular, the authors first present three hypotheses on CSI, which justify the feasibility of using CSI for more accurate indoor location. The authors then present the DeepFi system design, which includes an offline training phase and an online localization phase. In the training phase, CSI information for all the subcarriers from the three antennas if the WiFi card is collected from accessing the device driver and is analyzed with an autoencoder with four hidden layers. The proposed greedy learning algorithm uses a stack of restricted Bolzmann machines (RBMs) to train the deep network in a layer-by-layer manner to reduce complexity. Moreover, for each layer of the RBM model, the authors adopt the contrastive divergence with one-step iteration (CD-1) method to update weights, which has lower time complexity than other schemes, such as Markov chain Monte Carlo. In the online phase, a probabilistic fusion method based on radial basis function (RBF) is developed for location estimation. To reduce the computational complexity, packets are divided into several batches of equal size. Because packets are processed in parallel in batches, the processing time can be significantly shortened when dealing with a large amount of packets.

The proposed DeepFi scheme is implemented with a laptop and wireless router with low-cost Intel 5300 WiFi cards. The authors conducted extensive experiments in two representative indoor environments, i.e., a living room and a computer laboratory to validate its performance. DeepFi is shown to outperform several existing RSS and CSI-based schemes in both experiments. The effects of different DeepFi system parameters and different propagation environments are also evaluated in the experiments. The experimental results clearly confirm that DeepFi can perform well in these scenarios.

The major contribution of this paper is to propose the first deep learning based design for indoor WiFi fingerprinting. It is worth noting that this work was conducted before the release of AlphaGo in Oct. 2015 and the release of TensorFlow in Nov. 2015, which triggered the great interest on applying deep learning/machine learning to networking problems. This work is the first to introduce deep learning to solving indoor localization problems and clearly demonstrates the feasibility and the high potential of the deep learning based approach.

Following this work, the authors have published a body of work on applying various deep learning algorithms to indoor fingerprinting [6,7,8], which also led to several US provisional patents. This work also triggered considerable interest in the community. Since its publication in Jan. 2017, this paper has been the Top 1 most downloaded in most of the months (except for two months, when it was the Top 2 most downloaded) among all papers published in *IEEE Transactions on Vehicular Technology*. In a short period of less than two years, this paper has received 149 citations, while its conference preliminary version received 75 citations, according to Google Scholar (as of Dec. 1, 2018).

In summary, this paper made a great contribution in presenting the first deep learning based WiFi indoor fingerprinting solution. The proposed approach is implemented with commodity WiFi and demonstrated to achieve an accurate and robust localization performance. It is also well received in the community, as indicated by the high download and citation numbers in less than two years.

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