https://doi.org/10.20965/jrm.2019.p0367

Review:

Introduction to Simultaneous Localization and Mapping

Takashi Tsubouchi

Faculty of System and Information Engineering, University of Tsukuba
1-1-1 Tennodai, Tsukuba, Ibaraki 305-8577, Japan
E-mail: tsubo@roboken.iit.tsukuba.ac.jp

[Received April 22, 2019; accepted May 7, 2019]

Simultaneous localization and mapping (SLAM) forms the core of the technology that supports mobile robots. With SLAM, when a robot is moving in an actual environment, real world information is imported to a computer on the robot via a sensor, and robot's physical location and a map of its surrounding environment of the robot are created. SLAM is a major topic in mobile robot research. Although the information, supported by a mathematical description, is derived from a space in reality, it is formulated based on a probability theory when being handled. Therefore, this concept contributes not only to the research and development concerning mobile robots, but also to the training of mathematics and computer implementation, aimed mainly at position estimation and map creation for the mobile robots. This article focuses on the SLAM technology, including a brief overview of its history, insights from the author, and, finally, introduction of a specific example that the author was involved.

Keywords: SLAM, autonomous mobile robot, probabilistic process, mapping, localization

1. Introduction

Simultaneous localization and mapping (SLAM) is currently a core issue in mobile robot technology. It may be slightly difficult for those who do not specialize in mobile robot technology to understand the meaning of "simultaneously" carrying out localization and mapping. A human has the ability to simultaneously estimate his/her own position and the position of an object on the ground with reference to a coordinate system fixed on the ground while moving in that environment, regardless of whether he/she is in a known or unknown environment. SLAM is an attempt to artificially realize this type of an ability using electronic sensing and computer engineering technology, as well as by adequately utilizing a mathematical framework. In light of the recent publishing of a special issue on SLAM in the Journal of Robotics and Mechatronics, the author attempted a small review of SLAM, based on his own understanding. This article gives a simple introduction of the history of SLAM along with a description of the situation in its early days and gives an introduction to existing research outcomes from the authors.

2. Overview of Simultaneous Localization and Mapping (SLAM)

2.1. History

The technological aspects of SLAM for mobile robots are concisely summarized in [1–3]. After the 1980s, when prototype research on SLAM was started, these references were written consecutively from the mid- to late 2000s, when the mathematical formulation to solve them had almost been achieved. These references introduce the expansion of the field of SLAM and some typical problem settings as well as the academic history of SLAM, and thus they are suitable for an overview of SLAM. Tomono published a textbook [4] including source code for a program that solves typical problem settings of SLAM. It is an extremely useful reference, as it includes an implementation of the theoretical contents introduced in various references. In addition, [a] provides an appropriate and informative summary of information released during the implementation of SLAM.

Because of the desirable sound of the acronym "SLAM," it has already become established as the acronym that represents "simultaneous estimation of self-location and map for robots." Durrant-Whyte et al. [1] point out that this acronym first appeared in a mobile robotics survey paper [5] in the 1995 International Symposium on Robotics Research. However, in fact, research strongly related to the concept of what is now called SLAM had already been started in the middle of the 1980s. In the period of ten years following that time, various relevant research outcomes were reported. As a compilation of research during that period, this research paradigm was given the name SLAM by Durrant-Whyte et al., and [5] was written.

