Real-time Medical Devices Inventory Tracking – a Hands-on Experience

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***Abstract*—The recent pandemic posed a challenge to several healthcare systems, exposing limited resources and inefficiency in managing PMDs (Portable Medical Devices). This paper reports the experience of an approach enabling hospitals to efficiently find their resources and maximize the usage of PMDs in emergency situations, such as pandemics or natural disasters, when a sudden increase in demand may be anticipated. The key novelty relies on the use of smartphones provided to hospital employees replacing typical stationary gateways spread across a hospital, functioning as mobile gateways with a front-end that assists staff in locating PMDs. As employees approach tagged PMDs, they update their locations in a real-time inventory tracker, delivering accurate data. Experiments were evaluated by contrasting two techniques (fingerprinting and multilateration) based on two different locations (an office and an apartment complex) in Zürich.**

***Index Terms*—Indoor Tracking, Inventory, Bluetooth Low Energy (BLE), COVID-19, Healthcare**

I. Introduction

Critical care unit facilities were severely strained in the event of a pandemic like COVID-19, which hindered the effectiveness of healthcare systems. It revealed various flaws in such systems throughout the world as a result of the unexpected rise in patient load, with authors assessing inefficiencies to respond effectively during times of crisis [2], [13]. Among these flaws, it was found that mechanical ventilators and supervision equipment (such as EKG, capnography monitors, infusion pumps, or pulse oximeters) were not adequately managed on hospital property and that, in the majority of cases, hospitals were understaffed [2].

Under increasing demands, traditional inventory management systems do not offer a workable solution to control the location and usage of these portable resources, known as Portable Medical Devices (PMD), in real-time [15], [6]. This includes real-time tracking systems, which are oftentimes too expensive for monitoring PMDs, once the installation of gateways is required throughout the hospital's infrastructure to receive localization data [4], [11], [1], [9].

To simplify communication and access to internal hospital services, healthcare institutions, most notably hospitals, provide their personnel with mobile phones. PMD-Track's key innovation leverage the staff's mobile phones to replace costly, fixed gateways or base stations. In comparison to conventional systems, a gateway-less tracking solution offers significant cost benefits in terms of hardware needs. As staff typically move throughout the hospital and cover large parts of its premises in their day-to-day, once they pass by or come in range, the location of tagged PMDs can be automatically updated in the inventory.

The PMD-Track design was first presented in [12], and this paper has a major focus to report the experience of its deployment and the lessons learned. In principle, PMD-Track's solution entails a mobile application that acts as a mobile gateway and updates a backend service with the location of recently spotted tags (*i.e.*, PMD tracked devices). This paper reports the comparison of two competing localization algorithms commonly used in indoor localization in two different test locations with the goal of finding an optimal trade-off between localization accuracy and associated deployment costs. As such, the lessons learned present a significant opportunity for a cost-effective operation in which smartphones, in use by hospital employees, can function as mobile gateways.

The remainder of the paper is organized as follows. Section II overviews the fundamentals. While Section III describes the design and implementation of the PMD-Track system, Section IV details the evaluation. Finally, Section V summarizes the work an considers improvements.

II. Related Work

This Section presents selected related work in the field of indoor tracking, which are relevant to the development of PMD-Track. Further details on the background and related work are presented in previous work [12].

[6] is a survey paper that covers a wide range of ideas, methods, and technologies on indoor localization. It also gives a mathematical basis for the different tracking methods and technologies, such as which path-loss models can be used in measurements that are related to geometry. [9] employs a trilateration algorithm using Bluetooth RSSI (Received Signal Strength Indicator) values and device's sensors data (*e.g.*, accelerator and gyroscope) to improve the accuracy of the position of devices using the iBeacon protocol. The authors use a Kalman Filter to estimate the real-time trajectory of the device. Although the accuracy of the iBeacon positioning is improved, the approach cannot be directly employed in PMD-Track as it relies on several (*i.e.*, 10) iBeacons for a 44 m x 17 m area, fixed stations to sample RSSI values, and smartphone sensors. In contrast, PMD-Track aims at reducing the number of fixed BLE tags.

