HIPS: Human-based Indoor Positioning System

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***Abstract*—Homo sapiens is a common, even if often uncredited, component of indoor positioning research. Despite the increasing number of automatic benchmarking platforms, performance of a positioning system is still typically evaluated by a graduate student with a smartphone in their hand. Powered by the varying levels of motivation, attention and spatial awareness, research assistants gather data while walking along predefined paths or visiting predefined locations. More importantly, however, these people are in charge of establishing the ground truth which has a direct impact on the final evaluation results.**

In this paper, we look into the widespread tacit assumption that human-based ground truth errors are negligibly small. Using a custom laser-based positioning method with centimeter-level accuracy, we experimentally invalidate the hypothesis of human localization infallibility in a series of 378 measurements with 7 volunteers. In static tests with three types of visual references, we observed human localization errors reaching values of 22 cm (with floor and ceiling markers) and up to 36 cm (with environmental landmarks). Such displacements can easily be the difference between the line-of-sight and radio-shadow locations and thus strongly affect the measured performance of a wireless positioning system.

The results of this work outline the limits of human-based indoor positioning performance and highlight the importance of correct implementation and reporting of ground truth methodology in indoor localization research.

***Index Terms*—Indoor positioning, ground truth, benchmarking, fingerprinting, performance evaluation, human factors.**

I. Introduction

Evaluation of an indoor positioning system requires the knowledge of the ground truth established either by direct observation or by an accurate reference positioning system. However, research labs and universities often do not have access to specialized benchmarking platforms such as [1], [2], and the evaluation is performed by a graduate student with a smartphone in their hand, who uses visual references to establish the ground truth. The accuracy of such a human-based indoor positioning system (HIPS) is typically assumed to be perfect.

Since current indoor positioning systems start to reach the one-meter accuracy milestone [3], inadequately established ground truth (GT) may seriously affect the evaluation results of the system under test. However, even well-described positioning experiments tend to provide surprisingly little details about their ground truth estimation methodology [4], thus making it impossible to assess the contribution of GT to the measured localization performance of the presented system.

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The aim of this paper is to evaluate the accuracy of the human-based indoor positioning and to stress the importance of adequate implementation and reporting of the ground truth measurement methodology. We experimentally quantify the human ability to accurately position smartphones in indoor locations (test points) defined by visual references such as floor and ceiling markers, or by generic environmental landmarks.

The contribution of this paper is three-fold. Firstly, we present a method for manual centimeter-level indoor positioning using a laser rangefinder and analyze factors related to the method's accuracy. Secondly, we experimentally demonstrate that HIPS performance is far from ideal, with the localization error reaching 22 and 36 cm for floor&ceiling markers and environmental landmarks, respectively. Finally, we discuss the impact of the human factors on the HIPS performance and suggest a method for improving the quality of HIPS-based ground truth. Considering the popularity of the HIPS in indoor localization research (including past formal competitions [5]), the results of this study should be of interest for the whole indoor positioning community.

The paper is organized as follows. Section II provides a review of the related work and relevant GT referencing methods, and further elaborates the motivation of the study. Sections III and IV describe our methods, the GT measurement system and the experimental setup. In turn, Section V presents the results. Finally, Section VI summarizes the results, discusses their implications for the field and outlines an approach for augmenting HIPS performance.

II. Background

No indoor positioning method is complete without an estimation of its performance, which includes comparison of the system's output with the known ground truth (GT) data. The GT can be provided by a more accurate reference positioning system, or established as a predefined path or a set of discrete points which are then visited by the test device. Despite the key role of GT in the performance evaluation process, details of the GT measurement methods are often only implied or even neglected altogether in experimental reports [4].

There are a number of specialized benchmarking platforms designed to evaluate indoor positioning systems. Robot-based platforms with highly accurate reference systems enable automatic comparison of different localization methods with minimal human effort. Some of these systems are summarized in Table I. As follows from the table, the typical GT accuracy of such systems is in the order of tens of centimeters.

