Making Pier Data Broader and Deeper:

PDR Challenge and Virtual Mapping Party

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Abstract. Big data can be gathered on a daily basis, but it has issues on its quality and variety. On the other hand, deep data is obtained in some special conditions such as in a lab or in a field with edge-heavy devices. It compensates for the above issues of big data, and also it can be training data for machine learning. Just like a platform of pier supported by stakes, there is structure in which big data is supported by deep data. That is why we call the combination of big and deep data "pier data." By making pier data broader and deeper, it becomes much easier to understand what is happening in the real world and also to realize Kaizen and innovation. We introduce two examples of activities on making pier data broader and deeper. First, we outline "PDR Challenge in Warehouse Picking"; a PDR (Pedestrian Dead Reckoning) performance competition which is very useful for gathering big data on behavior. Next, we discuss methodologies of how to gather and utilize pier data in "Virtual Mapping Party" which realizes map-content creation at any time and from anywhere to support navigation services for visually impaired individuals.

Keywords: Lab-forming fields · Field-forming labs · Big data Deep data · Pier data · PDR · IoT · IoH · VR · Service engineering

1 Introduction

To get a complete picture of an actual service field, the process involves measuring and modeling people, things, and environment with technologies such as geospatial internet of things (IoT) [1]. Then, based on the acquired situation, it "intervenes" in the field through augmented reality (AR)-based information support and robots, and promotes a behavioral change of customers and employees. This kind of methodology, involving the iteration of hypothesis and verification, could only be conducted in a laboratory. However, it is now becoming possible to transfer it to actual fields, a process that we call "lab-forming fields."

K. Murao et al. (Eds.): MobiCASE 2018, LNICST 240, pp. 3–17, 2018.
https://doi.org/10.1007/978-3-319-90740-6_1

Figure 1 shows the optimum design loop of service (observation, analysis, design, and application) and the technologies involved in each phase. One of the methodologies that employ this optimum design loop to improve and innovate is lab-forming fields, but there is also the concept of “field-forming labs”, which involves building or offering a virtual environment with high reproducibility to minimize the divergence with the actual field as much as possible, thereby bringing the knowledge obtained in a laboratory experiment (hypothesis and verification) closer to the knowledge that should be obtained in the real field.

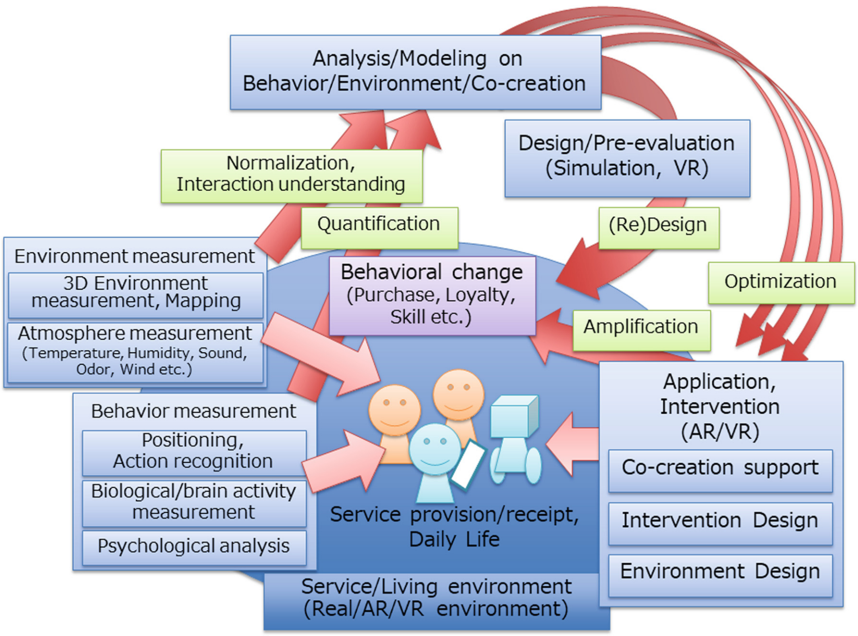

Fig. 1. Optimum design loop of service (observation, analysis, design, and application) for supporting human-centered co-creation.

