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Invited Paper

A Survey of Ground Truth Measurement Systems for Indoor Positioning

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Abstract: Various types of indoor positioning methods have been proposed. Accordingly, various ground-truth measurement methods have also been used. The selection of the ground-truth measurement method is crucial when appropriately evaluating the indoor positioning methods. In recent years, data-driven methods have been actively proposed, making the ground-truth measurement even more critical. Most existing survey papers only focus on classifying indoor positioning methods and datasets for evaluation. Our survey paper investigates the methods to measure the ground truth. First, we list the primary examples of ground truth measurement systems and summarize their characteristics, such as the scale, accuracy, and frequency when collecting ground truth. Then, we classify them into the following five categories: OMC, ToF/MFPS, SLAM, Manual, and Others. Their advantages and disadvantages are also discussed based on four indices: accuracy, coverage, device cost, and labor cost. Finally, we discuss the appropriate way to select the ground-truth measurement system for quantitative evaluation. Our survey will be the guideline for selecting an appropriate ground-truth measurement system for indoor positioning and indoor navigation.

Keywords: indoor positioning, navigation, ground truth measurement

1. Introduction

As many studies have been conducted, indoor positioning is an important research topic in mobile and ubiquitous computing. A wide range of its applications has been developed in navigation and robotics. Accordingly, several survey papers have been published [1], [2], [3], [4], [5], [6]. The primary objective of most existing survey papers is to classify indoor positioning methods and introduce datasets for evaluation.

A quantitative evaluation experiment is commonly conducted when evaluating indoor positioning methods or systems. In such an experiment, it is essential to investigate the difference between the estimated and ground truth positions, as referred to as the accuracy of the indoor positioning method. In this case, it is necessary to consider what kind of index should represent the accuracy and how to measure the ground truth.

In recent years, data-driven indoor positioning methods have been actively proposed. Therefore, the method to measure the ground-truth positions has become even more critical in order to be able to evaluate the accuracy of such methods. Proper indoor positioning accuracy evaluation leads to fair comparisons with other indoor positioning methods.

As aforementioned, the evaluation metrics and ground-truth measurement system are essential to evaluate the indoor positioning methods. However, they are not well investigated in the existing survey papers. With this background, we have formed a volunteer-based organization called the PDR Benchmark Standardization Committee, which continuously discusses the appropriate evaluation methods for indoor positioning.

In this survey paper, we summarize the methods, advantages, and disadvantages of the ground truth measurement systems for indoor positioning and discuss from which perspective the ground-truth measurement system should be selected. The survey method was carefully designed to ensure that important papers were not overlooked as follows.

(1) We searched keywords such as “indoor positioning,” “dataset,” and “ground truth” on Google scholar.
(2) Survey papers on indoor positioning datasets obtained from the aforementioned search were listed with priority given to those with the most citations, and their contents were checked.
(3) We found additional papers that were cited in those papers.
(4) (2) and (3) were repeated several times, and each paper was further investigated in depth.

Note that **Table 1** shows notation used throughout our paper.

In this paper, we mainly focus on indoor scenarios where the location of a person, robot, or mobile device is to be estimated. We hope this survey paper will contribute to selecting appropriate ground truth measurement systems in future indoor positioning

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Table 1 Notations.

IMU	Inertial Measurement Unit
LiDAR	Light Detection and Ranging
Wi-Fi	Wireless Fidelity
BLE	Bluetooth Low Energy
UWB	Ultra-wideband
GPS	Global Positioning System
DR	Dead Reckoning
VIO	Visual-Inertial Odometry
SLAM	Simultaneous Localization and Mapping
RSSI	Received Signal Strength Indicator
AoA	Angle of Arrival
ToF	Time of Flight
MFPS	Multiple Frequency Phase-shift
OMC	Optical Motion Capture

research.

2. Ground Truth Measurement Systems for Indoor Positioning

Various ground truth measurement systems are used for indoor positioning as shown in **Table 2**. They are appropriately selected according to the required accuracy and the experimental environment. For example, OMC-based ground truth measurement systems have high positioning accuracy and have been used to evaluate a wide range of methods such as DR, VIO, and AoA [7], [8], [9], [10]. Self-localization methods such as SLAM are used when the experiment is conducted at a larger scale than in the motion capture room, as in the experiment in Ref. [9]. Flueratoru et al. [23] used BS (Base Station) of consumer VR (Virtual Reality) to save cost compared with OMC.