TABLE I: Reference Positioning Systems and Benchmarking Platforms for Indoor Localization

System	Technology	Accuracy
EVARILOS [1]	Laser scanner & Vision	25 cm (average) [5]
RAWSEEDS [2]	Laser scanner& Vision	17 cm (average)
Schmitt et al [6]	Vision	6.7 cm (average)
UbiSense [7]	UWB	15 cm (95%)
ALPS [8]	Ultrasound	16 cm (average)

Unfortunately, automatic benchmarking solutions are not always available for logistical or financial reasons. As a result, evaluation of novel positioning methods is often delegated to cost-efficient and readily available research assistants. Although such human-based positioning systems (HIPS) were likely never benchmarked themselves, an (arguably flawed) twist of reasoning leads to a widespread unspoken assumption that HIPS performance is ideal and any errors are negligible.

To the best of our knowledge, the validity of this assumption has never been experimentally verified. However, according to our own experience, placing the test device exactly into the test location is a rather challenging task, especially when the experimental sessions are repeated over the course of days or weeks. The risk of inconsistent GT further increases when data collection is performed by different people.

At a first glance, motivation for this study might seem superficial. Given the typical Wi-Fi median localization accuracy of several meters [9], any possible contribution of GT imperfections would be negligible. However, in multipath environments (such as indoors) radio waves are subject to strong self-interference and small-scale variations [10], [11]. A deep radio shadow can be only few wave lengths away from the line-of-sight reception. As a result, Wi-Fi received signal strength (RSS) can significantly change even if the smartphone is moved by only a few centimeters [11]. Therefore, even small GT errors might lead to considerable differences in RSS fingerprints and thus have a disproportionally large impact on the measured localization performance.

In this study, we focus on HIPS' performance in evaluation of non-inertial positioning systems. Such systems are tested predominantly in a stationary manner using discrete test points [4]. The literature offers several methods of establishing GT coordinates of discrete test points:

- **Add-on markers**: test points are labeled on the floor or ceiling and the experimenter needs to stand over/under the mark. While markers can be deployed in any required spatial configuration and density, this method is applicable only in controlled settings, since adding markers might not be feasible in public spaces.
- **Environmental landmarks**: when the environment cannot be altered to include special markers, one could define test points by aligning them with generic landmarks in the environment, such as pillars, floor tiles, doors or furniture. With the possible exception of floor tiles, spatial distribution of such features is usually irregular, so the experimenters have to rely on visual relationships like "in front of the cupboard, aside of the door handle". Unfortunately, such definitions are open for interpretation, which can introduce a certain GT ambiguity among team members. (For instance, which point is the "front" of a wide cupboard?) In large environments with sparsely distributed landmarks (such as underground parking lots) the GT error is likely to increase even further.
- **Floor plan**. This method, used in the pioneering RADAR paper [12], allows the experimenter to visit arbitrary points in the environment and then define the GT location by clicking on the corresponding points on the screen. Floor plan GT is essentially equivalent to the previous one, as the experimenter still has to refer to the environmental landmarks for determining their position in the testbed. Moreover, several other factors — such as plan's resolution, zoom level and factual correctness — can further affect the accuracy. Moreover, choosing the GT location on a mobile device could be even more difficult due to the relatively large fingertip covering a considerable area of the small display (a phenomenon known as the "fat finger problem" [13]).

As this study focuses on human errors, it is important to acknowledge the discipline of human reliability assessment (HRA) [14]. The main goals of HRA — namely error identification, quantification and reduction [14] — are also addressed in this paper. Although HIPS errors are unlikely to lead to catastrophic large-scale accidents studied by the HRA, understanding the limits of human positioning performance is critically important for the fair evaluation of indoor localization systems.

III. Methods

In this paper we follow the typical evaluation scenario of a Wi-Fi fingerprinting system: a research assistant equipped with a smartphone visits a number of predefined test points and stays in each of them for a while, collecting Wi-Fi RSS samples.

The key difference of our approach is that the assistant's role changes from the all-knowing ideally accurate ground truth provider into a mere component of a human-based indoor positioning system, HIPS.

Similarly to smartphones, HIPS features multiple sensors suitable for localization, including visual, audio and tactile sensors. In this paper, we focus exclusively on vision-based HIPS localization using different types of auxiliary references, namely floor markers, ceiling markers and environmental landmarks.