[14] propose a low-cost, BLE-based room-localization system with an emphasis on the monitoring of patients in their residences (*e.g.*, apartment, house). The method relies on BLE beacons put in each monitored room and a smartphone held by the individual being observed. RSS fingerprints were gathered in the surveillance area, where samples are taken for about 30 seconds in each room. In two evaluation situations, the system's room estimate accuracy is 93.75%.

[10] provides an algorithm that finds the optimal beacon configuration for a given floor plan. The algorithm selects the configuration with the minimum number of required beacons that still ensure *unique localizability* in a predefined area. With this approach, the authors are able to localize with two instead of three or more beacons which results in 22-60% fewer beacons installed. This approach might reduce the cost of ownership in a system such as PMD-Track.

[5] minimize the work required to conduct a site assessment by combining WiFi radio signals, magnetic field measurements, and floor plan data into an advanced particle filter. Fingerprinting combines Wi-Fi RSS measurements with geomagnetic field readings and needs just the current room label, which significantly minimizes the labor required for site surveys. A discriminative learning-based landmark identification system predicts the user's position using room-level landmark fingerprints, RSSI range, and an improved particle filter.

Traditional inventory management approaches rely on manual input and update of data, *e.g.*, scanning a QR code on a smartphone to register objects. In addition, the use of portable medical devices requires a constant update of their position, which is typically prone to errors in manual input. Further, there exist real-time inventory tracking proposals [1], [4] that make use of expensive Bluetooth gateways scattered across a hospital's infrastructure. In contrast, PMD-Track eliminates the need for such gateways by relying only on mobile devices, tags, and anchor tags at known positions.

III. TECHNICAL DETAILS

This Section introduces PMD-Track's design considerations and requirements on an abstract level; they were:

- **Accuracy**: the goal of the proposed solution is the tracking of PMDs within hospitals or healthcare facilities, which are segmented into rooms. Thus, room-level tracking is required.
- **Heterogeneous Smartphones**: Deployed as a crowd-sourced application, smartphone brands and models may be heterogeneous and certain limitations may be experienced in the reception of BLE signals or in the usage of system resources. Hence, device heterogeneity must be taken into consideration.
- **Real-Time Location Data**: Near real-time or fresh data is crucial for applications such as PMD-Track. Outdated information can lead to inefficient processes and wasted resources which can ultimately lead to mistrust of users against the system. Thus, it is crucial to manage the user's expectations by communicating the staleness of information.

BLE tags linked to PMDs and BLE tags used as static reference points allow smartphones to localize spotted PMDs as medical personnel goes about their everyday tasks. When a smartphone is in range of a BLE tag, either fixed or mobile, it sends the RSFSI data to a backend service (*e.g.*, Apache Kafka), which uses multilateration of BLE signals from static tags (used as anchors with known positions) and mobile tags to calculate the position of the PMD and update it in real-time in the inventory.

Figure 1 illustrates PMD-Track's high-level architecture overview and serves as a reference to guide through the following sections. PWA stands for Progressive Web Application used as an hybrid page between mobile and desktop clients.

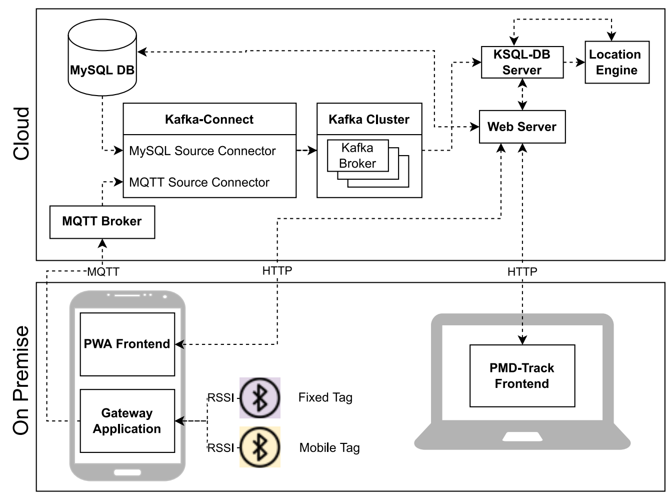

Fig. 1: PMD-Track Architecture

A. BLE Beacons

Two types of BLE beacons are distinguished in the prototype. *(i)* **mobile** beacons are attached to the assets one wants to track and are moving along with them. Their MAC address is associated with a specific piece of inventory, and *(ii)* **fixed** beacons are installed in predefined areas of the building and do not change their location. Their purpose is to serve as reference points for determining the current location of the scanning device within the building. Being able to locate the scanning device allows inferring the location of assets it has detected in its vicinity.