We have investigated several ground truth measurement systems and found that each method can be classified into one of the five categories: OMC, ToF/MFPS, SLAM, Manual, and Others. These five categories are described in detail in the following subsections.

2.1 OMC

OMC provides high accuracy and high sampling rate ground truth. If a rigid body marker is attached to the measurement target, not only the position but also the orientation of the rigid body can be measured with high accuracy. On the other hand, it has a high cost and small coverage area due to the camera arrangement. For instance, it can be used for measurements in a laboratory environment. Therefore, it is often difficult to apply it to measurements in a practical environment.

Schubert et al. [7] used OptiTrack [24] for GT measurements on the VIO benchmark data-set, using 16 infrared Flex13 cameras to track IR markers. Ogiso et al. [8] used OptiTrack to evaluate AoA positioning using acoustic sensors. Eighteen PrimeX 41 cameras are used to track IR markers. The PrimeX 41 is a higher-end model than the Flex13 and has the highest coverage of all the OptiTrack cameras. It has high resolution and a long strobe range, making it ideal for capturing minute movements and large spaces. Chen et al. [9] used Vicon to evaluate DR with an inertial sensor, using ten cameras (Bonita 10) to track IR markers attached to the measurement target, a smartphone. Burri et al. [10] used Vicon for evaluating VIO. IR markers were attached to the measurement target, a MAV (Micro Air Vehicle).

2.2 ToF/MFPS

A total station combines a laser rangefinder that measures distance and a theodolite that measures azimuth. The laser rangefinder measures distance using ToF or MFPS. The ToF measures distance based on the time the light pulse travels to the target and back. The MFPS measures the phase shift of multiple frequencies due to reflections and solves a series of simultaneous equations to calculate the distance to the target. The positioning of the total station is highly accurate. Therefore, it is often used to survey the topography for building construction. It can measure long distances of 1 km or more by itself. However, it must be in a LOS (Line of Sight) environment. Another disadvantage is that the sampling frequency is low (from 3 to 20 Hz) in the moving object tracking mode. A typical total station is used to observe a stationary position in the environment. On the other hand, there is a special case of a total station, it is the auto-tracking model. Auto-tracking model can measure the position of moving objects.

Yoshida et al. [11] used the TOPCON GT1205 [25] to evaluate DR using an inertial sensor. A prism, which was the tracking target, was placed above the head of a pedestrian, as illustrated in **Fig. 1**. They measured targets in a large and open outdoor environment. Burri et al. [10] used a Leica Nova MS503 to collect GTs for evaluating VIO. A reflective prism was attached to the MAV, which was the positioning target.

2.3 SLAM

SLAM is a technique that simultaneously estimates self-location and maps the environment. In particular, SLAM using image sensors is called Visual-SLAM, and SLAM using LiDAR is called LiDAR-SLAM. Visual-SLAM has more limitations than LiDAR-SLAM because it requires enough features point in images and a certain level of illumination. The accuracy of SLAM is highly dependent on the sensors used, the environment, scale, loop closure, and the availability of prior maps. The method is characterized by the ability to make measurements in more flexible environments.

Chen et al. [9] used Google Tango, an AR (Augmented Reality) platform developed by Google for mobile devices, to evaluate DR using an inertial sensor. They used Google tango to collect data over large office floors that OMC could not cover. Kawaguchi et al. [12] also used Google Tango to evaluate DR using an inertial sensor. They focused on the measurement targets being pedestrians; therefore, smartphones were easy to carry. Herath et al. [13] also used Google Tango to evaluate DR using an inertial sensor. By creating a preliminary map, they achieved an accuracy of less than 0.3 m error in a 10-minute measurement. Murata et al. [14] employed LiDAR-SLAM to evaluate integrated positioning using RSSI values from BLE and DR using a smartphone inertial sensor. The sensors used, a LiDAR (Velodyne VLP-16) and an inertial sensor (Xsens Mti-30), are both high-end sensors. The environment included three buildings with three or four floors and one basement. As a result, they were able to provide more stable positioning over a wider area than Google Tango. They were also expected to be more accurate. Ichikari et al. [15] adopted SLAM and IMU based DR as a ground truth for PDR evaluation. The unique feature of their approach is that they uses three different

Table 2 Ground truth measurement systems.