A. Ground truth measurements

Since questioning the HIPS performance automatically deprives us of a widely used and readily available GT positioning system, we need an alternative method for indoor localization of smartphones. Moreover, in order to qualify as a GT provider, that alternative system has to significantly outperform the HIPS itself. Unfortunately, robotic benchmarking systems were not available in our lab during this study; in any case, we expected their performance to be comparable to that of the HIPS and thus insufficient for an adequate evaluation.

Having no easy automatic solution, we have devised a manual measurement approach based on a Bosch PLR 50C digital laser rangefinder [15]. While a participant held the smartphone in one of the test points, the experimenter measured the distance between the smartphone and nearby walls (or windows). For safety reasons, the smartphone was kept below the eye level, and the participants were asked to turn their head away from the laser beam during GT measurements. This was an additional precaution, even though class 2 lasers (such as the one used in our rangefinder) are considered safe for accidental exposure because of the natural blink reflex [16].

In addition to the documented accuracy of the rangefinder (± 2 mm [15]), we considered a number of other factors that could contribute to the measurement error of the GT system.

1) Impact of the measurement on the smartphone position: While in theory the distance between a smartphone and a wall could be measured from either direction, estimation in the phone-to-wall direction would have required physical contact between the rangefinder and the smartphone. This way, however, the very procedure of measurement would be affecting the system under test.

In order to avoid any such effects, we employed a considerably more laborious wall-to-phone measurement approach. The rangefinder was placed on the wall surface (so that the laser beam was orthogonal to the surface) and moved around until the laser spot highlighted the nearest side of the smartphone. The minimal reading reported by the device was recorded for further processing.

2) Impact of the measurement on the human participant: Unlike other indoor positioning systems, HIPS has conscience, emotions and personal deadlines. Therefore, there was a possibility that the participants could try to speed up the tedious measurement process by 'catching' the laser beam with the test smartphone. In order to avoid the additional error introduced by such a cooperation, the participants were instructed to look away from the smartphone once they placed it into the test point.

3) Natural fluctuations of the handheld device: Human capability of maintaining a stable vertical posture has its limits even for healthy individuals. In NASA experiments [17], participants demonstrated $0.82°$ peak-to-peak body sway in anterior-posterior direction while standing steadily for 21 s, with eyes open [17, Table 2]. For a smartphone held 1.4 m above the floor, this corresponds to ± 10 mm of sway distance.

As rangefinder measurements were performed for each coordinate separately and the whole procedure took on average about 40 seconds, we must expect that the phone position was changing during the process. Therefore, measured x and y values do not necessarily mean that the smartphone has ever been in point (x, y), but rather somewhere within the 10 mm radius from that point. Although the fluctuations occur in the *measured* system itself rather than our GT *measurement* system, for clarity we still include the ± 10 mm error to the GT system error estimate.

4) Non-orthogonality of the laser beam: If the laser beam is not exactly orthogonal to the wall surface, the measured distance could be overestimated, thus increasing the GT measurement error. Assuming that the laser is aligned with the rangefinder's enclosure, the orthogonality requirement could be affected by uneven wall surface.

Local irregularities, such as uneven paintwork, was measured by placing a 30-cm ruler on the wall in several places; all imperfections were found to be less than 0.5 mm in height. Given the device base of 50 mm, that corresponds to $0.5°$ error. Larger-scale deformations, such as bended or tilted wall panels, were probed by aligning the laser beam in parallel with the wall, 5 mm from its surface, and measuring the position of the laser spot on a small box moved along the wall. The fluctuations were bounded to $0.1°$ (maximal lateral shift of 5 mm at 2.75 m distance). Combination of the local and larger-scale angular errors adds up to $\pm 0.6°$, which results in up to 10.5 mm/m lateral shift of the laser spot. However, such a deviation from orthogonality results in only $0.05\ mm/m$ distance measurement error, or 0.9 mm for the largest dimension (16 m) of the test room.

Summarizing the above considerations — the ± 2 mm error of the rangefinder, ± 10 mm of natural fluctuations (non-stationarity during the measurements), and approximately ± 1 mm of non-orthogonality error — we estimate the accuracy of our GT measurement system to be around ± 13 mm per axis for localization of a handheld smartphone. For stationary scenarios, such as localization of markers and landmarks, the accuracy was about ± 3 mm per axis. It should be noted that both estimates assume that the experimenter is free of error and all the rangefinder readings are recorded correctly.