2 Pier Data

Through lab-forming fields and field-forming labs, it is possible to acquire “big data” and “deep data”. Big data can be collected on a daily basis without much effort, but it is difficult to maintain its quality, and it has limited types. At this point, there is no clear definition of deep data, but for this work, we consider that it has characteristics that supplement big data, such as high quality, heterogeneity (including correct image, motion, gaze, biometric information, and brain activity data), and that it includes subjective data (surveys and interviews). Deep data are used as training data for supervised machine learning that is applied to recognize something from big data, or as basic information to deepen the qualitative understanding of the field, but it can only be obtained in special circumstances, such as sensing in a laboratory or an edge heavy field, or by asking surveyees.

A pier has a structure in which the platform is supported by stakes. Figure 2 can be interpreted as a structure in which deep data support big data. It is also possible to assume that, typically, a so-called platformer is good at gathering big data, and a so-called stakeholder which has knowledge and know-how in each field is good at gathering deep data. For these reasons, we call this combination of big data and deep data “pier data” (in reference [1], we formerly called pier data “comb data” because of the appearance of its structure. We have now changed its name to “pier data,” which we found more appropriate because it also contains the meaning of structure). By acquiring mainly big data with lab-forming fields and mainly deep data with field-forming labs, and by deepening and widening the pier data efficiently, we believe that it will be possible to comprehensively understand what is happening in the real world, especially in the service and manufacturing fields, which can then be more easily improved and innovated.

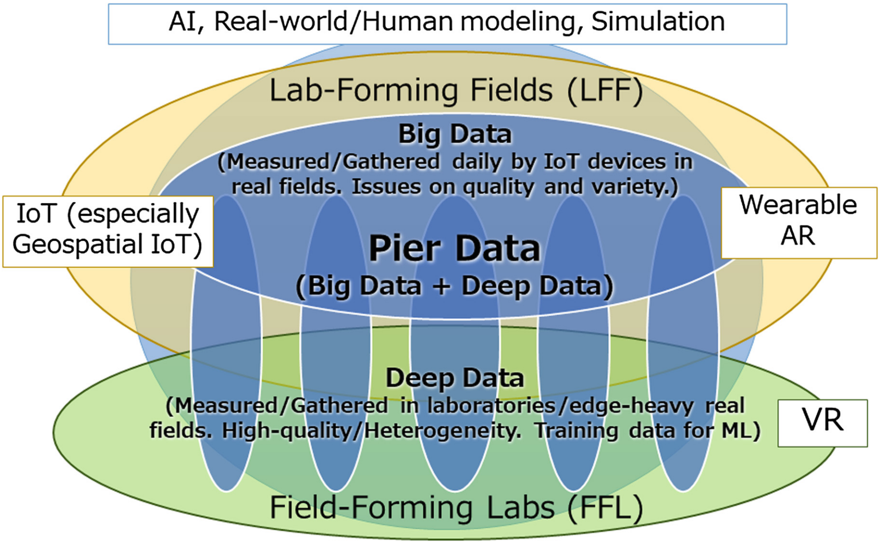

Fig. 2. Lab-forming fields and field-forming labs: Big Data + Deep Data = Pier Data

In this paper, we present two examples of activities that we are conducting to obtain wider and deeper pier data. The first is an outline of the PDR Challenge, a competition aimed at evaluating the performance of pedestrian dead reckoning (PDR, relative positioning for pedestrians), an efficient technology to collect big data by behavior measurement. Then, we discuss the methodology to collect and use pier data contained in a virtual mapping party that supports the map creation necessary for navigation for visually impaired people.

3 PDR

We have been engaged in R&D related to PDR [2, 3] since 2000 (Fig. 3). PDR is a technology that uses a group of sensors (commonly known as nine-axis sensors) that measure the physical quantity of three-axis components — acceleration, angular velocity, and magnetism — to estimate the posture of the sensors, as well as the travel speed and direction of the pedestrian carrying the sensors. With this, it is possible to learn the pedestrian's relative location.