Ground truth measurement system						Target system for evaluation		
Name	Sensor type	Technique	Scale	Accuracy	Frequency	Sensor type	Technique	Ref.
OptiTrack	Camera (Flex13)	OMC	MoCap room	0.1 mm	120 Hz	Camera IMU	VIO	[7]
OptiTrack	Camera (PrimeX 41)	OMC	4 m×4 m	0.1 mm	180 Hz	Acoustic	AoA	[8]
Vicon	Camera (Bonita B10)	OMC	Vicon room	0.5 mm	100 Hz	IMU	DR	[9]
Vicon	Camera	OMC	8 m×8.4 m×4 m	0.5 mm	100 Hz	Camera IMU	VIO	[10]
TOPCON GT1205	Total Station	ToF/MFPS	60 m×60 m	1 mm	3 to 10 Hz	IMU	DR	[11]
Leica Nova MS503	Total Station	ToF/MFPS	Large machine hall	1 mm	20 Hz	Camera IMU	VIO	[10]
Google Tango	Camera IMU	SLAM	Office floor (3000 m^2)	N/A	100 Hz	IMU	DR	[9]
Google Tango	Camera IMU	SLAM	Office floor	N/A	100 Hz	IMU	DR	[12]
Google Tango	Camera IMU	SLAM	N/A	30 cm (10 min)	200 Hz	IMU	DR	[13]
N/A	LiDAR (Velodyne VLP-16) IMU(Xsens Mti-30)	SLAM	21,000 m^2 (Incl. three buildings with multiple floors)	N/A	N/A	BLE IMU	RSSI DR	[14]
Google Tango HoloLens Perception Neuron	Camera Depth Camera IMU	SLAM DR	Office floor	N/A	N/A	IMU	DR	[15]
N/A	Camera	Manual	60 m×20 m (Factory) 40 m×40 m (Office)	N/A	1911 points (in 3 hours)	BLE IMU	RSSI DR	[16]
N/A	N/A	Manual	N/A	N/A	N/A	UWB	RSSI	[17]
N/A	N/A	Manual	Nagoya University Station	N/A	N/A	Wi-Fi Magnetometer IMU	RSSI Fingerprint DR	[18]
N/A	IMU Camera	DR Manual	Stairs Escalators Elevators Office environments Shopping malls Subway stations	10 cm to 1 m	100 Hz	Camera IMU	VIO	[19]
N/A	Barcode	WMS	110 m×76.5 m (Warehouse)	N/A	N/A	BLE IMU	RSSI DR	[20]
N/A	Camera	Marker	University of Pennsylvania	15 cm	3 Hz	Camera	SLAM	[21]
GTVision	Camera	Marker	GTroom Bicocca location	10 cm	N/A	N/A	N/A	[22]
GTlaser	LiDAR	Object Detection	GTroom Bicocca location	5 cm	N/A	N/A	N/A	[22]
HTC Vive1	Laser IMU	AoA DR	Small room	5 mm	N/A	UWB	ToF	[23]

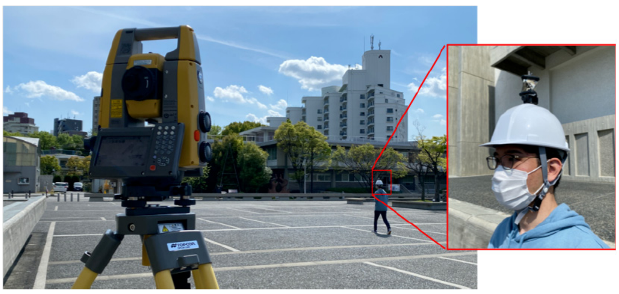

Fig. 1 An example of ToF/MFPS. TOPCON GT1205 is used for ground truth measurement [11].

systems, Google Tango, HoloLens, and Perception Neuron, together to obtain the ground truth, as illustrated in **Fig. 2**.

2.4 Manual

Manual labeling of the ground truth position has a low cost in terms of implementation. On the other hand, it requires much effort and is very time-consuming in order to create large data sets. In addition, the accuracy of positioning is likely to be low.

