Chapter 4
Sensing of Service Provision Processes

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4.1 Introduction

Comprehensive understanding and specific improvement of situations at service sites such as restaurants requires aggregation of big data related to Man, Machine, Material, Method, Mother nature (Environment), and Money (6 M) (Fig. 4.1) (Kurata et al. 2019a, b). Along with the popularization of internet-of-things (IoT) and artificial intelligence (AI), the realization of visualization or vision control, or 'Mieruka', has made steady progress in terms of tangible objects in 6 M such as facilities, equipment, ingredients, and cooked dishes.

Nevertheless, the development of Mieruka technologies and methodologies is still ongoing in terms of intangible issues in 6 M such as service provision processes and situations of service providers. Reportedly, a major disincentive is that information related to human behavior has not yet been obtained sufficiently. Japanese people spend around 90% of their time indoors, whether working or not (Shiotsu et al. 1998). In addition, restaurants that we specifically examine in this book are often occupied by indoor environments. Therefore, it is necessary to develop and use internet of humans (IoH) technologies, which are applicable indoors, including positioning technologies and human behavior measurement technologies. Collecting individual service provider data can be done easily in cases where the service process is repeated in a spatially limited area and in a short period of time. In many restaurants, however, moving in a relatively wide area and working are often combined. That combination poses a major barrier to data collection of each service provider. Therefore, it is crucially important to develop and use IoH technologies further for collecting data related to human behavior.

Accordingly, this chapter presents specific examination of measurement technologies of the service-provider-oriented part of 6 M (Man). First, we give an outline of

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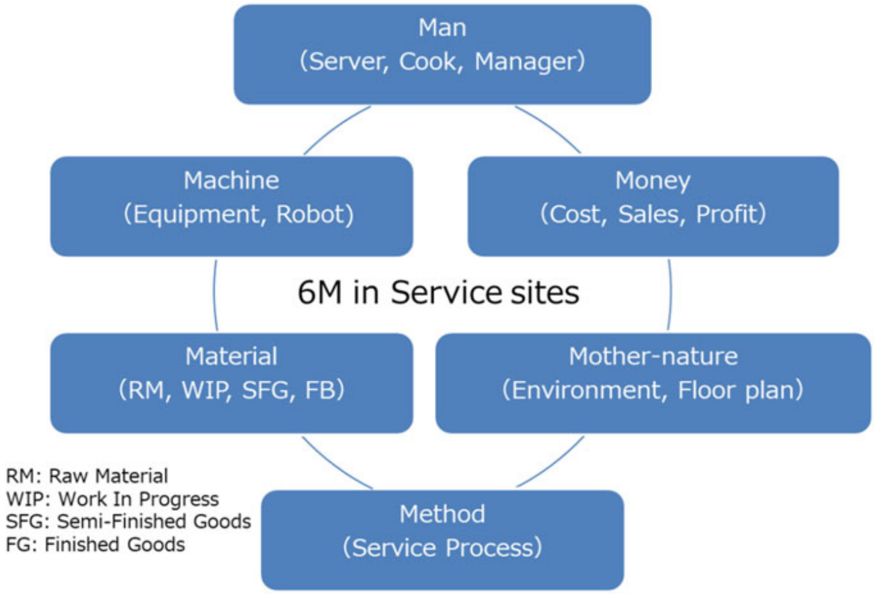


Fig. 4.1 6M (Man, Machine, Material, Method, Mother nature (Environment), and Money) in service sites

the concept of Lab-Forming Sites (LFS) and Site-Forming Labs (SFL) in association with the idea of a combination of Big data and Deep data (Pier Data) (Kurata et al. 2017, 2018). Next, we summarize IoH technologies including indoor positioning and action recognition. The costs and benefits of introducing IoH technologies at such sites are also explored.

4.2 Lab-Forming Sites and Site-Forming Labs

Figure 4.2 shows each technology and methodology in association with each phase of the service design loop (Takenaka et al. 2012; Kaihara et al. 2013), which consists of measurement, modeling, designing, and application. One can realize service-engineering based approaches for service improvement and innovation by utilizing technologies and methodologies for each phase of the service design loop as follows:

(1) Measure the behaviors of customers and employees and service/living environments (Tenmoku et al. 2011; Makita et al. 2013; Kato et al. 2016)
(2) Do As-Is comprehension for quality control (QC) circle activities (Fukuhara et al. 2013, 2014; Okuma et al. 2015)
(3) Do To-Be comparison for service operation planning (Myokan et al. 2016)
(4) Develop context-aware interface for service operation support