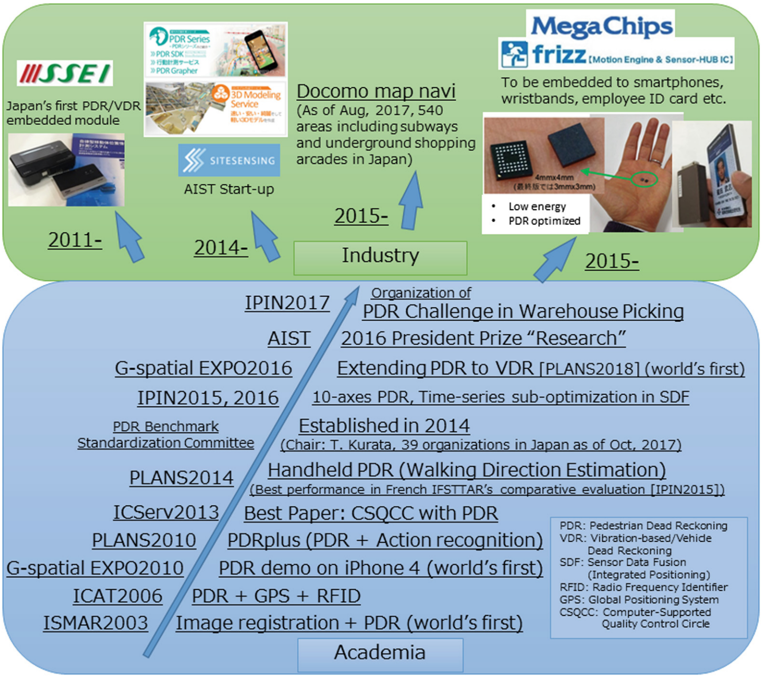

Fig. 3. History of AIST's PDR study

In many cases where a positioning system is to be introduced into an indoor service or manufacturing site, the cost of developing the physical and information infrastructure becomes a barrier that raises questions about its cost-effectiveness. The introduction of indoor positioning is one of the fundamentals of lab-forming fields, and, although it is beginning to be understood better with the dissemination of IoT-oriented thinking, there are still cases in which the effect of its introduction needs to be represented by a monetary value (alone). As a reference to the Nobel prize in economics laureate R. Solow's productivity paradox theory, we call this situation an indoor positioning paradox/dilemma. This paradox or dilemma, which does not occur with the use of outdoor satellite positioning, can be eased with the use of a relative positioning method like PDR. The best example of it is the indoor navigation in "DoCoMo Map

Navi" [4]. With a nine- or ten-axis PDR, a map (pedestrian space network data) and interaction with the user, it enables indoor navigation in about 560 underground shopping centers and subway premises across Japan (as of November 2017) without installing a physical infrastructure.

PDR can be classified into the inertial navigation system (INS) type, which estimates three-dimensional positions, and the steps and heading system (SHS) type, which estimates two-dimensional positions [5]. The former method [6] can provide a highly accurate three-dimensional positioning without depending on how each person walks. It does, however, have some limitations: because it is a method based on double integration of acceleration, it requires an accelerometer with easy calibration and high sensitivity, and the nine-axis sensor must necessarily be attached to the toe or shoe, where zero-velocity update (ZUPT) is possible.

We have been conducting research mainly on the latter type of PDR, the SHS [2, 3, 7, 8]. It is mainly composed of (1) attitude estimation, (2) estimation of walking direction, and (3) walking motion detection and walking speed (pace) estimation. Compared to the INS-type method, it has fewer limitations related to the position of attachment of the nine-axis sensor and calibration of the accelerometer. However, although the SHS-type is less limited than the INS type in terms of attachment position, it did have some limitations of its own. For example, the measurement with the SHS-type must be done in a stable condition by fixing a nine-axis sensor on the waist or chest, or by walking while holding and looking at the screen of a smartphone with a built-in nine-axis sensor.

