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Fine-Grained Localization of Unlabelled Users Based on WiFi

Review of:

Chen, X., Li, H., Zhou, Ch., Liu, X., Wu, D. and Dudek, G., 2020. FiDo: Ubiquitous Fine-Grained WiFi-based Localization for Unlabelled Users via Domain Adaptation. In WWW'20. ACM, 23-33

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ABSTRACT

The modern location-aware software applications are beginning to face a capability limit due to the location sources – such as GPS – which work at building-level resolution. The reviewed paper addresses the problem by utilizing the WiFi signal in a submeter-level localization system, called FiDo. The solution scans the WiFi propagation characteristics for location fingerprints – special signal samples indicating that a person is present at a specific monitored location at the time of the sample. FiDo is a domain-adaptive system featuring a simplified setup process that relies on labelled data from only two users. The system contains two modules: 1) a data augmenter for generating synthetic training data using a Variational Autoencoder and 2) a domain-adaptive classifier which trains on labelled and unlabelled data using a joint classification-reconstruction structure. Compared to the state of the art, FiDo achieves an increased F1 score by 11.8% and an improved worst-case accuracy by 20.2%.

1 Introduction

Location-based services are commonly perceived as providing the users with information about their surroundings. Increasingly, they also enable novel use cases such as geo-social networking, smart home automation, wireless security fence, cashier-less shopping, geo-based augmented reality, and indoor navigation/tracking.

To support these classes of functionality, location information needs to be available with submeter resolution. The typical location sources such as GPS, check-in data, and IP address geolocation are operating at house-level resolution or lower. One possible approach to addressing this gap has been the utilization of WiFi signals which are omnipresent and ubiquitous. Existing WiFi localization systems can be classified as either device-oriented or device-free. The device-oriented systems triangulate the user's device using the Time of Flight (ToF) (Vasisht, Kumar and Katabi, 2015; Wi-Fi Alliance, n.d.) and/or the Angle of Arrival (AoA) (Kotaru et al., 2015) to multiple access points (AP) with a priori measured locations. The device-free localization systems detect the presence of a person by passively monitoring WiFi signal propagation characteristics such as Received Signal Strength (RSSI) (Yang, Wu and Liu, 2012) and Channel State Information (CSI) (Chen et al., 2017b). Each characteristic reading is associated with a location label to create a device-free WiFi location fingerprint.

This paper introduces FiDo – a WiFi-based system for fine-grained user localization. As a device-free system, FiDo addresses the two key challenges to leveraging location fingerprints.

Challenge 1. It is not possible to build a fingerprint database containing data from all potential users. To address this challenge, FiDo introduces a data augmenter based on Variational Autoencoders (VAE) which captures the statistical features in the location fingerprints. The data augmenter is trained using labelled fingerprints from only two users. After this phase, it can be used to generate new synthetic labelled fingerprints for training FiDo's domain-adaptive classifier.

Challenge 2. After the system has been deployed, labelling new data is impractical and undesirable. To tackle this challenge, FiDo performs all further training on unlabelled data. Its domain-adaptive classifier module is built on a special neural network (NN) with joint classification-reconstruction architecture. A classification path extracts features from input data and tries to predict the location. A reconstruction path shares the feature extraction layers with the classification path. The reconstruction path is only used during training in order to adjust the feature-extraction layers with current unlabelled data which is easy to obtain.

The following sections outline the design of FiDo, the evaluation process, other related work, and summary of the findings.

2 Design

2.1 Definitions

A sending WiFi device has N_{TX} transmission antennas. A receiving device has N_{RX} receiving antennas. Each two WiFi devices communicate via $N_{SS}=N_{TX}\times N_{RX}$ spatial streams. Each stream is divided into N_{SC} frequency subcarriers.

This work's setup consists of one transmission antenna, three receiving antennas, and 30 subcarriers. At any given moment, the input to the localization system is represented by a vector containing the CSI (magnitude) values per carrier per stream, i.e. a total of 90 elements.

Let the finite set Ω with N_Ω elements represent all locations supported by the proposed framework. An input data point associated with a location label is called a labelled data point. It is denoted as $x_L[t]$ and the label itself – as $y[t]$, where $y[t] \in \Omega$. A location fingerprint is defined as a tuple of a labelled data point and its location label, i.e. $f[t] = (x_L[t]; y[t])$. Data points not associated with a label are called unlabelled and denoted as $x_U[t]$.

The mission of FiDo is to train a location classifier using all collected fingerprints F and unlabelled data points X_U, so that it can accurately predict y[t] given a new x[t].

2.2 Data Augmenter Module

The data augmenter aims at addressing **Challenge 1** by generating synthetic fingerprints which compensate for the lack of real training data. It captures the statistical features of labelled data and is only used during the training stage.

The data augmenter implements N_Ω VAEs, each of them dedicated to one location. During training, the fingerprints are separated in N_Ω subsets according to their location labels.

The generation of synthetic data is conducted solely by the VAE decoder component which samples inputs from a 10-dimensional random distribution and generates 90-dimensional synthetic data points. The 1-to-1 VAE-location mapping allows for each decoder to generate synthetic data for a specific location.

2.3 Domain-adaptive Classifier Module

The domain-adaptive classifier consists of two paths – classifier and reconstruction. Both paths start with a shared feature extraction layer that generates vector space embeddings. These feature vectors are used by the classification layer to predict location labels.