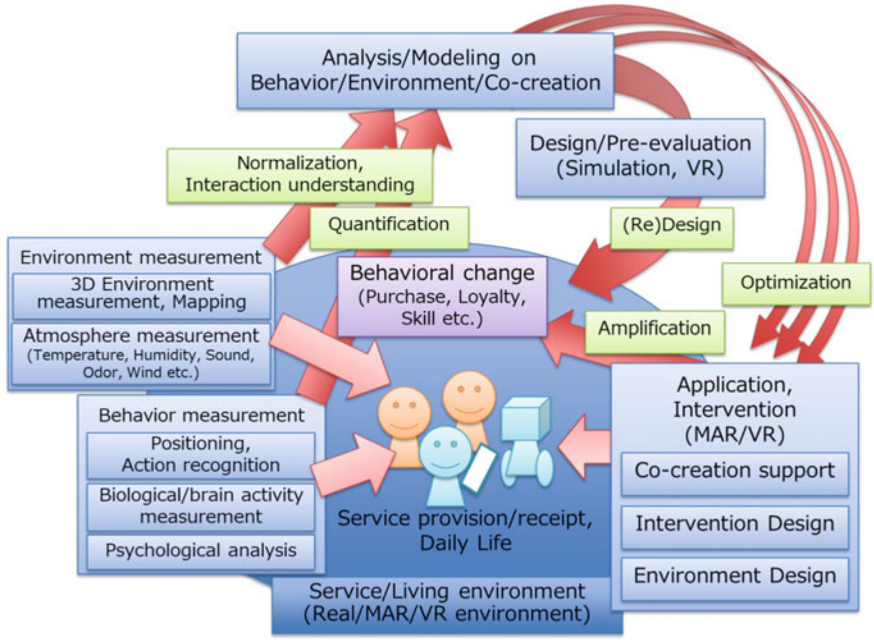


Fig. 4.2 Service design loop supporting human-centered co-creation

With the coming of IoT and IoH societies, approaches of those kinds, which we call "Hakatte Hakaru (Fig. 4.3)" in Japanese, are presumed to become more essential and ordinary.

There are two ways of realizing Hakatte Hakaru: Lab-Forming Sites (LFS) and Site-Forming Labs (SFL). To make these terms, we analogically used a term, "Terraforming," which designates the transformation of some planet such as Mars from its current environment to another environment that more closely resembles that of Earth so that we can live on the planet. We can illustrate what technologies are exploited for LFS and SFL in Fig. 4.4.

Fig. 4.3 Hakatte Hakaru: service design loop in Japanese

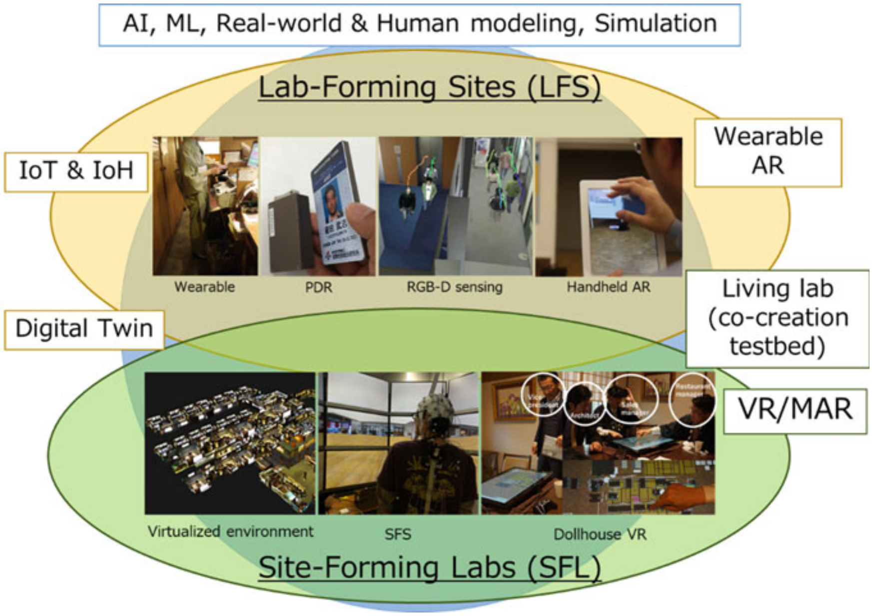


Fig. 4.4 Lab-forming sites (LFS) and Site-Forming Labs (SFL)

One can use LFS to transform real service sites into lab-like places for bringing methodologies in which hypothesis testing is conducted repeatedly by giving stimuli to service providers/customers and by observing the responses. Conventionally, it was not practical to realize such methodologies at actual service sites. However, the methods are finally coming into practical use by measuring service customers, employees, and service/living environments with IoT and IoH technologies including spatial computing for modeling and for comprehending actual service sites. At such sites, intervention is done with information provision using mixed and augmented reality (MAR) (Makita et al. 2014; Chang et al. 2015) or other interfaces and with physical actuation using robotic technologies (RT).

