Deviation Maps for Robust and Informed Indoor Positioning Services

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Abstract

The ability to position and track people and assets has become increasingly widespread and important in business and personal life. The prevalent means for such tasks is signal-strength-based, prominently WiFi-based, positioning, together with GNSS positioning. The latter, however, is insufficient for the majority of indoor environments in which most of our work and personal lives takes place. Signal-strength-based positioning, though, too, is error-prone in real-life building environments, suffering from large biases induced by the often many and complex attenuating elements in the environment. Additionally, in the prevalent signal-strength-based positioning methods, which rely solely on signal pattern matching, such biases and errors are hard to assess and thus positioning quality and glitches hard to predict.

We present an approach for assessing, visualizing, and counter-acting positioning biases and impairments in signal-strength-based positioning. This approach, centered around the notion of deviation maps, aim at improving positioning quality and predictability/reliability and, at the same time, at gaining knowledge and understanding of tracking quality. We seek to understand how the tracking quality is influenced by both positioning installation and building environment, and how the former may be altered to better suit the latter. We discuss results from applying our approach in a real-world large-scale work environment, a major hospital spanning 160,000 square meters, as well as lessons learned from the underlying experimentation-driven and use-centric design process. From these lessons we also derive directions for future work.

1 Introduction

Positioning and tracking moving targets, such as people and assets, is an increasingly useful and ubiquitous technology, enabling emerging services for, e.g., indoor navigational aid or work logistics in large indoor environments such as hospitals or airports. It also receives increasing attention in the scientific community, since it still comes with open problems: our personal and work lives predominantly take place in indoor environments. Here, tracking is more difficult to provide than outdoors, where GPS and other GNSS provide adequate tracking qualities for the majority of use-scenarios. For tracking in indoor or mixed indoor/outdoor scenarios complementing positioning technologies still compete and are yet to be improved further.

1.1 Background and Motivation on Robust and Transparent Signal-Strength-based Positioning

The predominant methods for indoor positioning are signal-strength-based. In the geometry-based notion, these utilize the received strength (RSSI) of signals (from, e.g., WiFi access points or Bluetooth beacons) to estimate
the distance to the respective signal emitters, using signal propagation models. If distances to sufficiently many emitters are estimated, the receiver’s position can be approximated, e.g., via lateration. Besides such geometry-, or model-based methods, empirical fingerprinting methods [1, 3] exist: These rely on a training database of locations fingerprints, i.e., empirical location-stamped signal measurements. A positioning request is then served by matching the input RSSI measurements with the most similar fingerprint(s) in the database.

**Impairment Sources** Indoor environments are challenging also for signal-strength-based positioning as these are characterized by the many and complex building elements attenuating the signals in different intensities. This not only hinders GNSS reception, but also impairs estimating distances from RSSI measurements. As attenuations are locally persisting phenomena, the resulting inaccuracies are locally persisting positioning biases rather than spatially uncorrelated random noise. Geometry-based positioning approaches suffer from these biases and spatial variations in signal strength; at the same time, these local biases may improve the accuracy of empirical location fingerprinting, as they allow for better distinguishing fingerprints at different locations.

**State of the Art** Judging from the scientific records on WiFi positioning, the subject may seem well researched and providing sufficiently accurate and reliable positioning in indoor and mixed indoor/outdoor use-scenarios, see, e.g., Kjærgaard [3] or Lymberopoulos [5] for surveys. The vast majority of approaches found in the literature are variants of empirical location fingerprinting; these methods are usually evaluated to provide higher positioning accuracy in experiments [1]. A recent investigation into experiences from stakeholders in positioning use-scenarios though revealed a variety of common issues [4], yet underrepresented in the literature. Many of these issues come inherently with (standard) location fingerprinting: (i) the costly (and often: also intrusive) collection of location fingerprints, which are required to cover (in fine granularity) the whole area in which the positioning service should operate, (ii) the need to collect such fingerprints anew in case of changes in the WiFi or building infrastructure, (iii) significant positioning breakdowns and outliers, especially in case of sparse or outdated fingerprint collections, (iv) great difficulties in predicting and assessing (the extent of) such flaws, and how to fix them. Additionally, as fingerprinting is essentially a pattern matching against all known fingerprints for each individual positioning request, it is as such often ill-suited to reflect the motion characteristics of tracked targets, e.g., the spatio-temporal coherence of the targets’ trajectory [6].