There are several reference examples reported from the 1980s to the early 1990s (such as [6–11]) that are related to self-location estimation or generation of environment maps for mobile robots, and that are aware of those functions being simultaneously carried out. According to the author's best knowledge, a LIDAR device small enough to be mounted on a mobile robot was not commonly available during those days. Thus, an ultrasonic ranging sensor or a video camera was used as an exteroceptive sensor in most cases. Unlike LIDAR, an ultrasonic ranging sensor does not have a directional resolution, and thus required a strong restriction, such as the environment surrounded by a plane. Video cameras with solid-state image sensing devices were already available, but there was no choice but to use cameras with the resolution (approximately equivalent to 0.7K) of analog television broadcasting in those days, as compared with currently-available cameras having resolutions of 2K or 4K. In addition, as for the video signal, an analog signal dependent on the broadcast standard had to be A-D converted on a computer side. Moreover, there was degradation of images caused by noise and synchronization fluctuations. The computer resources were poorer than those of today, and the calculation speed was slower. In such a situation, Cheeseman et al. reported that the use of a Kalman filter framework, with detection and matching of features of the same object at multiple places, was able to suppress an increase in the error variance of estimation positions of mobile robots by odometry [6]. As a map is expanded if the position of an object viewed at that time is mapped using the self-location that suppresses the increase in errors, SLAM was supposed to be carried out as the result. The Kalman filter is a Bayesian filter that assumes that the error variance of the state variable (in this case, the self-location of the robot) is estimated as a Gaussian distribution. It is imagined that this must have foreshadowed implementation of a later SLAM formulation which represented the position of a mobile robot or an object as a probability distribution. For example, the wordings that appear in the titles of those references such as "spatial uncertainty [6]," "consistent world modeling [7]," "fusing visual maps [8]," and "concurrent localization and map building [9]" provide implications that continue through to the current formulation related to SLAM.

2.2. Probabilistic Formulation for SLAM

Based on accuracy, it is possible to summarize self-location estimation of a mobile robot and appropriate mapping arrangement creation, i.e., mapping of an object in an environment using an exteroceptive sensor mounted on the robot, as follows.

1. If it can be assumed that the self-location of a mobile robot is constantly known accurately, or that the ambiguity of the self-location is extremely small, a map is created. The map is created by translating the observed position of an object on the ground as viewed on the coordinate system present in the robot (using the sensor mounted on it) into a coordinate system fixed on the ground, by means of coordinate transformation using each self-location.

2. If using a coordinate system fixed on the ground and the position of an object present on the ground is known accurately, or there is a map that has an extremely small ambiguity of the position of the object, an ambiguity of a self-location estimated by a robot using, for example, an interoceptive sensor can be reduced. In particular, the ambiguity can be reduced by observing the map and position of the corresponding object as viewed by the robot.

3. If there is a map that has an ambiguity in the position of an object present on the ground or the position of the object is totally unknown, and if the estimated self-location of the robot is ambiguous or totally unknown, the robot's self-location and the map can be estimated so as to reduce the knowledge gap or ambiguity as much as possible. This is performed using observation of the position of a corresponding object as viewed from the robot.

As is well known, the first issue is considered from a standpoint of a problem of "mapping," the second is a problem of "localization," and the third is a problem of SLAM. In the research from the mid-1980s, while researchers were aware of the concept of simultaneously estimating the self-location of a mobile robot and a map of the travel environment, they were thought of as an extension of a standpoint where either "mapping" or "localization" was dominant. Thus, an attempt to discuss a convergence of the mapping and self-location of the robot still seemed to be difficult. In the mid-1990s, Durran-Whyte described in [1] that, as a mathematical framework, an awareness and formulation that comprehensively considered an estimation problem of map generation and robot self-location as "a single estimation problem" had brought an essential breakthrough to solve SLAM. This paradigm made it possible to discuss the convergence of a result of SLAM, and to formulate a framework that guaranteed it. In the symposium [5] held in 1995 and introduced at the beginning of this article, Durrant-Whyte et al. called this problem "simultaneous localization and mapping," with the acronym SLAM. Here, the meaning of "simultaneous" implicates comprehensive mathematical handling of both information on the robot's self-location and map.

The itemized summarization written above used the expression "ambiguity of map and position of robot." In an attempt to solve SLAM, when comprehensively handling these concepts together as a single estimation problem, the means to express the "ambiguity" must be decided. It is common to consider this ambiguity with a mathematical framework formulated as a probability distribution, accompanied by a multidimensional random variable. First, each amount is defined as follows.

1. Time-series with the position vector of the robot at each sample time being a state variable:
$\boldsymbol{X}_{0:k} = \{\boldsymbol{x}_0, \boldsymbol{x}_1, \ldots, \boldsymbol{x}_k\} = \{\boldsymbol{X}_{0:k-1}, \boldsymbol{x}_k\}$.