B. Gateway Application

The gateway application is a BLE tracking program that is installed on the employees' smartphones and searches for nearby BLE beacons. Employees are not interrupted in their work because the software operates silently and in the background of the smartphone without demanding user participation. It analyzes nearby fixed and mobile BLE beacons and transmits the time-stamped data to a cloud service. For the gateway application to deliver up-to-date information, dependable and uninterrupted operation is crucial.

C. Communication between Gateway and Cloud

MQTT is utilized to ease communication between the gateway application and cloud service in PMD-Track. The gateway application connects to the MQTT broker and periodically broadcasts aggregated BLE scan data on a preset topic. A consumer application can also connect to the broker, subscribe to a topic, and handle messages received from the broker. The messages on the MQTT topic constitute a constant stream of events, each indicating a device encounters between the gateway (*i.e.*, smartphone) and a recently scanned BLE beacon - called *BleScanEvent*. Its attributes consist of a client ID that identifies the gateway application, a MAC address connected with the BLE beacon, an RSSI value, and a timestamp indicating when it was discovered.

D. Streaming and Static Data Processing

The *BleScanEvents* received in the cloud are small bits of information from various data sources, depending on how many gateway applications are currently running. There is no assurance that BLE beacons will be examined after a given amount of time since the gateway only identifies what is presently in range. If a beacon is lost or never arrives within range of a gateway, it will never be detected; hence, no *BleScanEvents* will ever be generated. In the context of asset tracking, detecting an item's absence is just as vital as detecting its existence. Consequently, it becomes necessary to store a specified, consistent inventory list as a foundation for data collection.

In PMD-Track, the inventory list is stored in a relational database as a table of BLE beacons along with their type (*i.e.*, *mobile*, *fixed*) and their *mac_address*. Similarly, a table stores a list of active gateway applications along with their *client_id* and human-readable *name*. Finally, a last table stores room information about the building.

E. Location Engine

The location engine receives a stream of enriched *BleScanEvents* and produces a stream of positioned *mobile* beacons associated with a location (*i.e.*, room). Thus, the asset associated with the *mobile* beacon has been located in the given room. Different localization techniques may be used to accomplish room-level positioning. This paper describes the experiments and lessons learned from a fingerprinting-based and a multilateration-based localization approach.

IV. Evaluation

PMD-Track was evaluated concerning model accuracy with different variables, such as number of BLE beacons and their placement. These experiments were conducted in a real-world setting and provided several insights.

A. Data Preparation and Test Locations

Preparing a single data set per test location is a fundamental step for the subsequent model training and comparison (*i.e.*, based on the same data set) of the two algorithms. The following steps for data gathering and preparation have been done in both test locations (*cf.* beacon deployment in Figure 2). Each room, labeled with a capital letter (A-Z), is equipped with a *fixed* BLE beacon, denoted by the MAC address below the letter of the room. The beacons are installed in the center of the ceiling of each room and the mapping between the room label and MAC address is being stored.

