Wi-Fi Fingerprinting through Active Learning using Smartphones

Le T. Nguyen  
Carnegie Mellon University  
Moffet Field, CA, USA  
le.nguyen@sv.cmu.edu

Joy Zhang  
Carnegie Mellon University  
Moffet Field, CA, USA  
joy.zhang@sv.cmu.edu

Abstract
Indoor positioning is one of the key components enabling retail-related services such as location-based product recommendations or in-store navigation. In the recent years, active research has shown that indoor positioning systems based on Wi-Fi fingerprints can achieve a high positioning accuracy. However, the main barrier of broad adoption is the labor-intensive process of collecting labeled fingerprints. In this work, we propose an approach for reducing the amount of labeled data instances required for training a Wi-Fi fingerprint model. The reduction of the labeling effort is achieved by leveraging dead reckoning and an active learning-based approach for selecting data instances for labeling. We demonstrate through experiments that we can construct a Wi-Fi fingerprint database with significantly less labels while achieving a high positioning accuracy.

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Active Learning, Wi-Fi Fingerprinting, Dead Reckoning

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Introduction

In order to reduce the cost and effort associated with deployment of indoor positioning systems, many approaches have been developed, which leverage an existing Wi-Fi infrastructure for positioning purposes. A large amount of attention was given to the Wi-Fi positioning approaches based on Wi-Fi RSSI (Received Signal Strength Indication) fingerprints, as these approaches can provide a relatively high indoor positioning accuracy in a multipath indoor environment [4].

Wi-Fi fingerprint-based approaches frame the positioning problem as a supervised machine learning problem, i.e., first a labeled dataset is used to train a prediction model, which is used to predict a user’s location in the online phase. It is well-known that training a Wi-Fi fingerprint model is a labor-intensive task, since it requires having a dedicated annotator manually labeling a large amount of training dataset. As pointed out in a previous research, the training phase can take up to several hours even for a small building [1].

In this work, we frame the problem of training a Wi-Fi fingerprint model as an active learning problem, where the goal is to minimize the number of labels needed for training while achieving high prediction accuracy [3]. We propose a system for constructing a Wi-Fi fingerprint database by leveraging dead reckoning and an active learning-based approach for selecting data instances for labeling. The proposed approach identifies a minimal number of data instances to be labeled in order to keep the positioning accuracy high.

As pointed out in previous research [6], having an initial Wi-Fi fingerprint database is an essential assumption for many positioning approaches. The main idea is to manually create an initial database and incrementally update it while the system is in use through crowd-sourcing techniques. With our proposed approach the initial Wi-Fi fingerprint database can be built up with minimal annotator’s effort. Once the system is deployed, the Wi-Fi fingerprint database can be incrementally updated using semi-supervised or unsupervised approaches [2].

In many cases the incremental database update is not possible. For example, it is well-known that Wi-Fi fingerprint-based systems are sensitive to the changes of the set of observable Wi-Fi access points (APs) [4]. In environments such as shopping malls, deployment of new Wi-Fi APs or failure of existing ones is not a rare case. Therefore, the training phase needs to be rerun periodically in order to keep the system up-to-date. Since our approach minimizes annotator’s labeling effort in each training session, the cost for system maintenance can be significantly reduced.

Related works

Labeling Wi-Fi fingerprints is labor-intensive since an annotator needs to manually provide reference positions of collected Wi-Fi fingerprints [4]. In the training phase an annotator is given a predefined set of suggested locations, where Wi-Fi fingerprints should be collected. An annotator iterates through the building, stops at every suggested location, starts collecting Wi-Fi fingerprints and pinpoints his or her current indoor position on a floor map.

Many researchers have tried to optimize the training process by automatically estimating the ground truth of Wi-Fi fingerprints autonomously without asking
annotators to label them. Woodman et al. [6] used
dead reckoning for estimating the location label of
Wi-Fi fingerprints during the training phase. However,
this work relies on high-quality foot-mounted IMUs
(inertial measurement units), which is a significant
barrier for a broad adoption of this technology.
Kim et al. [2] proposed a similar approach while using
off-the-shelf smartphones instead of foot-mounted
IMUs. Due to this fact the proposed system achieved
relatively low positioning accuracy, which is not
sufficient for many application scenarios.

In our work, we use off-the-shelf smartphones and do
not rely on any specialized hardware (in contrast
to [6]). In the training phase, we instruct annotators to
move continuously through a building without having to
stop at every location to annotate collected Wi-Fi
fingerprints. We use dead reckoning for predicting the
ground truth of Wi-Fi fingerprints. Due to the error
accumulation of the dead reckoning approach, our
system automatically identifies strategically important
locations based on active learning and asks an
annotator to provide labels only for these locations.
Thus, we minimize the number of labels needed for
building up the Wi-Fi fingerprint database (in contrast
to [4]). Additionally, our system is less sensitive to
magnetic interference since the ground truth of Wi-Fi
fingerprints are estimated based on more reliable
annotations. Therefore, our system achieves higher
positioning accuracy compared to [2].