By contrast, one can use SFL to transform laboratories into real-site-like places for bringing subjects' behavior and experimentally obtained results closer and closer to those which are presumed to be obtained at real service sites. For that purpose, VR environments are often developed and used (Nakajima et al. 2012; Hyun et al. 2010; Takashi and Kurata 2014; Takeda et al. 2014; Hikaru et al. 2015; Yuta et al. 2018). Such VR environments should provide reproducibility of real service sites, but the extent of reproducibility depends on what one wants to explore. It is noteworthy that we can also use benefits available from VR environments in SFL: well-controlled environments and various measurements such as gaze, biological, and brain activity measurements.

4.2.1 Pier Data

Through LFS and SFL, one can acquire “big data” and “deep data”. Big data can be collected on a daily basis without much effort, but it is difficult to maintain their quality. Moreover, the data are of limited types. No clear definition of deep data exists, but we consider for this work deep data have characteristics that supplement big data, such as high quality (including ground truth data), heterogeneity (including detailed motion, gaze, biometric information, and brain activity data), and the inclusion of subjective data (surveys and interviews). Deep data are used as training data for supervised machine learning, which is applied to recognize something from big data, or as basic information to enhance the qualitative understanding of the site. However, deep data can only be obtained in special circumstances such as sensing in a laboratory or at an edge heavy site, or by interviewing.

A pier has a structure in which the platform is supported by stakes, as in Fig. 4.5. It is similar to the structure in which deep data support big data. One can also assume that, typically, a so-called platformer is good at gathering big data. A so-called stakeholder with knowledge and know-how at each site can be good at gathering deep data. For these reasons, we call this combination of big data and deep data “Pier