The popularization of smartphones in recent years, especially, is highly expected to ease the limitations related to attachment or holding conditions even further. The estimation of walking direction mentioned in [3] is an essential technology for this purpose, and the main methods that have been proposed are: (A) based on the PCA (Principal Component Analysis) of acceleration amplitude, (B) based on a FLAM (Forward and Lateral Acceleration Modeling), and (C) based on FIS (Frequency analysis of Inertial Signals). According to a research report that made a comparative evaluation between these [9], the method with FIS [3] has produced an overall better evaluation result than the others.

The measurement range of an SHS-type PDR is limited on the ground and floor that are included in the map and floor plan; in other words, the estimation in the height direction is limited on the map and floor plan. In many cases, however, this height information is sufficient to obtain the position information of the target public (residents, customers, employees, etc.); therefore, this limitation is hardly a problem. As pressure sensors become more accessible and accurate, a 10-axis sensor, which is a nine-axis sensor with a pressure sensor added, also begins to be more widely used. There are also attempts to measure the travel in the vertical direction using this 10-axis sensor [7, 8, 10].

While many other absolute positioning methods, in principle, provide a positioning result that is a set of independently obtained results, PDR generates a continuous trajectory. The shape and displacement (change of speed and angle) of this trajectory includes characteristics of the movement of the person being measured, and it also allows to measure the type and intensity of the movement [13, 14]. Therefore, in some cases, it is more appropriate to consider PDR a means to measure behavior rather than a positioning method.

4 PDR Challenge

Indoor positioning technologies such as PDR are becoming essential to service observation and lab-forming fields based on the same [1]. Also, the increasing number of related publications in international conferences and the popularity of the competitions [13–16] are the reflection of the rapidly growing number of domestic and international companies and universities engaged in R&D and implementation of PDR. Also, because PDR is a relative positioning method, it requires a different evaluation method than that used in absolute positioning methods such as Global Navigation Satellite System (GNSS) and Wi-Fi positioning. Also, the description of its efficiency in articles and specification sheets of products or services is unified.

In this context, we established the PDR Benchmark Standardization Committee [17] in 2014 (endorsed by 39 organizations as of November 2017) as a grassroots activity. In 2015, we collaborated with the "UbiComp/ISWC 2015 PDR Challenge" [13, 14], and, in 2017, we organized the "PDR Challenge in Warehouse Picking" [18], a PDR competition in a logistics picking scenario, at the International Conference on IPIN 2017. Table 1 summarizes the characteristics of these two PDR Challenges.

Table 1. Comparison of the characteristics of PDR Challenge

	Ubicomp/ISWC 2015 PDR Challenge	PDR Challenge in Warehouse Picking in IPIN 2017
Scenario	Indoor pedestrian navigation	Picking work inside a logistics warehouse
Walking/motion	Continuous walking while holding smartphone and looking at navigation screen	Includes many motions involved in picking work, not only walking
On-site or off-site	Data collection: on-site Evaluation: off-site	Off-site
Number of people and trial	90 people, 229 trials	8 people, 8 trials
Time per trial	A few minutes	About 3 hours
Remark	Collection of data of participants walking. The data are available at HASC (http://hub.hasc.jp/) as corpus data	Competition over integrated position using not only PDR, but also correction information such as BLE beacon signal, picking log (WMS), and maps

The PDR Challenge in Warehouse Picking was carried out as one of the four tracks of the IPIN 2017 indoor positioning competition. The competitors entered as teams, and a total of 20 teams (five from China, four from South Korea, three from Japan, two from Taiwan, and one each from Germany, France, Portugal, Chile, and Australia) participated in the four tracks. Five among these teams (two from Japan, and one each from South Korea, China, and Taiwan) participated in the PDR Challenge in Warehouse Picking, which was won by the KDDI R&D Labs team.