**Simple and Robust Signal-Strength-based Positioning** Frustrated by these shortcoming, stakeholders in our experience often decide to resort to less accurate means of positioning, i.e., prominently purely geometry-based and very simple positioning algorithms such as weighted centroid (WC) positioning: In WC, a position estimate at a location \(q\) is computed as the weighted centroid of the observed beacons (for WiFi: access points), where weights are determined by the signal strength with which the respective beacons are received at \(q\). Such simpler means of positioning are often evaluated as less accurate, but are promising to be more robust and transparent, i.e., easier to assess in regards to expected quality and potential flaws. Additionally, in comparison with fingerprinting, for tracking moving targets, the resulting estimated trajectories tend to often contain fewer unrealistic position jumps and to overall better correlate with the actual movement [6]. This can be attributed mostly to that gradual changes of actual position can be expected to result in gradual changes in RSSI, which then implies gradual changes of position as estimated by geometry-based algorithms such as WC. The latter is essential in most typical WiFi positioning use-scenarios, some examples of which we will illustrate later on.

### 1.2 Introducing Deviation Maps

As motivated above, a desirable positioning concept based on signal-strength measurements would ideally combine the accuracy of location fingerprinting with the tracking robustness, the predictability, and the ease of deployment and maintenance of geometry-based positioning. As a proposal for such a combining positioning...
solution, we introduce, first informally, the concept of deviation maps, as illustrated in Figure 1: Shown are several positioning traces (black) traversing (part of) the hospital we utilized as our main test bed. For the trace marked blue, the positioning biases observed are shown as a light red area. With this knowledge, one can extract deviation vectors (red), which map the position estimates to the true locations along the route actually walked within the true route network (green). Obtaining these vectors is done similar to empirical location fingerprinting (EFP) [1], where signal-strength patterns are recorded at various locations. In contrast to EFP, these patterns are then distilled into deviation vectors, which comprise the deviation map, to capture the bias of said estimate with respect to the location of its recording and the (preferably: geometry-based) positioning method used.

Deviation maps thus indeed combine geometry-based positioning with fingerprinting elements: they can be used to de-bias a given, preferably geometry-based, position estimate by way of applying a carefully selected deviation vector, e.g., the one anchored closest to the yet biased position estimate, or a combination of such vectors. Deviation maps also improve over fingerprinting approaches in that their behavior is easier to assess and more predictable. Also, the resulting positioning is better protected against sparse areas and flaws in the fingerprint collection—as deviation maps allow for easy and smooth fall-back to the original positioning in areas and situations, where no (sufficiently trustworthy) de-biasing data in the form of deviation vectors is available.

Additionally, the visualization of a deviation map can simplify the assessment of biases and expected positioning behavior in given areas. It can be used as visual analytics tool for positioning system designers and deployment engineers, aiding them in assessing the performance of positioning system installations and improving them, e.g., by moving or adding beacons in bias-impaired areas.

2 Constructing and Applying Deviation Maps

We proceed to detail the concept of deviation maps. We then evaluate it against natural alternatives, i.e. geometry- and fingerprinting-based positioning methods, and discuss (the extent of) its benefits and shortcomings, as well as its impact in real-world positioning applications and derive tasks for future work.