IV. Experimental setup

The experiment was performed on the premises of the SnT research centre of the University of Luxembourg, in a $16 \times 6 \times 2.7$ m meeting room. The room featured an extensive set of ceiling-mounted fire sprinklers, pillars and framed windows (Fig. 1).

A. Types of references

In this paper, we focus on the following three types of visual references:

- **Ceiling markers** represented by fire sprinklers (3 cm in diameter);
- **Floor markers** represented by yellow Post-It notes (76×76 mm) with a cross indicating the center. These markers were placed approximately under the ceiling markers.
- **Environmental landmarks** defined as the crossings of imaginary lines originating from the window frames and pillars (see Fig. 1 and 2). While three test points were collocated with the marker-based ones, the other three were about 30 cm away from the corresponding markers due to the specifics of room layout (there was no suitable landmark aligned with markers 2, 4, and 6).

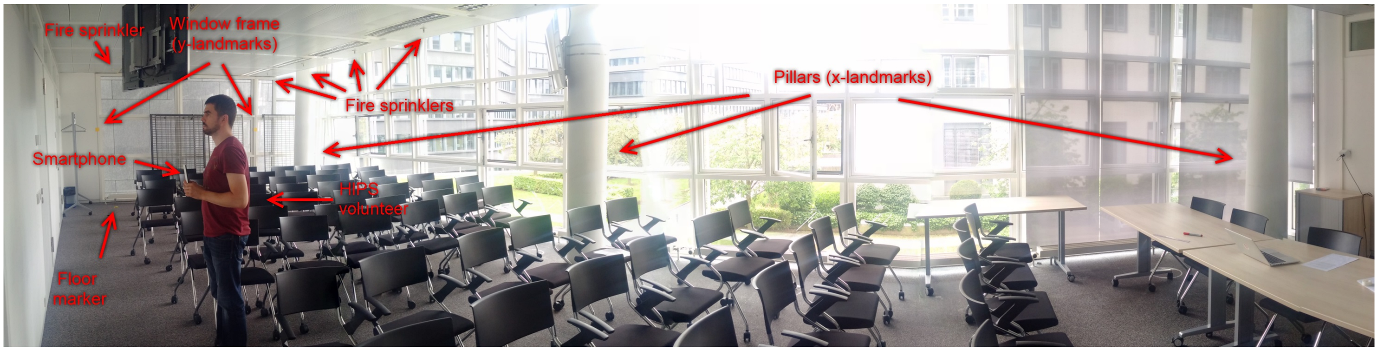

Fig. 1: Experimental testbed.

For each reference type we defined six test points as shown in Fig. 2. Ground truth coordinates of all the test points were measured directly regardless of their type.

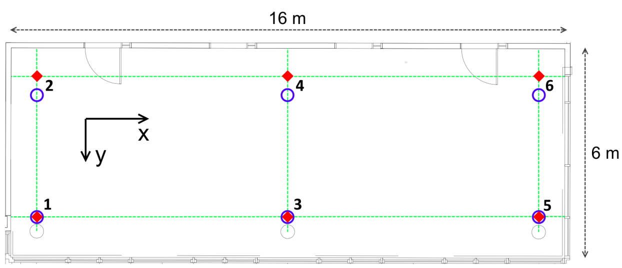

Fig. 2: Testbed layout. Floor and ceiling markers are labeled with blue circles. The environmental references are represented by the green lines aligned with pillars (x-landmarks) and window frames (y-landmarks); corresponding test points are labeled by red diamonds. Please note that test points 2, 4 and 6 are different for the marker-based and landmark-based scenarios.

B. *Participants*

The experiment was conducted with 7 graduate students of the computer and natural sciences department. None of them had previous experience in indoor localization experiments. All the participants were informed about the nature of the study and instructed to demonstrate their best-effort performance. The experimental sessions took approximately one hour per person; each participant received a 20 Euro gift card of a major online retailer as a compensation for their time.

C. *Procedure*

The experiment was divided into three parts, by the reference type. The phases were randomly ordered for each participant; this was done to reduce the possible unfair advantage of the first tests and to distribute the impact of fatigue evenly across all the reference types. In each phase, the participants visited all the six test points in a predefined order, using only one type of references (adherence to this rule was monitored). This procedure was repeated three times in order to estimate the repeatability (dispersion) of the HIPS localization results.