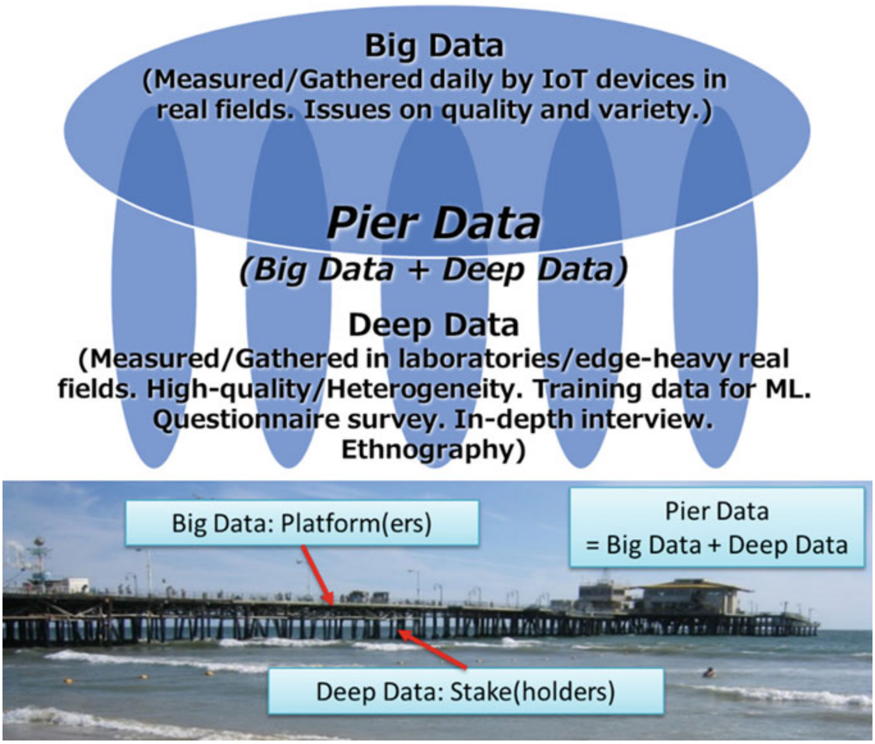


Fig. 4.5 Pier data: combination of Big data and Deep data

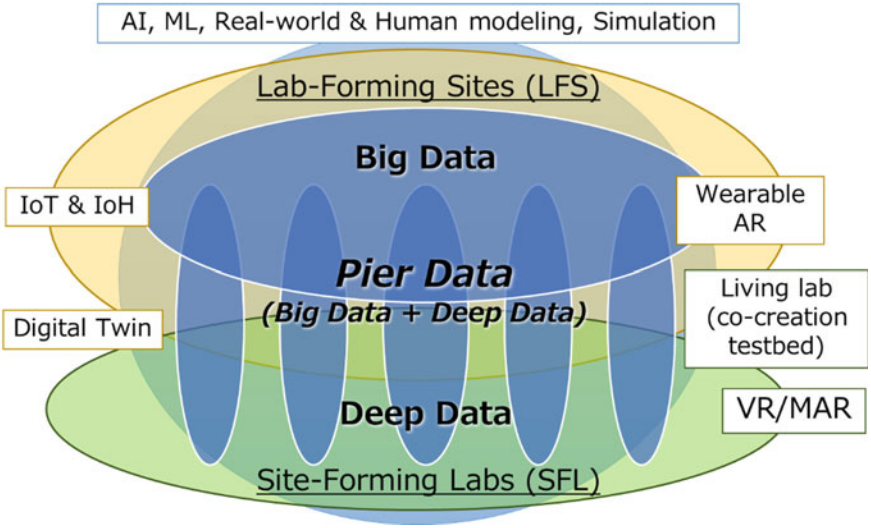


Fig. 4.6 LFS and SFL in association with Pier Data

Data". As shown in Fig. 4.6, one acquires mainly big data with LFS and mainly deep data with SFL. By making the pier data deeper and wider efficiently though LFS and SFL, it will be possible to understand what is happening in the real world comprehensively, especially at service and manufacturing sites for the improvement and innovation.

4.2.2 Research Cases of LFS and SFL

Although it might be difficult to conduct full-fledged research and development on LFS and SFL, many research cases have addressed the concepts of LFS and SFL with partial introduction and implementation. Table 4.1 presents studies conducted at AIST that are relevant to LFS and SFL.

Computer Supported Quality Control Circle (CSQCC) (Fukuhara et al. 2013, 2014; Takashi et al. 2015) was presented to facilitate As-Is comprehension and Before and After comparison on service provision processes in Japanese restaurants. In this case, employees' trajectories, point of sale (POS) and order entry system (OES) data were obtained from real restaurants on a daily basis. Restaurants' 3D floor maps were created interactively from a set of photographs (Ishikawa et al. 2013). Several indicators and indices were designed as work and skill evaluation. A Kaizen (improvement) plan was discussed while visualizing the obtained data, indicators, indices, and other information for improving service provision processes.

Table 4.1 Research cases of LFS and SFL in AIST

	Study Case	Measurement	Modeling	Design/ Pre-evaluation	Application/ Intervention
	Maintenance service (MAR-based support)	User position and orientation, Target objects, Machine condition	Machines, Road environments	N/A	Computer-supported work
Lab-Forming Sites (LFS)	**As-Is comprehension and Before & After comparison on service provision in restaurants (CSQCC)**	Employees trajectories, POS/OES data, Real environments	Work indicators, Skills, 3D Indoor environments	Kaizen plan by discussion with visualization	Improved service provision
	To-Be comparison of operation plans in warehouse picking	Trajectories of employees and carts, WMS data, Shelf layout	Picking work, Work indicators	Kaizen plan comparison by simulation	(Improved operation)
	Ethnography in a hotel (CCE Lite)	Trajectories of employees, Real environments, Interviews	Skills, 3D Indoor environments	N/A	N/A
Site-Forming Labs (SFL)	Marketing for product design in virtual stores	Trajectories/Gazes/Brain activities of subjects in VR, Real environments	Customer behavior, Indoor 3D environments	Product Design	(New product)
	Restaurant floor planning with multi-stakeholders (Dollhouse VR)	N/A	3D Indoor environments, Human body	Floor planning in collaborative VR	(Improved floor plan)

As described above, CSQCC is regarded as an example of LFS. "Dollhouse VR" (Hikaru et al. 2015; Yuta et al. 2018) is an example of SFL, which facilitates asymmetric collaboration among multiple stakeholders with two viewpoints: a top-down view using a large table-top interface and a first-person view using a head-mounted display. In this case, multiple stakeholders such as a restaurant manager, a sales manager, an architect, and an executive officer can discuss the rearrangement of a restaurant floor by moving tables and chairs in a virtual environment while using the Dollhouse VR system.

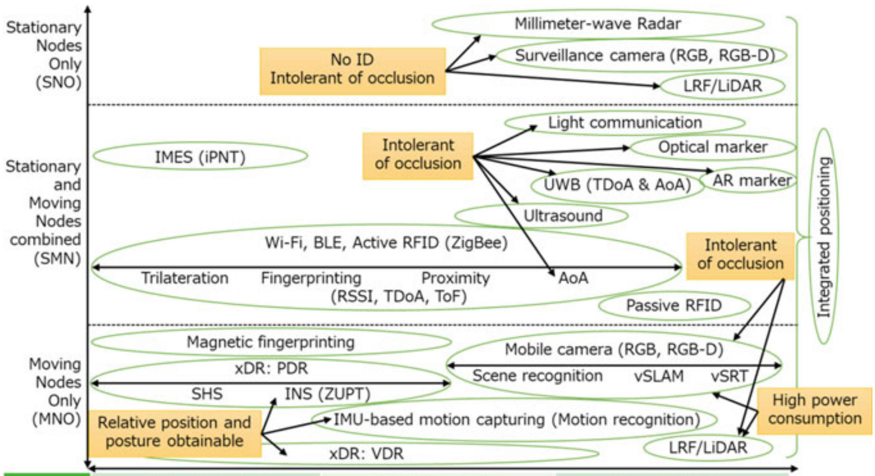
4.3 Internet of Humans

In various industries, and especially at restaurant sites, service providers' positions show strong correlation with the operation contents. Therefore, indoor positioning technologies are anticipated for greater use in service provision process analysis. If more microscopic motion data are obtained, detailed operational behaviors can also be analyzed. After summarizing indoor positioning technologies, the associated motion and operation recognition technologies are briefly introduced.