2. Time-series of a control input of the robot or time-series of a movement amount between sample times:
$\boldsymbol{U}_{0:k} = \{\boldsymbol{u}_1, \boldsymbol{u}_2, \ldots, \boldsymbol{u}_k\} = \{\boldsymbol{U}_{0:k-1}, \boldsymbol{u}_k\}$.

3. Set of time-invariant position vectors of a landmark on the ground: $\boldsymbol{m} = \{\boldsymbol{m}_1, \boldsymbol{m}_2, \ldots, \boldsymbol{m}_n\}$.

4. Set of observations of the object viewed from the robot at each time: $\boldsymbol{Z}_{0:k} = \{z_1, z_2, \ldots, z_k\} = \{\boldsymbol{Z}_{0:k-1}, z_k\}$.

Considering all these as random variables, and calculating the conditional probability distribution as

$$P(\boldsymbol{x}_k, \boldsymbol{m} | \boldsymbol{Z}_{0:k}, \boldsymbol{U}_{0:k}, \boldsymbol{x}_0) \quad \ldots \ldots \ldots \quad (1)$$

at the time k formulate an "online SLAM problem" [3]. In other words, while the robot moves by $\boldsymbol{U}_{0:k}$ from an initial position $\boldsymbol{x}_0$ of the robot, a column $\boldsymbol{Z}_{0:k}$ of the surrounding observation is obtained by the exteroceptive sensor of the robot. With these, the position of the robot $\boldsymbol{x}_k$ and the set $\boldsymbol{m}$ of the position of the object at the time k are collectively and simultaneously calculated as a probability distribution. In this formulation, it is assumed that while moving, the robot generates its estimated self-location $\boldsymbol{x}_k$ and the map $\boldsymbol{m}$ together using the information obtained thus far, every time $\boldsymbol{z}_k$ and $\boldsymbol{u}_k$ at the "current" time k are sequentially obtained. Therefore, it is called an "online SLAM." In contrast, there is a formulation of

$$P(\boldsymbol{X}_{0:k}, \boldsymbol{m} | \boldsymbol{Z}_{0:k}, \boldsymbol{U}_{0:k}, \boldsymbol{x}_0) \quad \ldots \ldots \ldots \quad (2)$$

called a "full SLAM problem" [3]. This is a problem when calculating all the positions of the robot at each time from the initial position of the robot, together with the map. In other words, it is a formulation to calculate the time-series $\boldsymbol{X}_{0:k}$ of the map $\boldsymbol{m}$ and the self-location using the time-series $\boldsymbol{Z}_{0:k}$ and $\boldsymbol{U}_{0:k}$ of $\boldsymbol{z}_k$ and $\boldsymbol{u}_k$ to the time k. It is first assumed that this calculation is carried out after information has been accumulated for a certain period. At any rate, with these formulations as the starting point, the problem can be solved by deforming the description (Eq. (1) or (2)) of this probability distribution in accordance with the setting of the problem (e.g., expressing it with the product of the appropriate probability distribution). For instance, when an object is observed at a specific position, obtaining the observation can be described as calculating a conditional probability distribution of

$$P(z_k | \boldsymbol{x}_k, \boldsymbol{m}) \quad \ldots \ldots \ldots \ldots \quad (3)$$

and the position $\boldsymbol{x}_k$ after movement by the control input $\boldsymbol{u}_k$ from the position $\boldsymbol{x}_{k-1}$ can be described as calculating a conditional probability distribution of

$$P(\boldsymbol{x}_k | \boldsymbol{x}_{k-1}, \boldsymbol{u}_k) \quad \ldots \ldots \ldots \ldots \quad (4)$$

Eq. (3) is an expression for calculating the observation $\boldsymbol{z}_k$ under a condition where the map $\boldsymbol{m}$ and the position $\boldsymbol{x}_k$ of the robot are given. In contrast, there is a desire to calculate the map $\boldsymbol{m}$ and the robot position $\boldsymbol{x}_k$ under a condition where the control history $\boldsymbol{U}_{0:k}$ and the observation $\boldsymbol{Z}_{0:k}$ are given. From this relationship, the application of a Bayes' theorem connecting a conditional prior and a posterior probability is conceived. On the assumption that the probability distribution of the random variables appearing here is a normal distribution, a Kalman filter can be derived from the formulation of the Bayes' theorem. Therefore, a Kalman filter often appears when a SLAM problem is solved.