After being equipped with a turned-off LG Nexus 5 smartphone, each participant was instructed to hold the device vertically and to bring it into the test point location as accurately as possible, so that the center of the device would align with that of the test point. Once the participant was ready, the experimenter moved around the room and measured the distances from the nearest walls, windows or pillars to the test smartphone.

Since Wi-Fi fingerprinting systems typically focus on 2D localization, the distance to the floor was not predefined. Instead, the participants were asked to choose a comfortable height and maintain it throughout the study. Although height measurements were foreseen by our initial plan, they proved to be rather awkward in practice and were left for future work.

V. Results

This section presents the results of experimental evaluation of HIPS localization performance with different types of visual references. Overall, we collected 378 measurements (7 participants $\times$ 3 reference types $\times$ 6 test points $\times$ 3 repetitions).

Besides the traditional cumulative distribution function (CDF) of the error distance, we were also interested to estimate HIPS stability – that is, the human ability to consistently revisit the same test point in repeated measurements. The corresponding metric of spatial dispersion is called the *standard distance deviation* (SDD), which is defined as [18, Eq. 8.7]:

$$sdd = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n} + \frac{\sum (y_i - \bar{y})^2}{n}}$$

where $n = 3$ is the number of measurements, $\bar{x}$ and $\bar{y}$ are coordinates of the mean center of all the three measured points:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i; \qquad \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$$

In other words, SDD is the average distance between the measured points and their mean center. This metric was calculated independently for each test point and each participant.

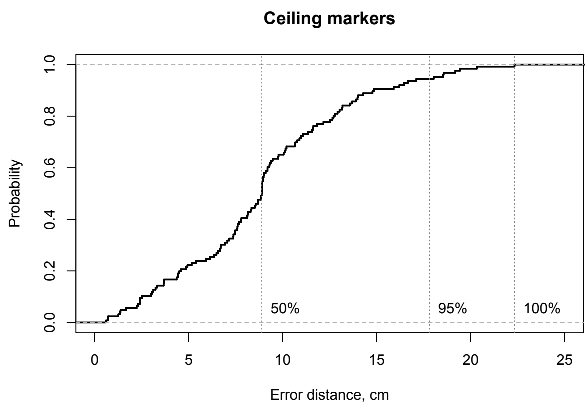

Fig. 3: HIPS positioning performance using ceiling markers (all participants).

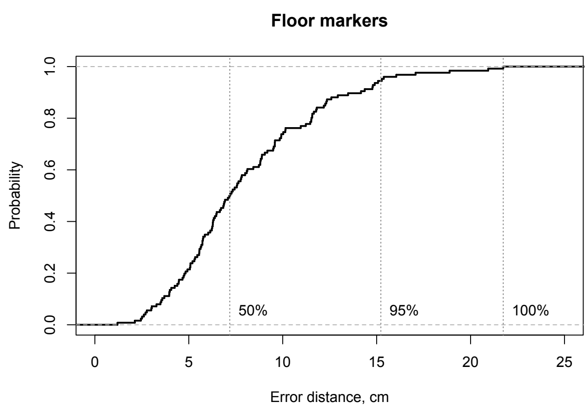

Fig. 4: HIPS positioning performance using floor markers (all participants).

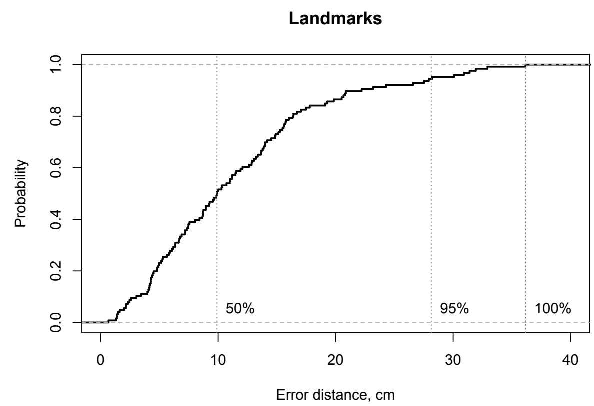

Fig. 5: HIPS positioning performance using environmental landmarks (all participants).