More formally, we define a deviation map to be a space partition, each cell of which holds information about the positioning biases as observed in the cell with respect to a given positioning method. For ease of exposition, we will assume that the later is chosen as weighted centroid positioning, but the deviation map concept is not limited to this choice. Furthermore, for practicality and ease of presentation, we assume the space partition to be a of the form of a regular two-dimensional grid, intended to cover (one floor of) the area the positioning system is intended to cover. The cell’s information about positioning biases is stored in the form of deviation vectors, which capture the positioning errors, i.e., the offsets between ground-truth positions and the respective positions estimated from signal-strength measurements at that location.

2.1 Constructing a Deviation Map

The procedure for obtaining the deviation map is illustrated in Figure 2, together with a visualization of (part of) a deviation map for an example environment, a large hospital complex. The input to the construction algorithm consists of training sets of time-stamped location estimates $e$, computed from WiFi measurements by a given positioning algorithm. To aid intuition, we assume that each of these training sets forms an estimate trajectory

\[1\] A more complete and technical account of this first evaluation of the deviation map concept and some variants is given in [2].
Constructing the deviation map for each training measurement:

- Identify ground truth position closest in time.
- Construct deviation vector corresponding to the estimate.
- Store the deviation vector in the cell covering the estimate’s location.

The example deviation map given in Figure 2 (right) illustrates the use for explorative visual analytics: large deviation vectors indicate areas that suffer from large positioning biases; these areas should be explored further.

Figure 3: De-biasing of positioning estimates through deviation maps: procedure (left) and an example set of WiFi weighted centroid positioning traces (right), before (top) and after (bottom) applying deviation maps.

2.2 De-Biasing Positioning Estimates Using A Deviation Map

We now describe, using the illustration in Figure 3, how a position estimate, obtained by the weighted centroid or any positioning algorithm, can be de-biased by incorporating the empirical bias information encoded in a deviation map. Just like the location estimates used for building a deviation map, each location estimate $q$ to be de-biased is computed by the given positioning method from a (potentially aggregated) WiFi measurement. We start by collecting the (possibly empty) set $D_q$ of deviation vectors deemed relevant for de-biasing $q$. For this, we first determine the deviation map’s cell $c_q$ containing $q$. In the recruiting process variant, that was found superior
### Table 1: Empirical evaluation of tracking accuracy in a large hospital complex for location fingerprinting and geometry-based positioning, without and with de-biasing through deviation maps. Given are mean and median errors (in meters), w.r.t. to two metrics, and with 1/6, resp. 1/3, of the traces reserved as training data.

<table>
<thead>
<tr>
<th>Method</th>
<th>1/6 for training Mean</th>
<th>1/6 for training Median</th>
<th>1/3 for training Mean</th>
<th>1/3 for training Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Empirical Fingerprinting</td>
<td>18.45</td>
<td>9.49</td>
<td>6.50</td>
<td>3.48</td>
</tr>
<tr>
<td>Weighted Centroid (WC)</td>
<td>17.70</td>
<td>10.05</td>
<td>17.84</td>
<td>10.01</td>
</tr>
<tr>
<td>WC + Deviation Maps</td>
<td>13.73</td>
<td>6.63</td>
<td>12.32</td>
<td>5.56</td>
</tr>
<tr>
<td></td>
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The evaluation results, in particular those with respect to the $E_U$ metric, provide evidence that de-biasing using deviation maps on top of geometry-based positioning improves (the accuracy of) the latter drastically. This claim generalizes also to geometry-based algorithms as we obtained similar results as for WC also for the investigated alternatives of Bayesian- and model-based positioning—see [6] for details regarding these methods.

Secondly, the evaluation also shows evidence of the anticipated graceful degradation in case of missing or spares deviation vectors, i.e., missing local ground-truth in the form of de-biasing information: Although deviation maps-enhanced WC-positioning is outperformed by empirical location fingerprinting if larger amounts of training data are available, the reverse is true if less training data is available (and thus covers less parts of the environment traversed by the remaining traces). Here, deviation maps perform as well or even better than empirical fingerprinting, as measured by the $E_U$ metric, suggesting that deviation maps indeed require less (coverage by) training data to perform robustly.