If $\boldsymbol{x}_k$ is not considered as a random variable but as if the time-series of the position from the initial position of the robot as a determinate value is known, it becomes a problem setting that considers a probability distribution of

$$P(\boldsymbol{m} | \boldsymbol{X}_{0:k}, \boldsymbol{Z}_{0:k}, \boldsymbol{U}_{0:k}) \quad \ldots \ldots \ldots \ldots \quad (5)$$

corresponding to a mapping. In contrast, if the map $\boldsymbol{m}$ can be considered as if it has already been known by another means and has been determined, it becomes a problem setting that considers a probability distribution of

$$P(\boldsymbol{x}_k | \boldsymbol{Z}_{0:k}, \boldsymbol{U}_{0:k}, \boldsymbol{m}) \quad \ldots \ldots \ldots \ldots \quad (6)$$

corresponding to localization. The formulation by Eq. (1) or (2) is inclusive of both. Localization can also be read as the limit with the ambiguity (error variance) of $\boldsymbol{m}$ being zero in these expressions, and mapping can be read as the limit with the ambiguity of $\boldsymbol{X}_{0:k}$ being zero.

Thrun et al. wrote a compilation of a probabilistic, mathematical handling of SLAM in 2006 [12] which is now a reference textbook for handling SLAM. However, from the point of view of carrying out recognition of an object while permitting an event variation and ambiguity, this is not limited to a problem of estimation of the mobile robot self-location and map, but can be regarded as a problem of pattern recognition and machine learning in a broad sense. The mathematical framework in this understanding is summarized in a wider sense in the tome [13]. Interestingly, both references were published in the same period of time. Reading both references and focusing on the parts related to each other will deepen a theoretical understanding of SLAM. For instance, Figure 2.2 on page 25 of [12] graphically illustrates a dynamic Bayes network, whereas the style of this illustration is an expression called "probabilistic graphical models" in [13], and is described in detail in Chapter 8 of [13]. To describe the currently-targeted probabilistic process using this expression is to analyze the specific structure of the process, and is a useful means for specifically deforming Eq. (1) or (2) in our problem. In other words, various types of theoretical derivations and efficient implementations have been carried out by deforming these expressions with various assumptions and using them as a starting point. There are various excellent references that have been published, and hence we do not get further into detail here.

2.3. Some Remarks

There are two personal remarks from the author related to handling SLAM as a mobile robot technology. The first remark concerns the usage of the SLAM acronym. In consideration of applications for causing a mobile robot to travel in an actual environment, there is an impression that there are few actual situations where the robot self-location and map must always be simultaneously estimated. For example, when a robot is required to travel in an environment, there are relatively more applications in which the environment map is first obtained, in accordance with which the robot repeatedly travels a required section based on a mission assigned to the robot.

In this case, obtaining the first environment map has its main subject in mapping and the confirmation of self-location for subsequent traveling has its main subject in localization. Even though SLAM is used this case, its main purpose here is individual localization and mapping. Accordingly, to prevent the main subject of the research and development from becoming ambiguous, it is necessary to distinguish whether the main subject is related to a method of SLAM itself aiming at the algorithm, performance improvement, and/or evaluation, or individual mapping and localization that use SLAM as one means.