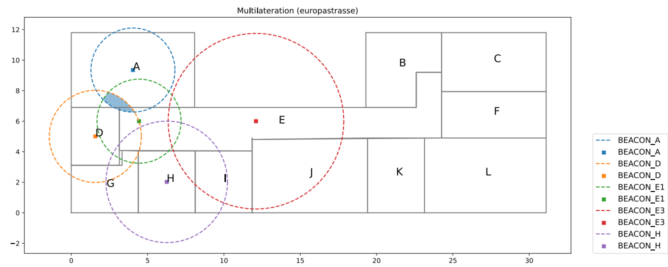

Fig. 2: Beacons Placement Office Floor Plan at Europastrasse

After preparing the test location with beacons, the data set can be gathered. In this process, a person visits each room and takes a certain amount of RSSI samples of beacons that are in range within that room. Recording the RSSI samples is done using a smartphone app. The user enters the room label where the sampling takes place and the app starts to perform repeated BLE scans. Within each scan - which only lasts a few seconds - the app records the MAC address and RSSI value of the *fixed* beacons it detected. At the end of each scan, the detected beacons and RSSI values are stored in a new data point along with the room label.

Once thousand data points are collected within the same room, the person stops the app and moves to the next room where the procedure is repeated. Repeating this for k rooms yields the final data set of $k*1'000$ rows and $k+1$ columns as one column accounts for the room label. As the data collection is terminated after a fixed number of measurements, the final data set is balanced by containing an equal number of samples per class/room.

B. Model Training

Upon completion of the data collection, the two models may be defined, fitted, and assessed. A k-nearest neighbors (kNN) classifier is used for the fingerprinting model, and a modified implementation of a multilateration technique for approximating the room based on geometric calculations is described.

kNN is a non-parametric, supervised learning method and a popular choice for RSSI-based fingerprinting [7], [3], [8]. When used for classification, an unseen data point is classified by a majority vote of its neighboring data points, with the data point being assigned to the class most common among its k nearest neighbors. K is typically chosen to be a small, odd number to avoid a deadlock situation. The training phase consists of storing the k-dimensional training samples and their associated class labels. In the classification phase of an unlabeled vector q, its k nearest neighbors are calculated from the training data set, based on the chosen distance metric.

Eventually, the class label of q is determined based on the majority of its nearest neighbor's class labels.

$$class(q) = majority(k\_min(\| q - v_i \|))\forall v_i \in train$$

For PMD-Track, the train-test-split was set to 0.2, k was set to 7, and l_2 norm (euclidean) was used as the distance metric.

Multilateration localization determines the position of an object by calculating the intersecting point based on the distance to at least 3 known reference points. This geometric-based localization yields a geospatial position with x and y coordinates. In non-line-of-sight conditions, determining the distance based on the RSSI value is error-prone due to environmental signal interference. Further, in the case of PMD-Track, instead of an exact position, room-level granularity suffices.

RSSI noise can affect distance estimations. Instead of a deterministic junction point, an overlapping intersection region may occur. This junction area combined with floor plan data offers room-level coverage; hence, the asset is most likely in the room with the greatest coverage. Multiple intersections may have distinct cardinalities. If there are many crossings with the same maximum cardinality, another selection criterion is used. To this end, the notion of *radii sum* is introduced. Given an intersection set $s_{inter}(i) = \{c_1, c_2, ..., c_n\}$, the radii sum is defined as the sum of the individual radii r_{c_k}.

Such a situation is depicted in Figure 2 where there exist three intersections with cardinality 3 ($\{A, D, E1\}$, $\{D, E1, H\}$, $\{H, E1, E3\}$). Based on the fact that RSSI noise increases with distance, a strong RSSI signal is more stable and accurate than a weak signal. The radius of the dotted circles inversely correlates to the signal strength (*i.e.*, the stronger the RSSI signal, the smaller the radius). Thus, the smaller circles provide a more accurate indication on the actual distance than larger circles. On this premise, the intersection set $\{A, D, E1\}$ is considered the most reliable intersection to be used for room label prediction. Overlaying it on the floor plan reveals that room A has the largest coverage area.

C. Preliminary Experiments

An office and an apartment complex were used as test sites. Both fingerprinting and multilateration-based techniques were trained and assessed on initial data from both test sites. The objective is to minimize feature input space (*i.e.*, number of beacons) while increasing model accuracy. A data column represents a beacon or feature. As the original data set was collected with one beacon per room, training and assessing the model with alternative beacon configurations may be done by studying a subset of the columns at a time.