4.3.1 Indoor Positioning Technologies

One can readily find from Fig. 4.7 that technologies of so many different kinds exist for indoor positioning. The horizontal axis is basically a combined axis of the degree of error as an indicator of positioning performance and the area covered by a unit cost as an indicator of cost performance. Because those two factors have strong dependency in general, they are presented as a horizontal axis, as in this figure. The horizontal axis is divided into three categories. In this chapter, they are designated for convenience as "Macro-positioning", "Mezzo-positioning", and "Micro-positioning". The vertical axis presents system configurations that comprise "Stationary nodes only (SNO)", "Stationary and moving nodes combined (SMN)", and "Moving nodes only (MNO)".

With micro-positioning technologies, more precise position data is obtainable. However, micro-positioning technologies invariably have shortcomings. For instance, the MNO systems for micro-positioning such as mobile camera and Laser Rangefinder (LRF)/LIght Detection And Ranging (LIDAR) (Kuramachi et al. 2015) tend to consume more power than systems for mezzo/macro-positioning. Also, SNO systems such as millimeter-wave radar, surveillance camera, and LRF/LIDAR often



	Macro-positioning	Mezzo-positioning	Micro-positioning
Err (m)	3 – 10	1	0.3
Area/$	Large	Middle	Small

AoA: Angle of Arrival, AR: Augmented Reality, DR: Dead Reckoning, IMES: Indoor MEssaging System (Indoor GPS), IMU: Inertial Measurement Unit, INS: Inertial Navigation System, iPNT: indoor Position, Navigation, Timing, LIDAR: LIght Detection And Ranging, LRF: Laser Rangefinder, PDR: Pedestrian DR, RADAR: Radio Detection And Ranging, RGB-D: RGB & Depth, RSSI: Received Signal Strength Indicator, RTT: Round Trip Time (two-way ToA), SHS: Steps and Heading System, SLAM: Simultaneous Localization and Mapping, TDoA: Time Difference of Arrival, ToF: Time of Flight (ToA: Time of Arrival), UWB: Ultra Wide Band, VDR: [Vibration-based] Vehicle DR, xDR: DR for something, vSLAM: visual SLAM, vSRT: vision-based Spatial Registration and Tracking, ZUPT: Zero Velocity Update

Fig. 4.7 Indoor positioning technology map

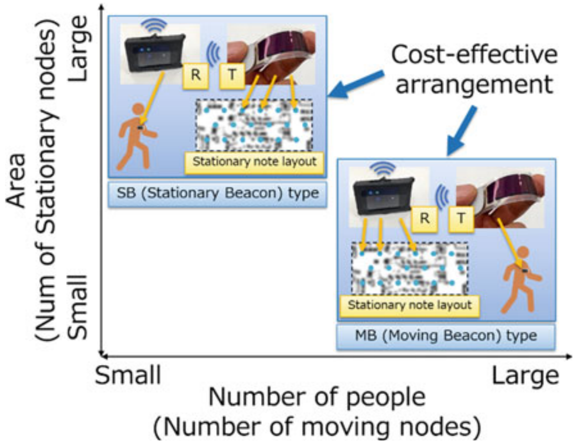


Fig. 4.8 Combination of stationary and moving nodes: SB type and MB type

have great difficulty in assigning or finding an ID for each subject. Moreover, they are not tolerant of occlusion no matter what they are micro-positioning or macro-positioning. Micro-positioning systems combining stationary and moving nodes such as light communication, ultra-wide band (UWB), ultrasound, angle of arrival (AoA) of a radio wave, and AR-marker-based methods also are not tolerant of occlusion.

The most popular system configuration is expected to be SMN. Figure 4.8 shows the cost-effective arrangements of stationary and moving nodes when we build SMN systems. In general, transmitters such as BLE (Bluetooth Low Energy) beacons and passive RFID (Radio Frequency IDentification) tags are much less expensive than receivers or transponders such as smartphones and IoT gateways. In cases with a larger area and fewer persons measured, it is better to choose transmitters as stationary nodes and receivers as moving nodes for reasons of cost. We designate such an arrangement as stationary beacon (SB) type, and the opposite arrangement as moving beacon (MB) type. The benefits and shortcomings of the SB type and the MB type are presented in Table 4.2.

