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# ACCES: Offline Accuracy Estimation for Fingerprint-based Localization

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***Abstract*—In this demonstration we present *ACCES*, a novel framework that enables quality assessment of arbitrary fingerprint maps and offline accuracy estimation for the task of fingerprint-based indoor localization. Our framework considers collected fingerprints disregarding the physical origin of the data. First, it applies a widely used statistical instrument, namely Gaussian Process Regression (GPR), for interpolation of the fingerprints. Then, to estimate the best possibly achievable localization accuracy at any location, it utilizes the Cramer-Rao Lower Bound (CRLB) with interpolated data as an input. Our demonstration entails a standalone version of the popular and open-source Anyplace Internet-based indoor navigation service in which the software modules of *ACCES* are integrated. At the conference, we will present the utility of our method in two modes: (i) Collection Mode, where attendees will be able to use our service directly to collect signal measurements over the venue using an Android smartphone; and (ii) Reflection Mode, where attendees will be able to observe the collected measurements and the respective ACCES accuracy estimations in the form of an overlay heatmap.**

## I. Introduction

Fingerprint-based indoor localization systems can achieve very high accuracy (i.e., 1-2 meters), as it has been shown extensively in [1]. The particular techniques store signals from wireless, light or magnetic signals in a database at a high density, coined a *Fingerprint Map* (*FM*). A user can then compare, using known localization algorithms, its currently observed signal fingerprint against the FM in order to find the best match. For example, our in-house *Anyplace*[1] Internet-based Indoor Navigation Service [2] takes an advantage of crowdsourcing-based fingerprint collection and achieves superb accuracy.

Even though the accuracy of localization can be estimated coarsely after the location request (i.e., the *online* mode), from a design perspective, it is very important to know the positioning quality of *FM* at a fine granularity in different areas of a building in *offline* mode, i.e., shortly after the data for the measurement map is collected, prior to any location request. A system operator who is aware that low accuracy is expected in some part of a building could take action to extend the positioning infrastructure (e.g., install additional beacons) and/or offer incentives to crowdsourcers to contribute more data in that area.

[1]Available at: http://anyplace.cs.ucy.ac.cy/

The problem of offline accuracy estimation for fingerprint-based localization was not thoroughly tackled so far. Existing approaches are either empirically-driven [3], thus, not being theoretically solid, or require some knowledge of the data model (e.g., radio-signal propagation) [4], hence, are not suitable for complex data (e.g., ambient magnetic field).

In this demo, we present *ACCES* [5], which is a novel framework for offline positioning accuracy assessment at arbitrary locations given the *FM* and disregarding the data origin. Our approach is constructed in three steps: First, we apply a black-box technique for fingerprints interpolation based on a widely used statistical instrument called *Gaussian Processes*. This tool allows to: (i) predict sensor readings at chosen locations given the initial input data (*FM*); and (ii) estimate the uncertainty of such predictions in the form of the variance of a Gaussian distribution. Then, given such predictive distribution, we derive a theoretically solid lower bound for the uncertainty in the location estimation, i.e., the localization error, in the form of a *Cramer-Rao Lower Bound* (CRLB). The CRLB construct is used in estimation theory to derive lower bounds on the variance of an estimator of deterministic parameters. We utilize the derived CRLB as the *ACCES navigability score* for *FM*, evaluate it at the fine grid of locations over the venue and show the results in the form of a heatmap.

## II. Overview of ACCES Prototype

We have implemented a prototype of ACCES in the popular and open-source Indoor localization architecture coined Anyplace [2]. In this section we summarize our developments by providing further details on the internal operation of our developments. Our demo consist of the three components.

The first component comprises the GPR interpolation algorithm. Given a FM as an input, GPR outputs a predictor, which can be used for estimation of the measurements at arbitrary venue locations. Even though such interpolation may appear to be computationally expensive, as long as the FM is not changed, the predictor is not subject to recalculations. Moreover, if the complete venue is split into the smaller parts (e.g., rooms, corridors) and for each such part separate predictor is found, changes of the FM in one such part, do not affect predictors in other parts.