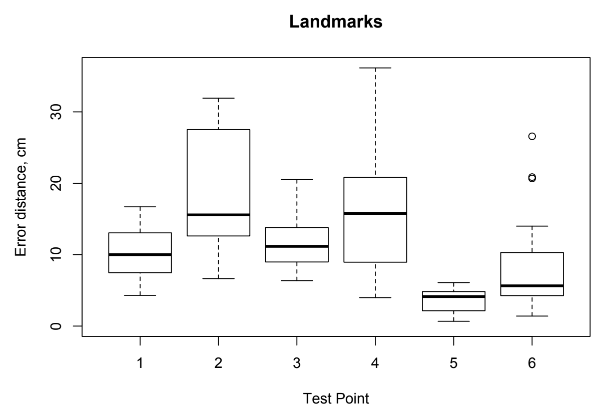

Fig. 6: Localization error of landmark-based HIPS in different test points.

A. Ceiling markers

Fig. 3 shows the HIPS localization performance when using ceiling markers. The median error was 8.9 cm, while the 95^{th} percentile error reached 18 cm. The maximal observed error among all the participants and all the test points was 22 cm. In 95% of the measurements, standard distance deviation was within 5.8 cm.

B. Floor markers

Floor markers proved to be slightly more reliable than the ceiling ones: the median error was only 7.1 cm, and the 95^{th} percentile of the error decreased to 15 cm (Fig. 4). Standard distance deviation was less than 6.0 cm in 95% of the measurements. The accuracy was comparable among all the test points.

C. Environmental landmarks

Environmental landmarks resulted to be the least reliable type of visual references: while the median error was only 1 cm larger than that of the ceiling markers (9.9 cm vs. 8.9 cm), the 95^{th} percentile of the error increased to 28 cm. The ambiguity of landmark references also showed in the slightly increased spatial dispersion: SDD value was within 7.0 cm for 95% of the measurements.

In contrast to the marker-based references, localization performance of landmark-based references widely varied among the test points (Fig. 6). As one could intuitively expect, the error depended on the distance to the landmarks. For instance, points 2 and 4, which are away from both x and y landmarks (see Fig. 2), were associated with the highest errors; in turn, significantly smaller errors were made in test point 5 which was only 70 cm away from either landmark.

D. The human factor

In contrast to more conventional positioning solutions, HIPS is an extremely complex system with a vast set of internal and external parameters, such as mood, spatial awareness and physical shape. While in some cases the offered reward might have motivated the participants to enlist for the study, it could not guarantee their best-effort performance.

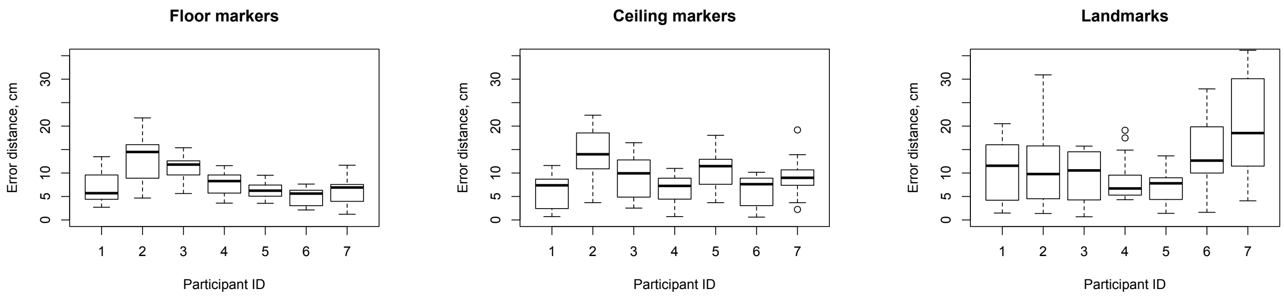

Fig. 7: Localization error per person.