4.3.2 Example of Indoor Positioning Systems

This section briefly introduces an indoor positioning system that we developed (Fig. 4.9) as an example of actual systems to ascertain their concrete shape. This system is categorized as an integrated positioning system (Ishikawa et al. 2011) consisting of Dead Reckoning for X (xDR) (Kourogi and Kurata 2003, 2014; Kohei et al. 2017), Received Signal Strength Indicator (RSSI)-based BLE positioning, and map constraints. The system has two features suitable for introduction into actual service sites. The first feature is that the system uses xDR, which includes pedestrian dead

Table 4.2 Benefits and shortcomings of SB and MB types

Type	SB	MB
Stationary node	Beacon (Small, Inexpensive)	Receiver/Transponder
Moving node	Receiver/Transponder	Beacon (Small, Inexpensive)
Positioning error	SB <= MB	
Positioning outside AoIs	Possible	Impossible
Remarks	Moving nodes can be used for measurement of orientation, speed, action recognition, human-machine interface, etc. Meaningful shape of trajectory.	Lower physical load for the users. Less need for battery charge/change of moving nodes.

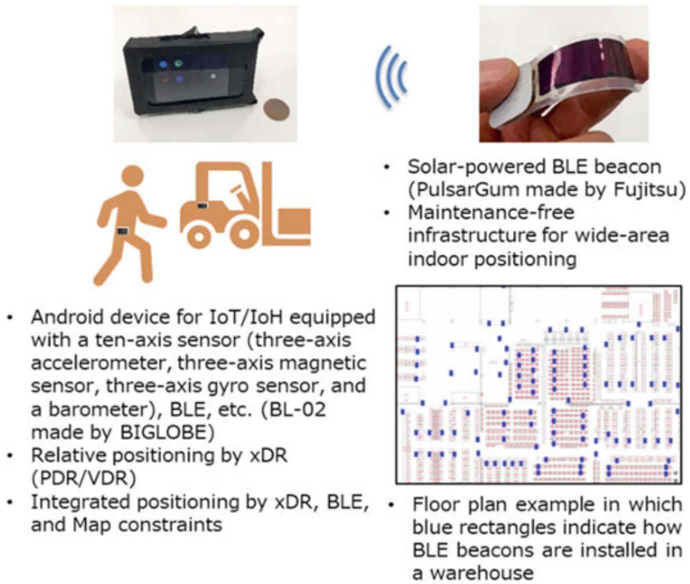


Fig. 4.9 Integrated indoor positioning system

reckoning (PDR) and vehicle dead reckoning (VDR) as methods of relative positioning. The second feature is that solar-powered BLE beacons are used as stationary nodes placed around the areas of interest (AoIs).

Although solar-powered BLE beacons are 2–3 times as expensive as typical battery-powered BLE beacons, the combination of xDR and BLE positioning makes it possible to reduce the number of BLE beacons to only a fraction of the number necessary for BLE positioning. A battery-free setup is possible without increasing initial installation costs. Additionally, a battery-free setup obviates battery replacement, greatly reducing operational costs. However, because this configuration inherently requires lighting as a source of energy harvesting, positioning performance must be sustained even at irregular time intervals of BLE signal transmission because of insufficient lighting.

Stationary nodes are naturally placed for covering AoIs. However, many flow lines or activities might occur outside of those expected areas. In some cases, such data are crucially important for service provision process analysis. Although BLE positioning leaves nothing to do, flow lines can be traced with xDR. As hardware for moving nodes, workers can use embedded modules or smartphones equipped with a nine-axis or ten-axis sensors, as described hereinafter. Also, because cameras are often difficult to bring in and install on site because of issues of cost, privacy of customers and mental load of employees, the system does not necessarily require vision-based positioning technologies.

4.3.3 PDR

The authors have been engaged in R&D related to xDR, and especially to PDR, since 2000 (Fig. 4.10). Fundamentally, PDR technology (Kourogi and Kurata 2003, 2014; Kohei et al. 2017) uses a group of sensors (commonly known as nine-axis sensors) that measure three-axis acceleration, three-axis angular velocity, and three-axis magnetism to estimate the sensor posture, as well as the travel speed and direction of a pedestrian carrying the sensors. One can estimate the pedestrian's relative location. Along with increasing demand for indoor positioning technologies including PDR from industries of various kinds, international indoor positioning competitions are becoming popular (Kaji et al. 2015; Katsuhiko et al. 2016; Lymberopoulos and Liu 2017; Ichikari et al. 2019). For instance, "xDR Challenge in industrial scenarios 2019" was designed to compare integrated indoor positioning algorithms developed by the respective contestants using real data from an actual restaurant site and a manufacturing site (Fig. 4.11).