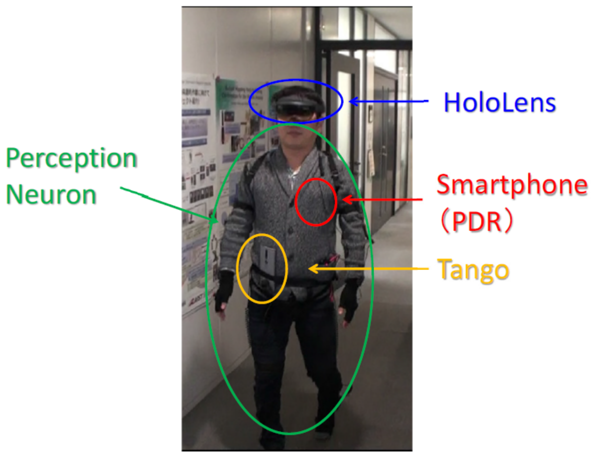

Fig. 2 Ground truth measurement using three types of systems: Google Tango, HoloLens, and Perception Neuron [15].

Maehata et al. [16] used method labeling with camera images to evaluate integrated positioning using BLE RSSI values and DR with an inertial sensor. Bregar et al. [17] used pre-defined correct coordinates to evaluate positioning using UWB RSSI values. They linked sensor data to correct coordinates by measuring UWB on anchors placed on a 1-meter grid. Ban et al. [18] evaluated positioning that integrated Wi-Fi RSSI, geomagnetic fingerprint, and DR by following a predetermined path. Assuming that the percentage of elapsed time in the total time and the percentage of walking distance in the total distance of the path are equal, the location to be at each time was determined. Cortés et al. [19] corrected the paths estimated by DR with camera images and used them as GTs. By combining DR and manual correction, they were able to label at a sampling rate as high as 100 Hz.

Here, we consider the task of extracting the position of a person from the camera image. If the coordinate transformation of the camera image and the target environment can be performed, the work is no longer completely manual, and the labor cost can be reduced. On the other hand, it would be difficult to set continuous correct values when manually plotting positions.

2.5 Others

Ichikari et al. [20] obtained the ground truth generated only from information obtained from normal operations in a warehouse. Employees used WMS (warehouse management system) in the warehouse and scan barcodes on shelves when picking up packages. The input time and device location were used as the ground truth for evaluating integrated positioning using BLE RSSI values and DR using a smartphone inertial sensor. This method makes good use of the infrastructure of the warehouse. However, the provided ground truth location is sparse.

Pfrommerr et al. [21] proposed a method in which a mobile robot estimates its position by capturing images of markers placed in the environment with a camera. This method can robustly measure GT even in glassy spaces or environments where the robot is moving from indoor to outdoor locations, which LiDAR and cameras are not very good at. On the other hand, it is very labor intensive to set up the markers.

Ceriani et al. [22] argued that a positioning method with sensors completely independent of the mobile robot was needed to create a reliable ground truth. Such one method is GTvison. It is a method of positioning a robot by capturing images of markers placed on the robot with a camera placed on the environment side. This method is less expensive than OMC, but less accurate. It also requires labor for camera calibration. The other is GT-laser. It uses multiple laser scanners placed on the environment to detect the robot and calculate its position. Since the sensors are placed on the ground, they have less visibility than ceiling-mounted cameras and provide two-dimensional positioning.

Flueratoru et al. [23] proposed a low-cost, high-precision positioning method that used the BS (Base Station) of the VR. The actual BS used was the HTC Vive1 BS, which is much less expensive than an optical motion sensor and achieves an accuracy of 5 mm. On the other hand, the coverage is small.

3. Guideline for Selecting Ground Truth Measurement System

This section lists the indicators that should be used when selecting a ground truth measurement system of indoor positioning values and summarizes the characteristics of each technique for measuring the ground truth. It also summarizes the best-performing system for each indicator. Furthermore, we discuss what criteria should be used to select a ground truth measurement system because, in general, no method is superior in all indicators, and there are advantages and disadvantages.

Table 3 The features of the measurement method of ground truth for indoor locations.

Sensor type	Accuracy	Coverage	Device cost	Labor cost
OMC	0.1 mm–0.5 mm	Small	High	High
ToF/MFPS	1 mm	Large (LOS)	High	Middle
SLAM	1 cm–1 m	Large	Low (Camera) High (LIDAR)	Low
Manual	10 cm–1 m	Middle	Low	High

3.1 Indicators

Table 3 summarizes the characteristics of each ground truth measurement system for indoor positioning. Accuracy and coverage are summarized from Table 2.