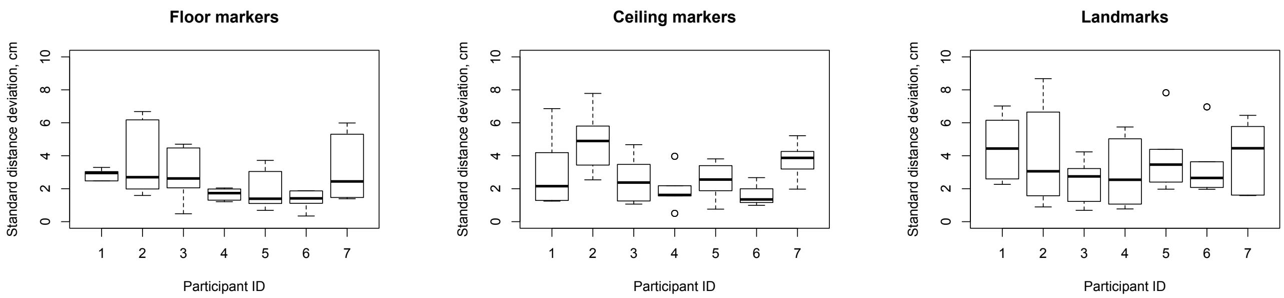

Fig. 8: Personal precision.

Personal results of the volunteers (presented in Fig. 7 and 8) demonstrate a considerable variation of HIPS performance on person-by-person basis. For instance, participants 4 and 6 demonstrated an impressive, better than 2 cm, repeatability in marker-based tests (Fig. 8). On the other hand, the average error of participant 2 in the floor-marker test was almost twice higher than for the rest of the group (13 cm vs 7.2 cm) (Fig. 7). However, since controlling the psycho-physiological parameters was beyond the scope of this study, we cannot offer a plausible explanation for the observed differences.

Another difference of the HIPS from automatic systems is that HIPS is prone to fatigue. One-hour long experimental sessions proved to be rather tiresome for everyone involved. This could have been aggravated by the fact that the use of personal mobile devices was banned during the study in order to minimize distractions. Four participants asked if they could use the test or a personal mobile device for entertainment during the experiment. One participant reported entering a trance-like state during the series of repeated measurements. Another one asked for background music.

Obviously, we cannot generalize the experience based on a group of seven people to the whole population of research assistants. However, these observations represent the experimental evidence that in separate cases research assistants might attempt multitasking, possibly affecting the data collection process. This possibility should be taken into account by the team leaders who might want to advise their assistants on the range of acceptable entertainment activities.

VI. Discussion and Conclusion

The results of the study confirm the centuries-old observation attributed to Seneca the Younger: "*errare humanum est*" ("to err is human"). The localization accuracy of HIPS is far from perfect, depends on a range of uncontrollable factors and varies from one person to another.

In particular, HIPS performance depends on the type of the visual references used for positioning. In our tests, the participants fared best with what was below them (floor markers), slightly worse with what was above them (ceiling markers) and worse of all — with what was around them (environmental landmarks). Indeed, dedicated floor and ceiling markers resulted in better accuracy and repeatability than generic landmarks of the indoor environment. While the obvious suggestion would be to always establish the ground truth using add-on markers, this may not be feasible in public or thoroughly cleaned places. In such cases, environmental landmarks remain the only option for establishing the ground truth. Nevertheless, it is important to understand the limitations of the landmark-based GT and place the evaluation points near the landmarks whenever possible.

While our experimental setup with six well-separated and distinct test points was rather lightweight, more realistic scenarios involve more test points with higher spatial density. As a result, tracking the progress of the data collection becomes challenging and HIPS can accidentally skip a point or confuse the order of test points. While these types of human mistakes were outside the scope of this study, they may result in even larger GT errors.

A possible approach to improve the quality of human-based ground truth is to provide the data collecting person with inexpensive consumer-grade laser rangefinders. With this approach, coordinates of the test points can be defined and recorded as a set of distances to nearby landmarks, and the person would be able to easily place the test device exactly into the required location. This approach might also improve GT data consistency in multi-person and long-term experiments.

One of the lessons learned from the Microsoft Indoor Localization Competition 2014 was that "not all evaluation points are equal": some test points are easier to localize accurately than the others [5]. Tens of centimeters of HIPS errors observed in our study can easily be the difference between an 'easy' and a 'difficult' point, and the performance of the tested system can be severely underestimated. Therefore, it is important to understand the significance of adequate ground truth measurements and to provide comprehensive information on the used ground truth estimation methods in the future publications.

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