The second component consists of the CRLB computation algorithm. Given the predictor from the first component, it is used for evaluation of the accuracy estimate (*ACCES* score) at

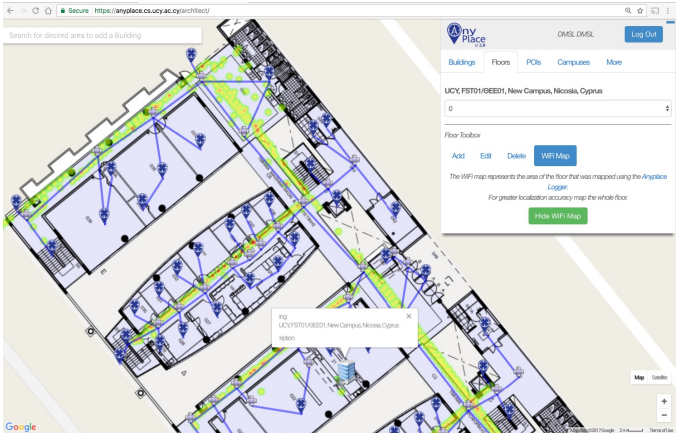


Fig. 1: ACCES on top of Anyplace will enable architects to assess in the form of heatmaps the quality of the collected fingerprints before launching the service to users.

arbitrary locations. Key advantage is that it does not require any knowledge of the underlying data sources. Additionally, If the parameters of GPR (e.g., kernel) are unknown, predictor can be used as a black-box with accuracy estimates evaluated using numerical approximations, or else, analytical representation can be derived.

The third component is the Anyplace IIN service [2], which allows to interact with users for creation of venues, uploading floor plans, fingerprint mapping, FM analysis and localization. The Anyplace software stack consists of five main modules, including the Server, the Data Store, the Architect, the Viewer and two client applications running on Android smartphones, namely the Logger and the Navigator. The Server module contains the complete backend application logic of the service, including the modeling, crowdsourcing and API functionality. The Anyplace Architect is a Web App that enables users to design and upload building structures to Anyplace. The Anyplace Viewer is a respective Web App that allows search and navigation off- the-shelf, without installation or logistical challenges. The combined Anyplace Navigator and Logger is a native Android application, which allows users to: (i) observe their current location on top of the floor plan using Wi-Fi FM localization; and (ii) collect Wi-Fi fingerprint readings and upload them to our Server.

## III. Demonstration Scenario

During the demonstration, the attendees will be able to appreciate the key components of the *ACCES* framework.

### A. Demo Artifact

We have implemented our framework using *Python* programming language with the use of GPR implementation from the open-source *scikit-learn* library. Both interpolation and accuracy estimation algorithms are implemented as standalone script applications. For the purpose of data collection and interaction with users we utilize our Anyplace Logger application, which communicates with our central Anyplace server and allows users to perform fingerprint mapping. In order to analyze obtained fingerprint data (without altering server and client infrastructure) we deploy separate modified Anyplace Architect module on a laptop, which serves several purposes: (i) fetching fingerprint maps from the main Anyplace server instance; (ii) computation of the accuracy estimates using our solution; and (iii) their visualization with a heatmap.

### B. Demo Plan

**Collection mode:** In this mode, conference attendees will have an opportunity to collect Wi-Fi fingerprint data in crowdsource manner across the conference venue and observe them in real-time using the Logger application. Conference building floor plans will be prepared and uploaded to Server in advance. After installing the Navigator/Logger application, attendees will be able to find the conference venue building in the list of available buildings. Then, on the Logger screen in the application they would be able to observe the locations of the already collected fingerprints across the venue. Finally, by enabling fingerprint recording in the Logger, attendees would be able to walk along the conference venue and collect Wi-Fi fingerprint data, which will be uploaded to Server and, subsequently, displayed on the Logger screen.

**Reflection mode:** In this mode, conference attendees will be able to observe the impact of fingerprint collection on the accuracy estimate, visualized in the form of a heatmap on top of the venue floor plan (see Fig. 1). As it is described in subsection III-A, we will deploy separate server instance on a laptop for demonstration of our solution. User interface is built on top of the Architect component in way that it will allow attendees to: (i) observe the collected fingerprints; (ii) request accuracy estimates calculation from the actual fingerprints; (iii) visualize accuracy estimates via an overlay heatmap with a blue color representing smaller *ACCES* scores (better accuracy) and red color representing larger *ACCES* scores (worse accuracy); and (iv) switch between FMs collected during different time periods to observe the *ACCES* scores.

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