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2 Training traces are those gathered on one or two of the six mobile devices used. Numbers in Table 1 have been obtained by cross-validation over the choice of training devices.

3 See Mathisen et al. [6] for a more detailed discussion of these metrics.
4 Discussion and Future Research Directions

In the following, we present lessons learned from the evaluation summarized above as well as from additional exploratory investigations concerning in particular design decisions regarding (variants of) the deviation map concept. We furthermore describe items we consider relevant for future investigations emphasizing on the potential benefits of deviation maps for positioning applications.

4.1 Positioning Accuracy, Graceful Degradation, and Larger-Scale Investigations

Varying Evaluation Setups In terms of positioning accuracy deviation maps not only improve geometry-based positioning, they may also outperform fingerprinting, especially if the fingerprint collection is sparse or flawed. This holds even in the face of the (arguably: less informative [6]) $E_D$ metric, for which fingerprinting shows comparatively better results. Simple empirical fingerprinting reports collected fingerprints, i.e., locations traversed in a collected training trace\(^4\). A main reason for high accuracies of the $E_D$ metric lies in the experimental setup: due to the limited main route network, many locations along a given test route are likely to have been traversed in training already. Thus, fingerprinting may map to such positions. This results in a very low $E_D$ error, but in an $E_U$ error often several tens or hundreds of meters large. We thus expect lower fingerprinting accuracies for even more realistic, i.e., larger, and more diverse, data sets, spanning more of the building complex. Hence, a more thorough investigation of even larger scale is called for, specifically to compare deviation map-enhanced positioning versus fingerprinting for different extents and densities of ground-truth collections.

Another extension is to evaluate also for other modes of ground-truth collection. In particular, fingerprint collection is done traditionally not while moving, but stationary, for periods of a few seconds, at numerous locations (usually arranged in a regular grid covering the deployment area). Potentially, this provides a more precise ground-truth; we believe, though, that this improvement is outweighed for typical positioning applications—especially those for which deviation maps suffice in terms of achieved tracking accuracy—by the ease (and potentially more use-case-realistic patterns) of collecting while moving naturally through the environment.

How to Collect and When to Ignore Deviation Vectors An investigation on an even larger scale than the one reported upon [2] may also be useful to ascertain and concretize best practices for (i) how to collect and aggregate deviation vectors in order to de-bias a concrete positioning estimate, and (ii) when to fall-back to geometry-based positioning and not use overly sparse, missing, or not trustworthy de-biasing information. The option to fall-back to geometry-based positioning and to prescribe how to combine geometry-based positioning with the empirical ground-truth information is probably the largest conceptual advantage of the deviation maps concept over classical fingerprinting. Thus, while the evaluation summarized here suggests concrete answers for how to do this best [2], the last word on this is likely to be deployment-dependent. Hence, these questions should be re-addressed in further deployments and with a more thorough analysis of the influences of parameters such as density of the WiFi network and building layout and structure.

There are several options for preprocessing the estimate trajectory points prior to computing deviation vectors. If it is known that the measurements were obtained by walking at constant speed, we would resample both the estimate and the ground-truth trajectories at fixed time intervals. However, our concept also allows to choose the set of trajectories for building the map, including the one focused on in our previous paper [2]: to use all trajectories individually. Alternatively, it is possible to use a single, representative trajectory for several walks along the same path. The advantage of the former approach is to have more data points and, hence, more deviation vectors to work with; this is advisable if the environment is expected to be noisy and thus to lead to outliers in future measurements. Using instead single representative trajectories may be advisable in larger

\(^4\)This holds for the most basic form of fingerprinting: reporting the nearest neighbor in signal space. Within typical environments such as hospital test bed used in our evaluation, the claim often holds also for, e.g., $k$-NN variants [1], since much of the collected data resembles straight walks along corridors.
4.2 Evaluating Tracking Quality Beyond Positioning Accuracy