For many cases in which a positioning system is to be introduced into an indoor service or manufacturing site, the cost of developing the physical and information infrastructure poses a barrier that raises questions about its cost-effectiveness. Although the introduction of indoor positioning is fundamentally important for LFS, cases exist in which the effect of its introduction must be represented solely as a monetary value. As a reference to R. Solow's productivity paradox, this situation can be

Fig. 4.10 History of xDR (PDR & VDR) research and development in AIST

Fig. 4.11 International indoor positioning competition called "xDR Challenge in industrial scenarios 2019"

called an indoor positioning paradox/dilemma. This paradox or dilemma, which does not occur using outdoor satellite positioning for free, can be eased using a relative positioning method such as PDR. An excellent example of it is indoor navigation by “DoCoMo Map Navi” (DoCoMo Map Indoor Navigation Area). A nine-axis or ten-axis PDR with a map (pedestrian space network data) and interaction with the user enable indoor navigation at about 600 underground shopping centers and subway premises across Japan (as of March 2019) without installation of a physical infrastructure.

Actually, PDR is classifiable into an inertial navigation system (INS) type, which estimates three-dimensional positions, and steps and heading system (SHS) type, which estimates two-dimensional positions (Harle 2013). The former method (Foxlin 2005) can provide highly accurate three-dimensional positioning without depending on how each person walks. It does, however, present some important limitations: because it is a method based on double integration of acceleration, it requires an accelerometer with easy calibration and high sensitivity. Also, 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 of the latter type of PDR, the SHS (Kourogi and Kurata 2003, 2014). It is composed mainly of (1) attitude estimation, (2) estimation of the walking direction, and (3) walking motion detection and walking speed (pace) estimation. Relative 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 does present some limitations of its own. For example, 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 is highly anticipated for further easing limitations related to attachment or holding conditions. Estimation of walking direction is a fundamentally important technology for this purpose. The main methods that have been proposed are: (a) based on the Principal Component Analysis (PCA) of acceleration amplitude, (b) based on a Forward and Lateral Acceleration Modeling (FLAM), and (c) based on Frequency analysis of Inertial Signals (FIS) (Kourogi and Kurata 2014). According to a research report presenting comparative evaluation of them (Christophe and Valerie 2015), the method with FIS produced the best evaluation result overall.

The measurement range of an SHS-type PDR is limited to the ground and floor that are included in the map and floor plan. Estimation in the height direction is limited on the map and floor plan. In many cases, however, this height information is sufficient to obtain position information of customers, employees, residents, and others. Therefore, this limitation represents only a slight difficulty. As pressure sensors become increasingly accessible and accurate, a ten-axis sensor, which is a nine-axis sensor with a pressure sensor added, will also become more widely used. Attempts to measure the travel in the vertical direction using this ten-axis sensor (Kaji and Kawaguchi 2016; Kaji et al. 2016; Ichikari et al. 2015) have also been announced.

Whereas many other absolute positioning methods such as BLE positioning, 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; it also allows measurement of the type and intensity of the movement. Therefore, it is more appropriate in some cases to consider PDR as a means to measure behavior rather than a positioning method (Makita et al. 2013; Kourogi et al. 2010).

4.3.4 Work Motion Recognition

If micro-level understanding of behaviors is required as in the analysis of hospitality in customer service and cooking, skills involved, etc., then the use of position data alone is insufficient. Inertial measurement units (IMUs) as in moving nodes for xDR, go beyond tracking position because they are also capable of capturing the type and size of motion, allowing for micro-level analyses of work motion and safety management by detecting falling movements. Figure 4.12 depicts three examples of work-motion capture systems.

Typically, 10–20 IMUs are attached all over the body, as shown in the left example in Fig. 4.12. Although this sort of setup is usually permitted for short-term collection of data, the time involved in attaching and detaching the system and its potential to interfere with work tasks make such a system unlikely to be adopted for long-term, everyday use. The system in Fig. 4.12-center is designed to reduce the number of IMUs to only five, thereby rendering it less cumbersome for workers and reducing hardware costs. In this case, a smartphone is placed inside the ‘obi’ belt as one IMU and also as a BLE receiver.