The preparation of the PDR Challenge in Warehouse Picking was carried out along with the preparation of the Frameworx Logistics Open Data Contest [19]. The data of eight picking workers carrying a smartphone was collected. It included 10-axis sensor data and BLE beacon reception data, warehouse management system (WMS) data related to barcode reading during the picking work, as well as map information. One part of the WMS data was kept undisclosed and used by the organizers as the correct value in the evaluation of positioning error (evaluation point). The remaining disclosed part was made available for the competitors to use for position correction. By changing the amount of this undisclosed part — that is, the length of the section and time where position correction with WMS did not work — trial data were created with two levels of difficulty and offered to the competitors. Data that had been obtained at a different warehouse for training for the competition were also offered as a sample. Each competitor calculated the trajectory of each trial using the positioning program that it developed and submitted the result to the organizers.

Indices related to accuracy
- E_d – Index related to integrated positioning error
- E_s – Index related to PDR error based on EAG

Indices related to the trajectory naturalness
- E_v – Index related to the naturalness of travel speed
- E_f – Index related to position measurement output frequency

Specific indices for warehouse picking scenario
- E_o – Index related to collision with obstacles
- E_p – Index related to motions during picking work

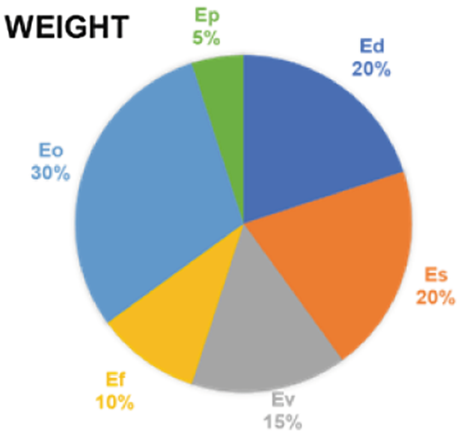

Fig. 4. Evaluation index (Top: individual indices; Bottom: weight of each individual index to total index Ec)

There were many discussions regarding the evaluation index and indicator at the PDR Benchmarking Standardization Committee and during the competition preparation, but we decided to use the individual indices shown in Fig. 4 and the total index, which is the weighted average of them. The detailed definition of each individual index can be confirmed on the website of The PDR Challenge in Warehouse Picking [18], but, in this paper, we discuss the "EAG (Error Accumulation Gradient)," the base of index Es, which is related to the error of PDR.

If the positioning result of PDR, which is a relative positioning method, is not corrected, the positioning error tends to accumulate. Reference [20] takes this into consideration and proposes using the positioning error per unit time (m/s) as an indicator. This proposed indicator, which we name EAG, is calculated based on the linear regression (intercept of 0) of the positioning error along with the elapsed time from measurement start time. Because PDR is often applied in real-time applications as in pedestrian navigation, the elapsed time from measurement start time is adopted to calculate the indicator.

Meanwhile, in cases where batch processing using all the data from measurement start to finish is possible, it is also possible to correct the position retroactively. Therefore, in the PDR Challenge in Warehouse Picking, we adopted the EAG obtained by linear regression (intercept of 0) of the positioning error along with the elapsed time to the past or future (the shorter one) from the time when position correction is possible as base of Es. In addition, after the competition, we also discussed the application of robust regression that takes the outliers into account (Fig. 5).

Table 2. Result summary of the PDR Challenge in Warehouse Picking

Team	Ec	Accuracy		Naturalness		Warehouse specific		Median error [m]	Error Accumulation Gradient (EAG) [m/sec]
		Ed	Es	Ep	Ev	Eo	Ef		
ETRI	5th 65.74	65.41	96.34	97.20	**100**	51.82	11.32	11.03	0.12
KDDI	**1st 91.16**	72.35	97.97	43.55	**100**	**99.88**	**100**	9.02	0.09
Nagoya	2nd 88.92	70.57	**99.20**	72.72	87.84	93.55	99.27	9.54	**0.06**
XMU	3rd 78.44	67.64	96.06	84.97	95.66	59.62	99.24	10.39	0.13
YZU	4th 77.95	**75.34**	97.74	**97.48**	99.09	45.53	**100**	**8.15**	0.09

The detailed results of the competition are posted on its website [18]. Although it is summarized in Table 2, here we discuss it further with the EAG as an example. This indicator can be used not only to evaluate the performance of PDR alone, but also to decide the design guidelines of the absolute positioning infrastructure to be included in integrated positioning.