The second remark concerns the size of the environment and the amount of information. When a mobile robot travels for a long distance for a long period of time, the map information obtained by SLAM will become very large. In addition, the distance to an object can become particular long outdoors, and an error of the distance can become large and its shape may be complicated, or there may be a space in which there is not any outstanding object near the robot. From such a point of view, handling SLAM in a robot that travels outdoors is a challenging problem. For example, there is a technology challenge called the "Tsukuba Challenge" that has been held since 2007, in which a mobile robot travels 2 km or more on a public road, such as an outdoor walking trail environment [14]. There are several reports of research related to SLAM being actually carried out in this Tsukuba Challenge and equivalent outdoor environments. For instance, this journal reports [15–19] and so on. Use of a video camera as an exteroceptive sensor will result in an extremely massive amount of image information. In this case, matching and tracking are frequently carried out between multiple images, with a focus on feature points from scale-invariant feature transform (SIFT) feature amounts and those from a combination of an accelerated segment test (FAST) and rotated binary robust independent elementary features (BRIEF), i.e., "Oriented FAST and Rotated BRIEF" or "ORB" feature amounts [20]. In most cases, SLAM is carried out without generating a dense map as an image, but rather by generating a sparse map using only feature points [16, 18]. In an environment wherein a person lives his/her daily life, he/she is capable of:

1. simultaneously estimating the surrounding environment and his/her own position,
2. noticing a difference, if any, between previous and current situations if in a known environment, and
3. continuing to be constantly aware of his/her current position.

Accordingly, when such an ability has to be given to a robot, novel efforts will have to be continuously made regarding the proper approach to be taken when new behavior spaces larger and larger are required for the robot. Thus, the topic of SLAM will be ongoing discussion.

Fig. 1. A product of the scanner for forest measurements named OWL (Optical Woods Ledger) of AdIn Research, Inc. [27].

3. SLAM Application Examples

Lastly, examples of SLAM applications used by the authors will be introduced. The authors have long been carrying out research on SLAM and associated application technologies (for instance, [21–26] and the like). Among them, as an application example for mapping using SLAM technology, a contribution by the authors related to forest measurement is introduced. In addition, a localization example is introduced in an environment using ORB-SLAM.

3.1. Forest Measurement as a SLAM Application

In a forest environment, and in particular in an artificial forest, there is a need for constantly monitoring the growth situation of planted trees, so as to estimate the timber volume as a resource amount in a thinning plan and at the time of logging. In this monitoring, it is necessary to examine target trees growing in a research target area defined in the forest in terms of the position, number, diameter at breast height of each tree, crown height, and the like. Conventionally, all of these measurements were carried out manually, using a tape measure or the like. For instance, in a case of manually conducting this work in a study area of approximately 30 m in a valley-ridge direction and 10 m in width, it is necessary for a group of three to take an on-site measurement for approximately one to one and a half hours. In addition, the obtained measurement values must be organized in an office thereafter, which is time-consuming.

This work can be mechanized by introducing the SLAM technology, and a dramatic improvement of the work efficiency would be expected. Thus, between approximately 2008 and 2015, the authors developed a measurement device called "Optical Woods Ledger" (OWL, shown in **Fig. 1**), in cooperation with AdIn Research, Inc. and Forest Revitalization Systems Co., Ltd. This is a one-legged device with a small LIDAR mounted on a rotating table. When the device is held still at a point in a