**Wi-Fi Fingerprinting Through Active Learning**

In this section, we describe our proposed system for
continuous collection of labeled Wi-Fi fingerprints
leveraging dead reckoning and active learning.

**Supervised Wi-Fi Fingerprinting**

Wi-Fi fingerprinting is a process of building a Wi-Fi
fingerprint database in the training phase. A standard
supervised Wi-Fi fingerprinting involves four
components shown in Figure 1. The training phase
consists of multiple Wi-Fi fingerprinting sessions, each
starting with a Wi-Fi Scanner scanning for surrounding
Wi-Fi access points (AP). As a result the system
obtains a Wi-Fi scan $w$ which contains information
about Wi-Fi AP's BSSIDs (Basic Service Set
Identification) and the corresponding RSSIs:

$$w = [(BSSID_1, RSSI_1), (BSSID_2, RSSI_2), ...]$$  (1)

In each Wi-Fi fingerprinting session (at time $t$) an
annotator is asked to provide a location label $l_i$ for the
collected Wi-Fi scan $w_t$ in order to build up a Wi-Fi
fingerprint $f_t = (w_t, l_i, c_t)$. $c_t = P(L_t = l_i)$ is the
confidence of the location label $l_i$ where $L_t$ represents
the true location of an annotator at time $t$. The
confidence $c_t$ has the maximum value if the location
label $l_i$ corresponds to an annotator's true location $L_t$.
To simplify the notation we will use $c_t$ to represent the
confidence of the label associated with the Wi-Fi scan
$w_t$. For the supervised Wi-Fi fingerprinting approach,
we assume that the annotator's labels are correct.
Thus, $c_t = 1$ for all $t$. The created Wi-Fi fingerprints are
stored in a Fingerprint Database $F = \{f_1, f_2, ...\}$.

As mentioned above, Wi-Fi fingerprinting session is
repeated for each location in a building. Thus, the
number of required labels is proportional to the size of
a building and the granularity of the location coverage.
The proposed system extends the supervised approach by adding a dead reckoning component integrated with an active learning-based query mechanism.

**Continuous Fingerprinting using Dead Reckoning**

In this work, we use Dead Reckoning (DR) to initially predict location labels of Wi-Fi fingerprints. DR is an approach of estimating an annotator’s current location based on their previous location and inertial sensor readings. We use a step-based dead reckoning approach, which detects steps, predicts their length and direction based sensor readings [5]. These estimations are accumulated over time in order to build up an annotator’s expected trajectory.

Figure 1 shows a DR component as a part of the proposed continuous Wi-Fi fingerprinting system. In the training phase, an annotator is instructed to walk through the building. While the Scanner continuously scans for surrounding Wi-Fi APs, DR is used to estimate the location labels of the Wi-Fi scan. Specifically, a Wi-Fi scan $w_t$ is associated with the location $l_i$ of a step estimated by DR to build up a fingerprint $f_t$.

Since the error of DR estimations accumulates over time, we define $c_t = c_{t-1} \cdot \sigma$ to model the decreasing confidence of the location predictions. $\sigma$ is the rate of the confidence decrease ($0 \leq \sigma \leq 1$) and its value depends on multiple factors including the quality of the sensors and the actual sensor readings [2].

**Wi-Fi Fingerprinting through Active Learning**

Due to the error accumulation of DR, the estimated labels become unreliable especially for long trajectories (as shown in Figure 3). In order to address this issue we propose an active learning approach for selecting unreliable predictions. These predictions are presented to an annotator, who is asked to correct the predictions by dragging them to a correct location (indicated as a dashed line and the hand in the figure). The user interface for correction is shown in Figure 2.

![Figure 2: User interface allowing an annotator to correct the DR prediction by dragging the points to a correct location.](image-url)

Figure 3: Figure shows the trajectory predicted by using DR compared to the reference trajectory. Error of DR prediction increases over time making the location label unreliable.
In this work, we propose 2 approaches for selecting data points based on 1) confidence thresholding and 2) correction model. With the first approach we select datapoints based on their level of confidence. As mentioned above, the confidence of location label decreases over time as DR predictions become unreliable (as shown in Figure 4). When the confidence of a label decreases under a certain threshold $\tau$, we ask an annotator to provide a correct label.

Figure 4: Confidence of predicted location labels decreases over time as DR prediction become unreliable (shown on the left). Through confidence thresholding, an annotator is asked to correct the prediction when its confidence decreases under a certain threshold (show on the right). Through the correction the confidence of a label increases to 1.

Practically, this approach corresponds to asking an annotator to label every N steps, where N depends on the confidence threshold. Figure 5 shows an example for $N = 10$, i.e., an annotator is asked to label every tenth step. By setting $\tau$ to 1, we achieve an effect that every step will be labeled by the annotator, i.e. we fall back to the fully supervised fingerprintint approach. By setting $\tau$ to 0 we rely completely on DR and do not ask the annotator to label any steps.