For example, Nagoya University's team's EAG is 0.06 m/s, or 3.6 m/min. Supposing that there is a service or manufacturing site planning to introduce an integrated positioning system that includes this PDR system and that the specification for positioning error required for that field is within 4 m on average, it is possible to build a design guideline that states that it is necessary to incorporate an absolute positioning method capable of correcting the position with an error of 0.4 m or less about once per minute (3.6 + 0.4 = 4.0). In this case, ultrawideband positioning, BLE positioning with an AoA (angle of arrival) method, and positioning using installed cameras [21] are some absolute positioning methods that would apply.

Supposing that the required specification for positioning error is the same, less than 4 m on average, and that the absolute positioning methods had already been decided on multilateration or fingerprinting with BLE the average positioning error of which is around 3 m. In this case, even if the frequency of BLE positioning is once every 16 s, it is possible for PDR to update the positioning result in the interval between two positioning points with BLE and the result satisfies the required specifications (0.06 * 16 + 3.0 = 3.96).

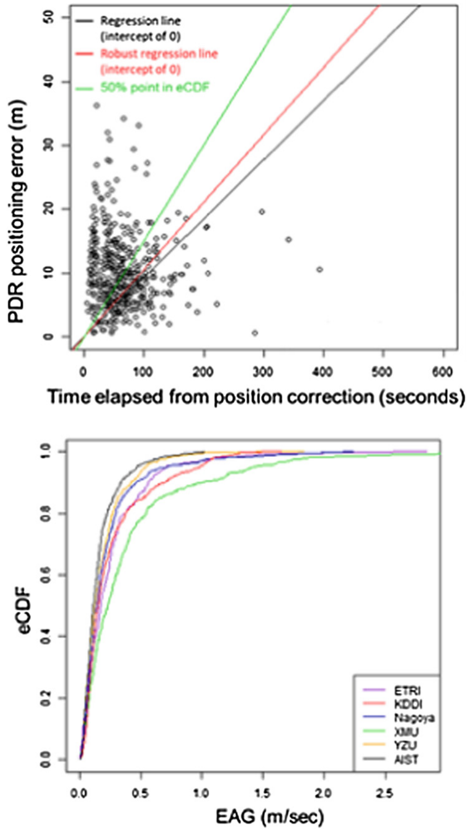

Fig. 5. Example of EAG (m/sec) (Top: Regression lines, Bottom: eCDF of EAG calculated from each evaluation point)

5 Virtual Mapping Party

In Sects. 3 and 4, we discussed the PDR, one of the essential positioning technologies to collect big data using lab-forming fields. This section and the next focus on the methodology to collect and use pier data based on field-forming labs and virtual mapping party, which supports the map making needed for walking navigation for visually impaired people [22].

Our research related to movement support for visually impaired people began with the development of a navigation system for visually impaired people that uses previously mentioned positioning technologies such as PDR and GNSS (satellite positioning) [23, 24]. “Point of Interest (POI)” information refers to general map content offered even in navigation for sighted people. This includes destination candidates, such as establishments and stores, as well as landmarks that can be recognized from distance. The navigation for visually impaired people, however, is expected to offer, in addition to POI, “Point of Reference (POR)” [25, 26] information. Examples of POR are braille blocks on the ground and floor, utility holes, car stoppers, stairs, environmental noise, smell, and other information that helps with the user’s safety and current position grasp. Our navigation system was developed to provide both POI and POR, but because POR contents are not yet fully developed, collecting them was challenging.