1) Model Accuracy vs Number of Beacons: Input feature combinations are taught beacon subsets. The next part analyzes model accuracy under different input feature combinations. All data classes/rooms are evaluated. As a non-skewed data measure, accuracy was utilized. Figure 3 depicts the number of samples per class, demonstrating that both data sets are well balanced with regard to the class members.

To evaluate the accuracy of a specific input feature combination, the data set is first partitioned into a training and testing set with an 80% and 20% split respectively. Subsequently and in the case of kNN, the model fits on the training set. Finally, the accuracy is calculated on the testing set by computing the number of correctly classified samples divided by the total number of samples in the testing set. Cross-validation is performed to achieve a more reliable accuracy score by repeatedly training and testing the model on different train-test-splits.

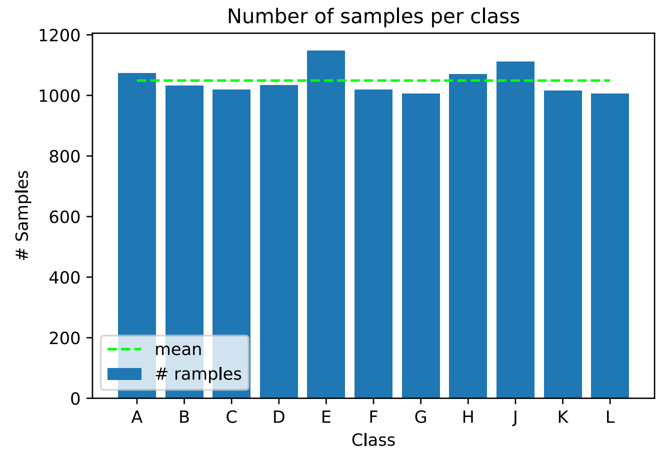

Fig. 3: Europastrasse Office Test Location

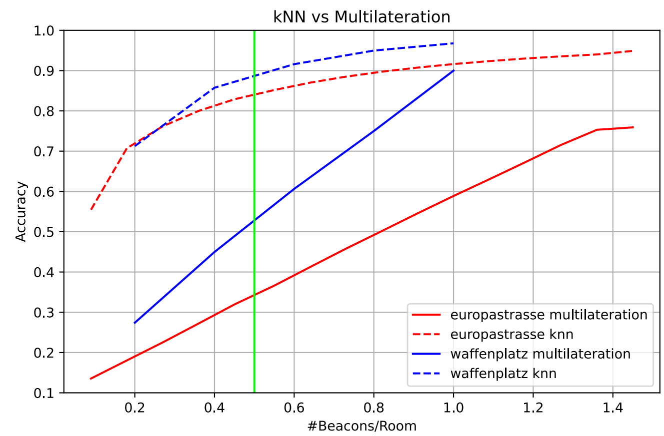

Fig. 4: Accuracy Threshold

As mentioned above, a feature combination is a subset of the total number of features. Thus, there are feature combinations of length $1, 2, ..., d$ where d is the number of available features. Performing this evaluation is computationally expensive due to the high number of combinations.

$$combinations = \sum_{i=1}^{d} \frac{d!}{i!(d-i)!}$$

For the office and apartment test location this yields a total of 65'535 and 31 combinations respectively. In the following analysis, accuracy scores are grouped by the number of features involved and averaged.

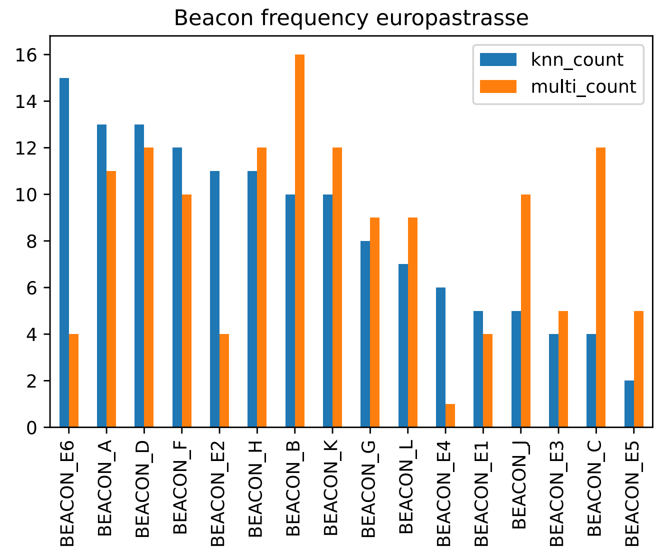

Fig. 5: Beacon Frequency Office (Europastrasse)