The classification path is trained only with augmented location fingerprints and no unlabelled data. The reconstruction path is trained with both labelled and unlabelled data. It features an auto-encoder layer that tries to reconstruct the original input data point from the feature vector. The reconstruction path is only used during training – it ensures the feature extraction layer is representative of the unlabelled data.

By training the reconstruction layer using unlabelled domain-specific data, the system achieves domain adaptation and addresses **Challenge 2**. Only the classification path of the classifier is used during normal operation of the system.

2.4 Hyperparameters

Relatively shallow NN architecture is used due to the limited amount of labelled data which is insufficient to train a deep solution. Shallow neural networks have the advantage of adapting faster to new domains.

3 Evaluation

3.1 Experiment Setup

The setup consisted of: 3m×4m office room, 8 predefined locations, 70cm minimum distance between locations, Dell Latitude E7440 PC with Intel 5300 WiFi chip connected to TP-Link AC1750 WiFi router, N_{TX}=1 (router), N_{RX}=3 (laptop), N_{SC}=30. Nine people take part in the experiment with height in the 155-186cm range and weight in the 45-88kg range. The router is sending 100 packets/s consuming a bandwidth of only 50Kbps. Each volunteer stays at every location for 60s, moving freely and naturally while remaining at the location. Recording is repeated 5 times resulting in 100×60×5 data points collected per person per location. Train and test data are split as described in Table 1.

	Users	Labelled Data	Unlabelled Data
Training	ID2&ID4	5K	~ 1.08M
Testing	ID1-ID9	~ 1.08M	n/a

Table 1: Train/test data split

3.2 Evaluated Systems

- **AutoFi (Chen et al., 2017b)** – baseline system. Only leveraging labelled data. Detects an empty (new) room using CSI variances and adapts by invoking a built-in mapping function
- **FiDo data augmenter plus AutoFi classifier (VAE-only)** – only leveraging labelled data
- **FiDo domain-adaptive classifier only (DAC-only)** – utilizing both labelled and unlabelled data
- **FiDo** – the complete system

3.3 Experiment Setup

Due to the relatively small number of labelled data points, AutoFi is not able to generalize well over diverse sets of users. The two systems, which use one of FiDo's two components independently from the other, show improved performance compared to AutoFi. The complete FiDo system demonstrates cumulative improvement surpassing the performance of both components when used independently.

	Recall	Precision	F1 Score
AutoFi	72.9%	75.8%	0.727
VAE-only	81.0% (+8.1%)	81.1% (+5.3%)	0.807 (+0.080)
DAC-only	80.8% (+7.9%)	81.0% (+5.2%)	0.807 (+0.080)
Fido	84.6% (+11.7%)	85.0% (+9.2%)	0.845 (+0.118)

Table 2: Average recall, precision and F1 scores of different systems across all locations and IDs.

3.4 Robustness

Robustness to user height in AutoFi is not very strong, with accuracy dropping from 95% to 67% if the test user is 10cm taller than the example user. The other three systems are more robust to height differences with accuracy remaining above 80%.

AutoFi is also not very robust to user weight, with accuracy dropping to 59.8% if the test user is 30kg heavier than the example user. The other three systems are more robust to weight differences with accuracy remaining above 80%.

Robustness to different days. Accuracy of FiDo is improving as it is re-trained with unlabelled data every day. AutoFi could only adapt using its mapping function, so its performance is not improving over time.

3.5 Training Convergence

Training convergence for FiDo is achieved at the 300^{th} epoch.

4 Related Work

Classic WiFi localization relies on RSSI which has lower resolution but data is easier to obtain and analyze. CSI allows extraction of geometrical information such as ToF and AoA. Some systems extracting ToF and AoA from CSI include:

- WiTrack2.0 (Adib, Kabelac and Katabi, 2015) performs multi-person localization operating in indoor environments. Based on ToF of radio signals reflected off human bodies
- SpotFi (Kotaru et al., 2015) provides decimeter-level resolution achieved by identifying direct paths between target and AP by measuring ToF and AoA
- CUPID2.0 (Sen et al., 2015) improves localization scalability by combining ToF-based trilateration with signal strengths

Other systems are using ToF and AoA in conjunction with Doppler shift information (encoded in the noisy CSI phase factor) in order to track location of moving people but are much harder to calibrate. More recent methods based on CSI fingerprints alleviate users from carrying devices:

- PinLoc (Sen et al., 2012) uses clustering classification technique
- ConFi (Chen et al., 2017a) applies convolutional NNs to signal visualizations

CSI data has also been leveraged in the following applications besides localization:

- Crowd counting (Xi et al., 2014)
- Gesture recognition (Jiang et al., 2018) (Zheng et al., 2019)
- Human identification (Korany et al., 2019) (Pokkunuru et al. 2018)
- Hand-written signature verification (Thoopsamut and Limthanmaphon, 2019)

It is worth noting that very few practical developments exist that are user- and environment independent.

5 Conclusion

This paper outlines FiDo – a system leveraging WiFi signals for domain-adaptive user localization with submeter-level resolution. FiDo addresses the key user localization challenge of generalizing over large and diverse sets of users by introducing a VAE-based data augmenter which is capable of synthesizing labelled training data. The system also addresses the challenge of difficult initial setup and calibration by introducing a domain-adaptive classifier featuring a joint classification-reconstruction architecture. The classifier is capable of training on both labelled and unlabelled data which allows it to extract domain-independent features. Experiments show that FiDo outperformed current state of the art system by achieving an increase of worst-case accuracy by 20.2% and providing the strongest robustness when handling data from diverse unlabelled users.

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