Table 3. Different characteristics of mapping activities

Type of activities	Location	Time	Remarks
Conventional mapping party	On-site	Sync.	• Deep understanding of the local situation • Development of community through face-to-face liaison • Influenced by local weather and level of congestion • Difficult to participate from distance • Mandatory skill for organizing events
Mapping party using smartphones app.	On-site	Any time (Async.)	• Deep understanding of the local situation • Easy mapping during free time (e.g. while commuting) • The position accuracy of the registered information depends on the positioning method • Difficult to participate from distance
Mapping party using crowdsourcing image sharing service	Anywhere (Off-site)	Any time (Async.)	• Crowdsourcing • Possible to participate from any place, anytime • Require previous collection of pictures • Possibly difficult to understand the local situation
Virtual mapping party	Anywhere (Off-site)	Any time (Async.)	• Crowdsourcing • Possible to participate from any place, anytime • The system supports the positioning of registered information • Simulation of the local site through VR • Require previous collection of environmental information such as pictures • Cocreation type in which visually impaired people can participate using AR tactile map

There is an event called “Mapping Party”, which is dedicated to making maps that include the collection of POI/POR. OpenStreetMap, the project that creates free map information that anybody can use, also frequently holds this mapping party event. Also, a mapping party aimed at creating maps for visually impaired people is specifically called a “Blind Mapping Party”. This kind of time-and-space synchronous event has some problems, though. For example, the participants need to gather at the appointed location and time, the success of the event is dictated by the weather, and it involves geographical and time-related limitations. The use of ICT technology to increase the efficiency of local participation-type activities is becoming more common. One of the most common methods is the support and optimization of local activities through the use of smartphone applications [27].

There are also some attempts to lower the hurdles related to the need of physically visiting the site. For example, Hara et al. [28] are using Google Street View to research the accuracy of the registered bus stop information collected by crowdsourcing. It requires caution, however, because distributing map contents created from information provided from Google products, such as Google Maps, to services outside of Google, raises legal concerns. An effective way to tackle such concerns is to use more open shared platforms of street-level images such as Mapillary [29] and OpenStreetCam [30]. Voigt et al. [31] are engaged in a "lab-base" approach (which is close to field-forming labs), which uses Mapillary and OpenStreetMap to collect map information from places other than the site itself. Table 3 summarizes the characteristics of each kind of mapping activity.

Figure 6 is a conceptual drawing of a virtual mapping party. Below are some characteristics of the prototypes and preliminary demonstrations being developed to implement this concept [22, 26]:

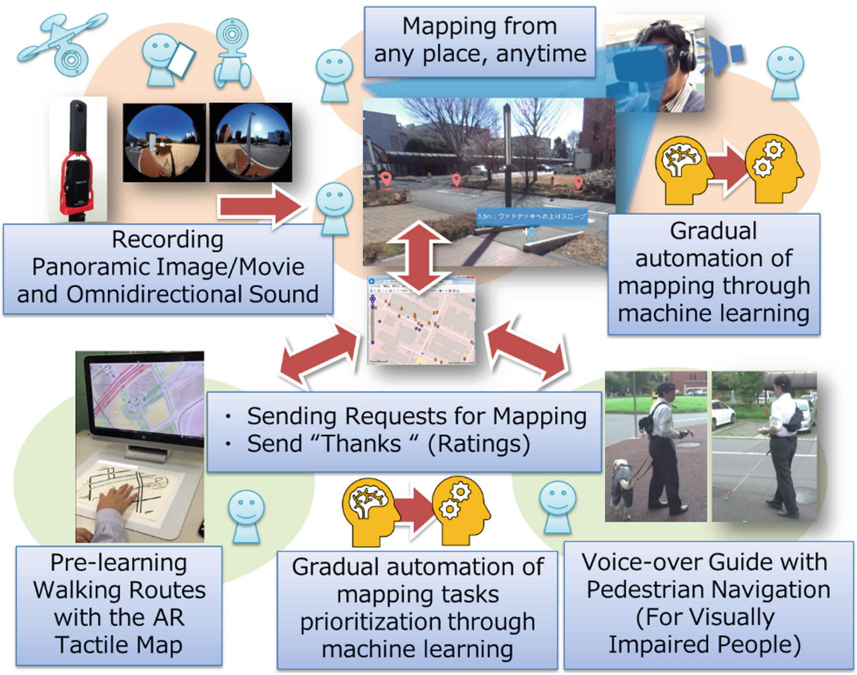

Fig. 6. Conceptual drawing of Virtual Mapping Party (includes items that have already been implemented and future challenges)