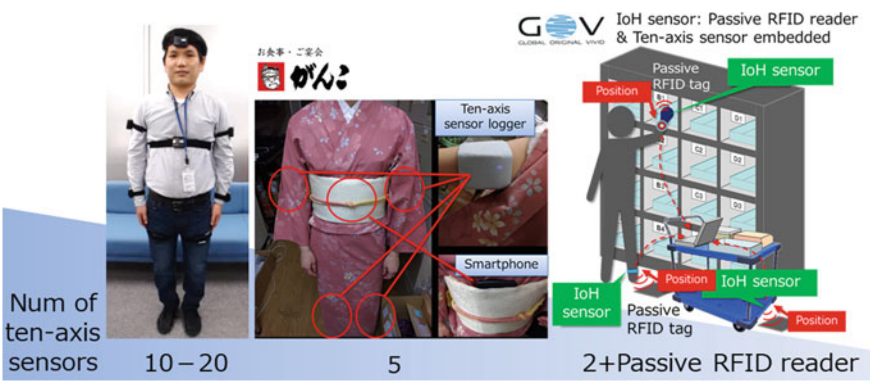


Fig. 4.12 Work motion recognition systems with different numbers of IMUs

Compared to a configuration by which IMUs are attached to the whole body, such configuration results in precision reduction of around 10–20%. The whole-body configuration provides the position and movement of each body part based on a skeleton model. In contrast, the partial body configuration, as shown in Fig. 4.12-center, means that some more detailed information related to work motion is missed. Then one must rely solely on local movement data from the available sensors. To address such difficulties, an integrated IoH sensor module with a wearable passive RFID tag reader (TECCO) and a ten-axis sensor module have been developed (Fig. 4.12-right). These devices enable the micro-level information lost in the decreased number of IMUs described above to be partially obtainable again by taking micro-positional data with an RFID tag reading. Thereby, improvement in the motion recognition precision can be expected.

4.4 Make Time Tangible

Generally, little objection arises to the importance of visualization associated with 6 M. However, regarding short-term data collection and one-time Before and After comparison as sufficient, using a single system sequentially at many sites to cut system acquisition costs, and not opting for continual long-term data collection simultaneously at many sites are common mistakes that can be made.

To shed light on these misconceptions, this section uses Fig. 4.13 to discuss some benefits of continual on-site measurement of data. The top and middle parts of the diagram show sites that are not collecting data continually, whereas the bottom shows a site that is. First, a common concern heard during on-site interviews is that workers are not used to their work being monitored, and that it will be difficult to

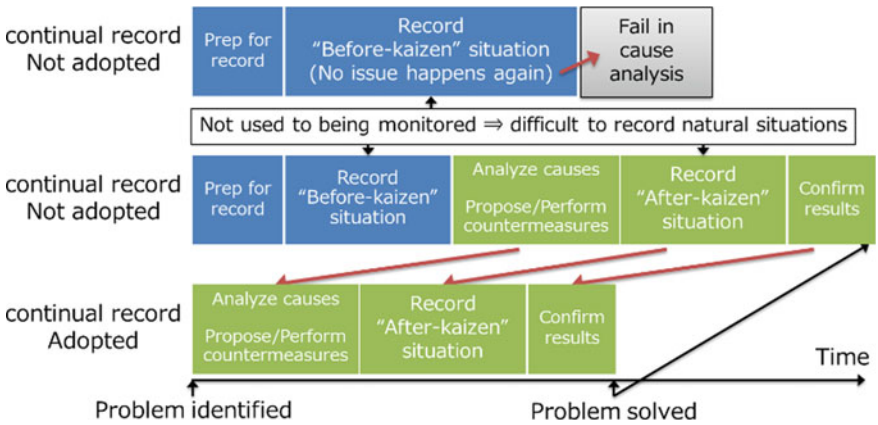


Fig. 4.13 Benefits of continual data collection

ascertain whether the resulting data reflect realistic and natural circumstances, or not. Continual data collection would allow such uncertainty to be dispelled.

One must consider how causes of found issues are analyzed and addressed. Typically (i.e., where continual data collection has not been adopted), the data collection system is only set up after a problem is identified, in which case one must wait for sufficient data surrounding the issue to be collected (a period that is designated as the "Before-data collection"). This waiting for collection creates a considerable time lag between the time when the difficulty is first identified and when its causes can begin to be analyzed and addressed. Furthermore, as presented in Fig. 4.13-top, if the exact issue of concern does not arise once again after beginning Before-data collection, then no data exist to analyze and identify causes.

Dashboard cameras in cars use accelerometers to detect incidents such as collision and sudden braking. They are able to keep records of such incidents for future use and for reporting of accidents. Similarly, with continual data collection at service sites such as restaurants, issues can be analyzed at any time, with seamless transition into data collection for confirming the effectiveness of solutions ("After-data collection"). In this way, issues can be addressed and remediated swiftly. This "Virtual Time Machine" concept (Hirose et al. 2004; Okuma et al. 2007) is expected to take root in more industry worlds in the future as 6 M visualization technology continues to develop and mature.

4.5 Conclusion

Even if large amounts of 6 M data could be gathered by IoT/IoH devices at real service and manufacturing sites, the data would not hold all the answers to elucidate the real sites comprehensively because big data in general entail issues of quality and variety. In-depth surveying such as retrospective interviewing can complement defects of big data. Nevertheless, such surveying invariably requires intensive effort with a high work load. In-depth surveying with subject screening (Nakajima et al. 2012) based on big data would alleviate the load. It would result in efficient surveying in terms of both breadth and depth. This idea is consistent with the idea of Pier Data. Demonstration of such a methodology at actual sites through further development of 6 M data collection and visualization technology including IoH technologies is a subject of our future work.

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