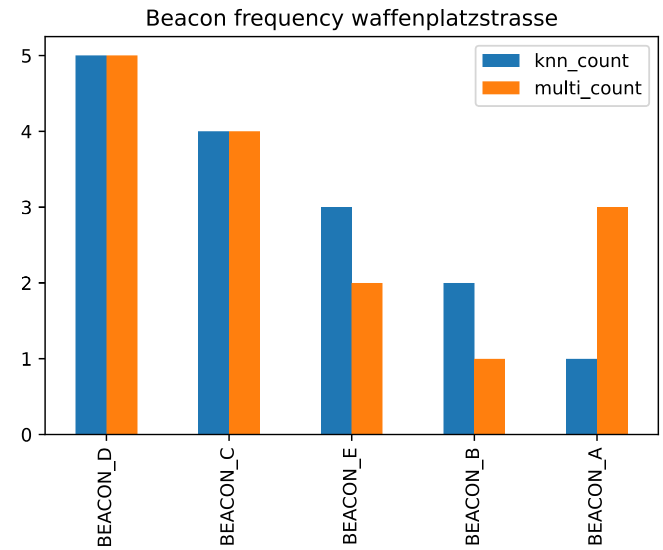

Fig. 6: Beacon Frequency Apartment (Waffenplatz)

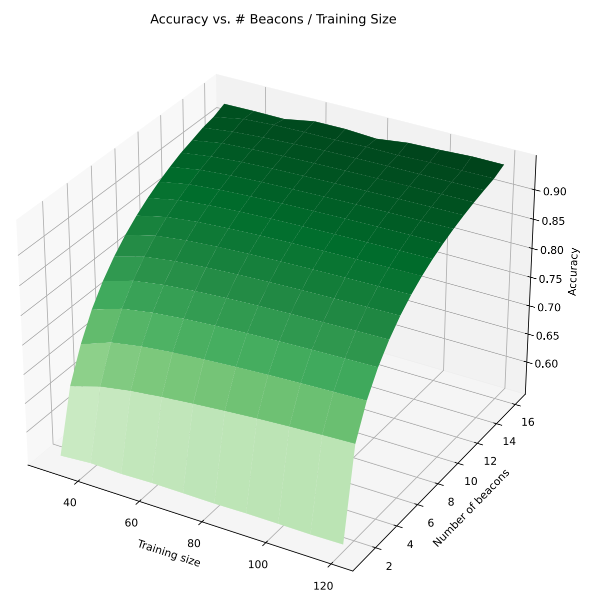

Fig. 7: Accuracy curve for office at Europastrasse

Figure 4 shows accuracy on the y-axis and the number of beacons per room ratio on the x-axis. For example, the green vertical line indicates the accuracy score for a beacon per room ratio of 0.5. For the office test location, this means that equipping half of all available rooms with beacons yields an accuracy of 35% and 83% on average for the multilateration-based and kNN-based approaches respectively. It is worth noting that the office test locations are equipped with 16 beacons and have 11 rooms, which explains the beacon-per-room ratio of up to 1.4. Based on this interpretation, one can easily observe that kNN performs considerably better than multilateration for all beacon per room ratios and across test locations. Further, it appears that accuracy for the fingerprinting-based approach grows logarithmically whereas the multilateration-based approach has a more linearly-shaped growth.

2) Model Accuracy vs Placement of Beacons: As a next step, an interesting question is to analyze the significance of individual beacons with respect to accuracy to better understand what beacons contribute more to accuracy than others. Combining this with floor plan information might reveal geospatial patterns as to where to place beacons on a floor plan to achieve maximum accuracy. To this end, the frequency is analyzed with which beacons occur in the top-ranking beacon configuration of each feature space length. In this sense, for each group of specific feature-length (*e.g.*, all combinations of length 3), the combination is selected which achieves the best accuracy score. Repeating this for all feature lengths and counting the occurrence of each beacon yields the bar plot in Figure 5 (Europastrasse only).