- Focused on supporting creation of map contents (especially POR) for visually impaired people
- Simulation of the field using a VR environment with omnidirectional movies and three-dimensional environmental sounds

- Uses information collected through the connection with other navigation and AR tactile map apps [26] and promotes the exchange of requests and evaluation between stakeholders
- The visually impaired users themselves can participate in the information collection activity
- Studying the feasibility of gradual automation of each task with machine learning

6 Virtual Mapping and Pier Data

The data collected with navigation applications and AR tactile maps (usage history, request to map a location, evaluation of map contents, etc.) is expected to be acquired while the service is used, and thus is considered typical big data. Because our virtual mapping applications can be linked with Mapillary, in case the environmental information used for mapping consists only of images, this environmental information may also be seen as big data.

However, images of the spaces where visually impaired people walk, such as sidewalks and indoor environments, are seldom registered in shared platforms of street-level images like Mapillary. Therefore, the environmental information for mapping should probably be considered close to deep data. If, however, the environmental information is composed of omnidirectional movies and three-dimensional environmental sounds, as well as their accurate position and orientation, then that environment information is naturally a deep data. When we are to conduct a demonstration experiment, the person handling the experiment collects the environmental information. We expect that, in the future, this will be carried out by the collaborators of users who require mapping, the users of navigation services, personal mobility, robots, drones, etc., and that the ecosystem to use this information will be incorporated into the society. This will enable the environmental information for mapping to be collected as big data.

We have developed a virtual mapping application that is intended to crowdsource the map-making process using environmental information. We are using this application in events like workshops at the National Museum of Emerging Science and Innovation (Miraikan) and preparing to distribute it so that it can be used in the way it was designed. Now, the application user needs to register the POI/PORs while browsing the environmental information, but this task can also be seen as a labeling task for environmental information — that is, a task of creating training data for machine learning. If the POI/POR candidates are automatically extracted by machine learning using these training data, so that the application user only needs to confirm it, the task efficiency should improve. If the learning process advances even further, automation will also become possible. This kind of gradual automation of the map-making process will be indispensable for a consistent development of map contents.

7 Conclusion

We outlined PDR, an effective technology to collect big data by behavior measurement, as well as its competition, the PDR Challenge. The definition of "pedestrians," according to the Road Traffic Act, includes wheelchair users, but since PDR is a relative positioning method based on the characteristics of biped walking behavior, it cannot be applied to wheelchair users. We previously proposed vibration-based vehicle dead reckoning as a method for relative positioning of wheeled vehicles [32]. These initiatives focused on implementing xDR (Dead Reckoning for x) or uDR (universal Dead Reckoning) and will certainly stimulate the collection of behavior-related big data and their use [33–35] even further.

The evaluation indicators related to benchmarking of vison-based spatial registration and tracking methods for mixed and augmented reality being discussed at the ISO [36] is divided into reliability indicators (error, completion rate), time indicators (frame rate, delay), and diversity indicators (number of trials, variety of trial content). This kind of discussion must be held at the PDR Standardization Committee and PDR Challenge as well, and it will probably be necessary to design indices and indicators related to efficiency (computational efficiency, energy consumption) and reproducibility (influence related to temperature hysteresis, local environment change, etc.).

We also discussed virtual mapping party, which supports the creation of the map contents necessary for navigation for visually impaired people. We mentioned our application cooperation with the open platform Mapillary to share street-level images, and our applications are also cooperating with the navigation application NavCog [37], which offers an open platform. We believe that this organic cooperation of the entire process, from map making to navigation and AR tactile map, will allow us to further widen and deepen the pier data to support the movement of visually impaired people.

Acknowledgment. The PDR Challenge in Warehouse Picking was carried out partially with the support of JST OPERA's "Elucidation of the Mechanism of Cooperation Between Humans and Intelligent Machines and the Creation of Fundamental Technology to Build a New Social System Based on Cooperative Value." The virtual mapping party was carried out with the support of JST RISTEX's "Development of a Movement Support System for Visually Impaired People by Multi-Generation Co-Creation."

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