**Application-centric Investigations** For certain positioning applications, not only the positioning accuracy traditionally assessed, but also the faithfulness of capturing the movement across a whole trip, in terms of directional changes, speed, and the avoiding of drastic outliers, is crucial [6, 7, 8]. This is similar to outdoor use-scenarios such as car navigation, where the application’s goal of depicting the car’s current position and extrapolating when to give navigational instruction. Additionally, the higher density of paths and crossings likely to be taken gives rise to a larger set of possible routes in large building complexes and thus imposes additional demands with respect to the positioning quality [7].

Figure 4 shows visual impressions of (facets of) indoor positioning scenarios identified by stakeholders (including position service providers and customers) as both common and crucial to operations. Figure 4 (left) shows aggregated movements between fine-grained semantic locations (top) and between departments (bottom). Figure 4 (middle) is an exemplary analysis of three common routes (in different colors) taken between two points. All data visualized is extracted from relatively noisy WiFi positioning. The positioning service and the illustrated analyses are used for logistical optimizations—in the cases above: of hospital facility management and work practices—but also for real-time responses, e.g., when determining whether tracked employees are following their assigned tasks or deviate from them (handling, e.g., an emergency yet undetected), at which time they arrive at the assigned location, and which tracking vehicle or equipment they are (co-)traveling with.

**Interoperability with Smoothing Filters** Earlier investigations have shown that in applications as sketched above often geometry-based positioning outperforms fingerprinting solutions. The investigations also suggest that this is due to the sometimes erratic fingerprinting positioning for moving targets—and due to that fingerprinting does not inherently promise spatio-temporal coherence, as each incoming WiFi measurement (set) is matched against collected fingerprints, but without reference to their locations or the most recent position estimates provided. This downside is often combated by smoothing techniques, such as particle filters—as evaluated on the given data set [6]—which can enforce positioning to adhere to the walkable paths given by, e.g., a building plan. As traditional fingerprinting most often already produces (potentially inaccurate but) walkable-path-adhering position estimates, it hinders the particle filter from eliminating or correcting erroneous estimates. For deviation maps a similar investigation into the compatibility with and additional benefit of smoothing techniques seems worthwhile. This holds in particular as deviation maps, like fingerprinting, extrapolate from (only partially matching) historical data and thus, over the course of tracking a moving target, may introduce artifacts which were not captured in the underlying (geometry-based) position trace the deviation map was applied to.

4.3 Integrating Deviation Maps with Further Visual Analytics Tools

Stakeholders of positioning systems, including providers as well as their customers, convey that assessment and transparency of positioning quality and peculiarities is of great value. While this goal is inherently hard
to achieve with fingerprinting, interactively visualized deviation maps can aid assessment, e.g., in quantifying biases, identifying problem-free versus heavily biased areas, and giving rise to improvement of the underlying positioning infrastructure. We plan to integrate interactively visualized deviation maps with visual analytics tools, as given in Figure 4, but also with interactive visualizations of signal strength propagation based on building models used also in model-based positioning. This will allow to visually observe the effects of moving around or adding further WiFi access points or other beacons. We believe that the integration of interactively visualized deviation maps and other visual analytics tools will facilitate sanity checking as well as improving positioning deployments.

4.4 Improving on Ease of Deployment and Maintenance

Future investigations of deviation maps in practical use-scenarios should also include an evaluation of efforts for deploying and maintaining positioning solutions—since as compared to plain geometry-based positioning, some effort is required also for deviation maps, foremost for ground-truth collection and integration. Our findings reported here suggest that compared with fingerprinting, deviation maps require less rigorous ground-truth collection to achieve comparable accuracy, and that outdated and erroneous ground-truth is less harmful to deviation maps. Furthermore, focused fixing and re-collection of ground-truth data is supported by using deviation maps also as a visual analytics tool; the effort in training staff to do so, though, is also yet to be assessed.

References