In reality, there are practical problems such as the need to prepare devices and the time and effort required to use devices to measure correct values. Therefore, device cost and labor cost are important indicators. In the previous section, the ground truth measurement systems were classified into OMC, SLAM, ToF/MFPS, Manual, and Others. Here, OMC, SLAM, ToF/MFPS, and Manual are considered the target systems. In Table 2, frequency is also an item. It is not included here because it is considered to be rarely the most important factor in selecting the ground truth measurement system. Although there were some exceptions, in general, the ground truth measurement system with high accuracy tended to have a high frequency. Frequency can be important when considering tracking objects with high moving speeds. However, the maximum speed that should be considered is often lower than that of outdoor positioning when considering indoor positioning.

3.2 Best System for Each Indicator

We summarize the best system for each indicator based on Table 3. For accuracy, OMC methods such as OptiTrack and Vicon are the best, achieving an accuracy of less than 1 mm, which is very high. For coverage, Manual or SLAM with high-end sensors is superior. A large space can be covered by ToF/MFPS if the environment has a good line-of-sight (LOS). However, a wide range of visibility is not always possible in an indoor environment. Therefore, the coverage of ToF/MFPS depends on the complexity of the assumed environment. In terms of device cost, Manual is the best because it does not require a dedicated device. SLAM using smartphones such as Google Tango is the second best in that it does not require an expensive dedicated device. Labor cost includes the following components: the time and effort required to set up the equipment in the environment, the time and effort required for the person who measures to wear the equipment, and the work that must be done by the person who measures during and after the measurement. SLAM has the lowest labor cost. It does not require the setup of the environment or the attachment of the device by the person in advance, nor does it require manual input of the correct coordinates during measurement. It is important to note that post-processing is required to align the coordinates of the data obtained by SLAM. If no map is given in advance, the starting position of SLAM becomes the origin, and the coordinate system is created from the direction at the start. Even if the initial position and orientation are determined, there may be position and orientation deviations from one measurement to the next, making simple integration inappropriate.

3.3 Criteria for System Selection

This section discusses the viewpoints from which a ground truth measurement system should be selected. When selecting a ground truth measurement system, it is first necessary to consider how much accuracy is required to evaluate indoor positioning methods and systems based on positioning. At the same time, it is necessary to consider the expected area size and pick a ground truth measurement system from the viewpoint of coverage especially when evaluating systems based on indoor positioning. Then, other factors such as Deice cost and Labor cost should be taken into consideration, and finally, a realistic ground truth measurement system should be selected.

It is important to note that this is the case when measurements are taken in a practical environment. For example, the measurement of ground truth must also be performed in a practical environment if you want to evaluate the accuracy of indoor positioning in an industrial field demonstration. Ground truth measurements must also be performed in a practical environment. In such cases, various restrictions at each site limit the ground truth measurement systems that can be selected. For example, what equipment can be installed in the environment, and how far apart are they? Are cameras allowed? Cameras are often not permitted, especially since they can acquire private information. If the operator is the measurement target, to what extent is it acceptable for the operator to wear a special device? After satisfying these constraints, the ground truth measurement system should be selected based on the required accuracy, coverage, device cost, and labor cost.

4. Conclusion

This survey paper summarized the ground truth measurement systems for evaluating indoor positioning methods. There are a variety of ground truth measurement systems. We classified the techniques as OMC, SLAM, ToF/MFPS, Manual, and Others. Also, each case study is summarized in terms of Sensor type, Coverage, Accuracy, and Frequency.

Moreover, each sensor type is organized based on four indices: Accuracy, Coverage, Device cost, and Labor cost. We also discussed what kind of viewpoints should be used to select the ground truth measurement system.

We believe that the tables and discussions presented in this survey provide important clues for selecting the ground truth measurement system for future indoor positioning. If an appropriate system is selected, it is expected to lead to a proper evaluation of the accuracy of indoor positioning systems. This leads to a fair comparison with other methods.

We have formed a volunteer based organization called the PDR Benchmark Standardization Committee, which continuously discusses the state-of-the-art indoor positioning technologies. This survey paper is an outgrowth of those discussions. We are also currently surveying, classifying, and organizing indoor positioning evaluation methods. The result will be published next. Based on our survey paper, we will continue to work vigorously for the international standardization of indoor positioning evaluation methods.

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