Figure 5: Annotator is asked to annotate every tenth step while walking in the building.

With the second approach we impose a certain walking constraints on an annotator in order to further decrease the number of required annotations. When an annotator is send to collect data, we assume that he or she can follow simple instructions such as walking in straight lines and making only sharp turn. Assuming the given instructions are followed correctly to a certain degree, we can describe an annotator’s trajectory through a small set of labels.

Figure 7 shows an example trajectory of an annotator following the given instructions. Each point on the trajectory corresponds to a location where an annotator landed a step on the ground. The given trajectory can be described by a starting location, an ending location and locations of all the turns. These locations are called anchor points $\alpha_i$. 
If the anchor point locations are known, we can infer the locations of the step points $s_j$. Step points are locations of the intermediate steps between two anchor points. Assuming an annotator followed the given instructions, the step points lie on the line connecting two anchor points. Thus, instead of asking the annotator to label all the points, we ask him or her to label only the anchor points. From the provided labels we can infer the location of the remaining step points.

In the following experiments we apply cross validation to evaluate each approach. In each cross validation iteration we use data of one trajectory to train the Wi-Fi fingerprint model, which is then used to predict location of steps in the remaining trajectories. In this work, we use the k-Nearest-Neighbor approach for position prediction (with k empirically set to 3) [4]. The error of the prediction corresponds to the Euclidean distance between the estimated location and the known ground truth.

Evaluation of the Correction Model
Figure 8 shows the results of applying the active learning-based correction model compared to other models. The horizontal lines of each box plot shows the minimum error, 25th, 50th, 75th percentile and the maximum error. The circle indicate the average distance error. In the first experiment we use only DR to predict the location labels which are used to build a Wi-Fi fingerprinting database. Therefore, an annotator was asked to provide only one location label, which corresponds to the initial location of the trajectory. The remaining labels are estimated by using DR. In the second active learning-based experiment, we ask an annotator to provide location label for all anchor points. We compare the results with the fully supervised fingerprinting approach. With this approach, the publicly available area of the test building was divided into grids of 1-by-1 meters. For each grid cell, a user manually provided the location label while the system scanned for Wi-Fi fingerprints.

As expected, in the testing time the distance error of the DR-based approach is relatively high. However, by an annotator labeling the additional 6 anchor points we were able to decrease the distance error to a level
comparable with the fully supervised approach. From the results we can observe that the number of annotator’s labels of the active learning approach is lower compared with the supervised approach. Thus, with active learning we can significantly reduce the annotator’s labeling effort.

Moreover, with active learning we can achieve a higher granularity of location labels coverage. From the experiment results we can see that the total number of labels (annotator’s plus estimated labels) in the active learning experiment is higher then in the supervised case. One of the reasons is that with the active learning approach we obtain location labels for each step, whereas with the supervised approach the total number of labels corresponds to the number of coarse-grained 1-by-1 meter cells. Another reason for the higher total number of labels is the fact that the walking trajectory of the active learning approach covered a certain area of the building multiple times (as shown in Figure 6). In supervised case each location was visited only once.

**Figure 8**: Positioning error of an model trained on the DR labels, active learning (AL) labels and labels from the fully supervised approach.

**Evaluation of the Confidence Thresholding**

In this experiment, we evaluate the confidence thresholding approach. As mentioned in the previous section, by varying the threshold we can adjust the number of labels provided by an annotator. Obviously, the more labels an annotator provides, the better prediction model can be trained resulting in higher Wi-Fi positioning accuracy.

Figure 9 shows the results of varying the thresholds. Starting with a threshold $\tau = 0$ we achieve an effect of asking an annotator to label only the initial location. By increasing $\tau$ towards 1 we achieve an effect of obtaining more labels. For example for $\tau = 0.3$ we ask an annotator to label every 25th steps resulting in total 4 annotator’s labels. By setting $\tau = 0.5$ we ask an annotator to label every 10th steps, resulting in 15 annotator’s labels. The label error indicates the average error distance between the estimated labels and the ground truth of the labels. Obviously, the smaller number of corrections made by an annotator results in a higher average label error. By using labels with high label error in training phase results in less accurate prediction in online phase (indicated as Wi-Fi positioning error in the figure). From the results of this experiment we can observe that by reducing the total number of labels from 150 to 25 (6 times less) we can still achieve high Wi-Fi positioning accuracy.
Conclusion

In this work, we proposed a Wi-Fi fingerprinting system, which minimizes annotator’s labeling effort by framing the Wi-Fi fingerprint problem as an active learning problem. By leveraging the confidence measure and constraint information about annotator’s walking patterns, the system asks an annotator to label only “informative” data instances. Thus, the system reduces the number of annotator’s labels required for training a Wi-Fi fingerprint database. Through the experiments we showed that with significantly less labels the proposed system achieved positioning accuracy comparable to a fully supervised Wi-Fi fingerprinting approach.

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References