While the beacon frequency of kNN and multilateration-based approaches are almost identical in the apartment, the office test location shows another picture. For certain beacons, the frequency count for both models is in a similar range and may be off by a count of 1 to 2. However, there are beacons for which the discrepancy in the frequency count is higher. For example, most beacons in the hallway (E6, E2, E4, and E5) are more important for the fingerprinting-based approach than for the multilateration-based one. The experiments indicate general-pattern candidate locations for each localization approach. In the case of fingerprinting-based localization, beacons might be installed in pairs across a horizontally or vertically centered line with respect to the floor plan. Conversely, beacons might be best placed on the outermost, border rooms of the floor plan. Despite those observations, it is important to highlight the qualitative nature of these results. In the case of the apartment, the beacon frequency analysis was not conducted due to the low number of beacons (only 5 beacons).

Also, training size has a positive effect on model accuracy, as can be seen by the increasing accuracy score. Furthermore, notice that the positive effect decreases with an increasing number of beacons. For example, the accuracy of a 3-beacon model can be increased by 5% when using a training set size of 200 instead of 20. In contrast, with a 16-beacon model, the accuracy can only be improved by 2%. Figure 7 illustrates this behaviour in a 3D contour plot. Looking at the first derivative of the accuracy vs training size confirms that trend and additionally shows the diminishing marginal effect of additional training samples.

D. Lessons Learned

By leveraging smartphones, PMD-Track demonstrated it is possible to replace stationary with mobile gateways.

- Data pre-processing is the main driver for model accuracy. A straightforward data collection and imputation strategy are necessary to calculate intersections of tracked PMDs, fixed, and mobile beacons (*i.e.*, smartphones).
- Beacon placement has a significant impact on model accuracy. It is important to take into account the types of walls in the room, objects in the room, and possible interference to maximize the RSSI range.
- Distributed nature of PMD-Track presents challenges. Regardless of the localization mechanism, the system relies on a critical mass of individuals tracking PMDs. If there are not enough users to regularly cover the entire building, "blind zones" may arise where no up-to-date information is provided. Certain regions may still need fixed gates.
- Simplicity is key. PMD-Track's key strength lies in its lightweight hardware requirements, which yield multiple benefits such as a simpler setup process, less maintenance overhead, and most importantly, lower costs of ownership, as compared to existing tracking solutions.

In parallel to the experimental evaluation, an adaptation of the described system has been deployed at the emergency department of the city of Zürich, where it was used to track assets of the logistics division. PMD-Track was adapted to track assets outdoors through the use of the smartphone's GPS location as a reference point. This pilot proved that the PMD-Track's architecture is generic and can be adjusted to fit different use cases and input information (*e.g.*, GPS coordinates).

V. Summary and Further Improvements

This paper described the lessons learned during the construction and deployment of PMD-Track, a prototype, gateway-free, and distributed RTLS system. Two well-known localization techniques were built and tested at two real-world test sites. The evaluation was conducted by gathering a base data set at one of the test locations, where the accuracy of both localization algorithms was examined under a variety of input configurations. In non-line-of-sight settings, the accuracy of the fingerprinting-based technique exceeded that of one of the multilateration-based localization algorithms at both test sites by 15 to 45%. Moreover, it has been demonstrated that fingerprinting-based localization achieves the same degree of precision with half the number of fixed reference beacons.

In PMD-Track, basic data collection and imputation have shown acceptable accuracy. Further study and improvements of the 1 data collecting and 2 data imputation processes may contribute to de-noise the data set, resulting in higher accuracy scores for both localization methods. The next stage is to construct and incorporate the fingerprinting-based kNN classifier into PMD-Location Track's Engine. In addition, a mechanism for the distributed collecting of location fingerprinting must be created in order to compile the fingerprint database.

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