Anatomy and Deployment of Robust AI-Centric Indoor Positioning System

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***Abstract*—Indoor Positioning Systems are gaining market momentum, mainly due to the significant reduction of sensor cost (on smartphones or standalone) and leveraging standardization of related technology. Among various alternatives for accurate and cost-effective Indoor Positioning System, positioning based on the Magnetic Field has proven popular, as it does not require specialized infrastructure. Related experimental results have demonstrated good positioning accuracy. However, when transitioned to production deployments, these systems exhibit serious drawbacks to make them practical: a) accuracy fluctuates significantly across smartphone models and configurations and b) costly continuous manual fingerprinting of the area is required. The developed Indoor Positioning System *Copernicus* is a self-learning, adaptive system that is shown to exhibit improved accuracy across different smartphone models. *Copernicus* leverages a minimal deployment of Bluetooth Low Energy Beacons to *infer* the trips of users, *learn* and eventually build *tailored Magnetic Maps* for every smartphone model for the specific indoor area. In a practical deployment, after each trip execution by the users we can observe an increase in the accuracy of positioning.**

I. Introduction

Recently, we have witnessed great progress in the space of Indoor Positioning. The most popular techniques are those that offer good balance between the various costs (capital cost for development of sophisticated hardware and/or sensor installation, operational expenses for maintenance) and accuracy when positioning an individual inside an indoor environment.

Currently, state-of-the-art approaches leverage on signals that are frequently present in modern indoor environments such as Wi-Fi [1]–[4] and Bluetooth Low Energy (BLE) Beacons [5]–[7]. Both Academia and Industry have focused on exploiting non-human generated signals like the omnipresent Magnetic Field [8]–[11]. The latter approach has gained popularity due to cost savings as no specialized sensor installation and maintenance is required while good results have been reported in terms of accuracy. Today's large availability of advanced sensors, such as Magnetometer, Accelerometer, Gyroscope and other, commodity devices such as smartphones is creating the right conditions to make such approaches practically feasible.

In particular, magnetometers are becoming part of the defacto in-built smartphone sensors, inviting for using smartphones and the Magnetic Field as sole means for positioning users in indoor spaces. However, this introduces a new set of challenges. First of all, the discrepancies in Magnetic Field readings between different sensor and/or smartphone models are sufficient to introduce large errors in the process of magnetic-based positioning. Specifically, the norm in such an approach is to *fingerprint* the indoor area in order to generate its Magnetic Map [1] and then use the incurred map to position the user inside the given area. There are good chances that a user of the positioning system owns a different smartphone model than the one(s) used for creating the Magnetic Map of the area. It has been proven that this has a significant impact on the positioning accuracy [12], even from the most prominent commercial solutions in the market [13]. Moreover, a Indoor Positioning System (IPS) it is required to be robust to changes in the environment, like minor structural changes or the utilization of electrical appliances, such as the placement of electrical heaters. Such changes can potentially interfere with the Magnetic Map initially and, as a consequence, they will cause conventional solutions to fail.

Copernicus is a novel AI-Centric Organic Indoor Positioning System that provides robust positioning accuracy that is oblivious to the model of the smartphone used either for fingerprinting or for positioning. We briefly present our hybrid indoor positioning methodology that leverages both on the Magnetic Field and BLE Beacons, employing *zone-based positioning* [14] with BLE beacons on the *Particle Filter* [15] approach. *Copernicus* improves accuracy compared to commercial alternatives by approximately 15 meters on average. In [12], the authors present the theoretical foundation of *Copernicus*, and the advantages over other state-of-the-art techniques that are leading to such increment in accuracy.

The remainder of the paper is structured as follows: We briefly describe our methodology in Section II. In Section III we describe the demo scenario. Finally in Section IV we conclude summarizing the contribution.

II. Methodology

Copernicus' system employs an organic way to build a custom Magnetic Map for every smartphone model of a given location with only the aid of BLE beacons. This way, while the positioning service is being utilized, the service updates the Magnetic Map of the tested location for the user's smartphone model. The quality of Indoor Positioning is

[1] List of coordinates for the indoor area which are associated with their recorded Magnetic Field magnitude

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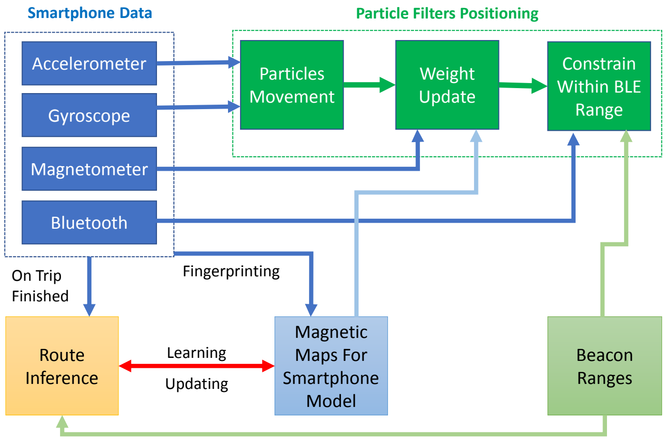

Fig. 1: Copernicus High-level Architecture

(a) Markers placed in the corridors (b) Bluetooth beacon

Fig. 2: Physical elements used to assist the Bootstrap Phase

constantly improving as the service learns the Magnetic Field readings for specific smartphone models.

While most IPS using beacons require that every (x, y) coordinate within the area must be in range of at least 3 beacons [16], our solution reduces this requirement to just 1, hence reducing costs without any loss in accuracy. Instead of focusing on creating one robust global Magnetic Map for all the smartphone models, our system is automatically retrained for the various models. *Copernicus*' high-level architecture is depicted in Figure 1.

A. System Bootstrap

Copernicus requires, as any IPS, a bootstrap phase in which the system is initialized. This phase is performed by the System Developer, thus the person in charge of administrating *Copernicus*. The System Developer must be provided with an image depicting the floor plan of the specific indoor area. After that, the System Developer needs to place few Bluetooth beacons in the area, approximately one every 435 square meters, and physical markers (see Figure 2). In a production deployment, the markers won't be a requirement, as we only need them for the evaluation of the system.

Finally, the System Developer uses the fingerprinting mobile application to record few trips that will cover the indoor area. The developed mobile application records the Magnetic Field values while the user is moving along routes that cover the indoor area. The recorded data are then submitted to the backend service and aggregated to compose the Spatial Map, which is a list of (x, y) pairs, of the area as well as the Initial Magnetic Map associated with the System Developer's smartphone model.

In a production deployment, this process would be carried out by the Area Administration, as the mobile application is self-contained and provides the necessary instructions. Once this process is completed, the system is ready to be exposed to the end users.

B. Positioning

For every user's positioning session, a Particle Filter algorithm is executed (see [12]). Initially, the particles are uniformly distributed in the indoor area and they are assigned a random initial orientation. If a Magnetic Map has been generated for the user's smartphone model, then *Copernicus* will leverage such Magnetic Map to optimize the execution of the Particle Field algorithm. If such a Magnetic Map does not exists, *Copernicus* will use an Initial Magnetic Map.

The client application monitors the user's movement and it moves the particles accordingly. Every particle is assigned a weight that represents the similarity between the Magnetic Field readings collected from the user and the value of the closest value to the particle's magnetic field recording of the Magnetic Map being used. Hence, the client application updates the particles' "position" as the user moves in the area.

Additionally, if we detect that the user is within range of a deployed BLE beacon then all the particles outside of the beacon's radius are deleted. At any point when we have very few particles remaining, new particles are added to the algorithm execution. The application reports in real-time the estimated position of the user as the weighted mean of all the particles. After the user finishes the positioning session, either by closing the application or standing still for a long period of time, the raw data recorded are passed to the *Route Inference* service (see Figure 1).

C. Route Inference and Tailored Magnetic Map Learning

The Route Inference service is able to infer the trip the user followed during the session with some probability. The intuition is that if the user makes a long enough trip in a complex indoor area (with corridors and turns). By leveraging the deployed BLE beacons, we can infer with postmortem analysis the route that the user followed. Essentially, we are replaying all the events recorded in the raw data and we attempt to reconstruct the actually followed path.

If the system does not have a Magnetic Map for the specific smartphone model, *Copernicus* will operate on a copy the Initial Magnetic Map. The output from the *Route Inference* service is essentially a list of tuples of the form $(x, y, magneticMagnitude)$, that the system uses to update the Initial Magnetic Map, creating a new map for the given smartphone model.

With this process, the Magnetic Map gets continuously retrained for the specific smartphone model without asking the user to perform frequent fingerprinting. Moreover this makes our system robust to structural changes as the Magnetic Maps of the users get constantly updated. The next time a user with the same smartphone model wants to use the indoor positioning service, the system will leverage on the trained magnetic map for the specific device type and offer more accurate positioning. Please, refer to [12] for detailed evaluation on the accuracy performance of *Copernicus*.

III. Demo Scenario

The most obvious advantage of *Copernicus* is its ability to provide a generic and robust estimate of a user's location in presence of unknown hardware. Thus, the ability to create a custom profile for each user's hardware and to use this additional information to provide a better service overall. Even after using few trips for training.

To demonstrate that, Let us assume two users utilizing *Copernicus*. We would refer to them as User1 and User2. Both users should use the same smartphone model. However, it does not have to be the same used by the System Developer during the Bootstrap Phase. In fact, the ability of the system to provide an accurate indoor positioning in cases where the smartphone model used for positioning is different than the one used during the Bootstrap Phase will be demonstrated.

We provide a testing Android application, shown in Figure 3, that assists the user in the execution of a specific trip. During this execution the user is required to report the arrival at each marker to notify the backend service about the completion of each trip leg. Upon completion of the trip, the accuracy is displayed on both the client application and separate web dashboard, which is used to supervise the experiment. The dashboard reports, in quasi real-time, information about the system's estimated positions for the timestamps when the user reported proximity to each marker, which is used in conjuction with the known position of the marker to provide accuracy report. User1 will execute the first trip. As she/he would be using a different smartphone model the system will show a low accuracy reported on the dashboard, depending on how different the sensors are with respect to the one used during the bootstrap phase. After completion of the trip and inspection of the results, User2 execute a different trip using the same smartphone model as User1. At the end of the trip, we expect the system to report an improved accuracy for User2 as *Copernicus* will have been able to train a profile for the new smartphone model during the trip of User1.

IV. Conclusions

Copernicus is a Magnetic-based Indoor Positioning System which evolves and gets automatically retrained to support the full range of smartphone models. Due to that, it only requires a minimal deployment and no manual maintenance. Its value can be demonstrated even with a limited number of trips.

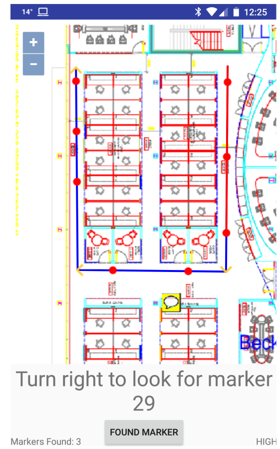

Fig. 3: A screenshot of the Android Testing Application

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