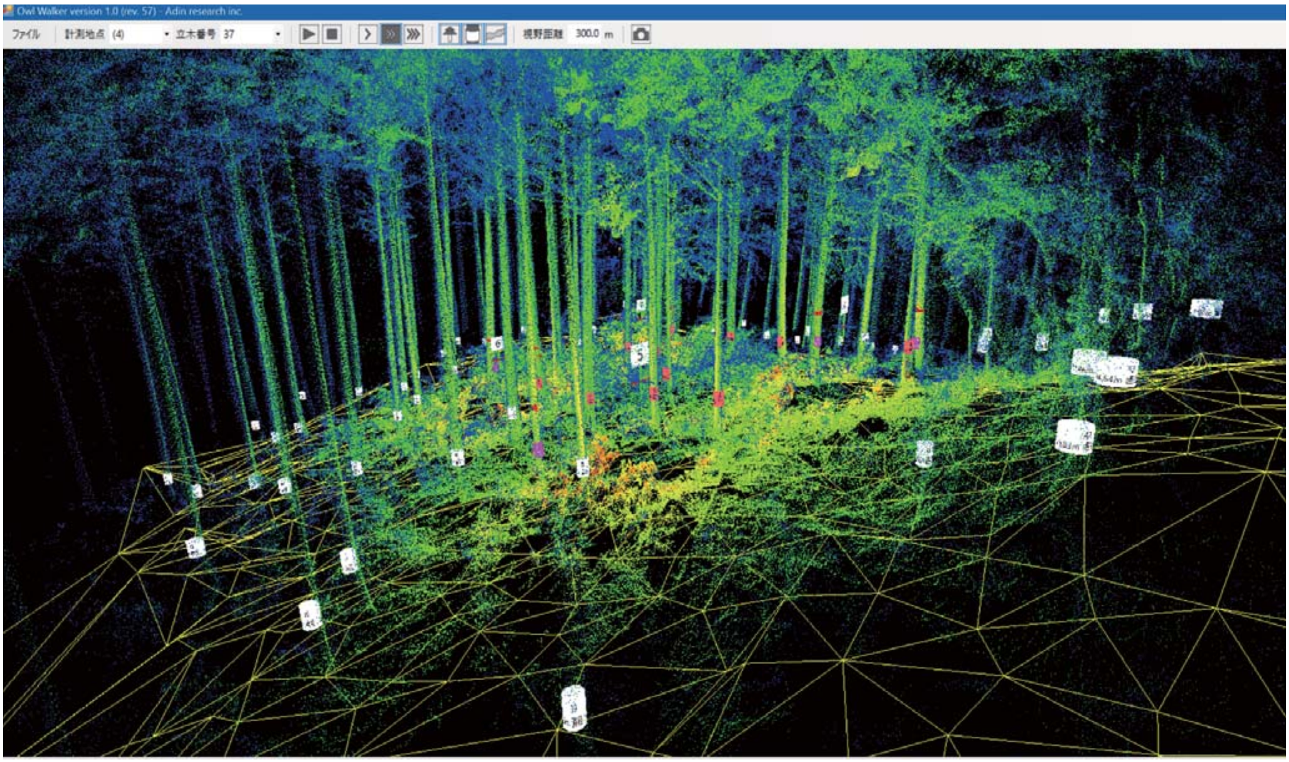

Fig. 2. Created map in a forest after scan matching based SLAM [27].

study area in the forest, a button is pressed to rotate the LIDAR on the rotating table, and its surrounding three-dimensional point crowd can be obtained. The device is developed so that measurement can be carried out with a simple operation of only pressing one button at the time of start of the measurement at the point the device held still. The measurement is done with a device that obtains sets of data of the three-dimensional point crowd at a few points for approximately every 10 m in the area under study. All the obtained sets of three-dimensional point crowds are connected as one map as a whole and are used for processing of obtaining the position of trees, diameter at breast height of each tree, crown height, and the like.

To connect the sets of three-dimensional point crowd obtained at multiple points without inconsistencies, map creation is carried out using a method [28] based on scan matching fostered in the SLAM technology [26]. However, as there is a relative distance of approximately every 10 m in the measurement, for scan matching to calculate the positional relationship between a measurement point and the next measurement point, using the former measurement point as the initial position, a simple application of the method [28] does not work well. Thus, in [26], standing trees, i.e., cylindrical objects were initially searched for from the three-dimensional point crowd calculated at each position, and the position of an intersection point between the center of the cylinder and a plane parallel to a forest slope face was calculated. The set of the intersection points resembles a constellation in the coordinate system, on a plane that is local to the measurement point. Positioning is carried out so that constellations obtained in this manner at multiple points overlap each other, and coordinate transformation between the local coordinate systems is calculated for each of the measurement points. In this manner, the positional relationship of each of the measurement points is calculated in advance. We have obtained a good result by conducting scan matching using this positional relationship as the initial value. **Fig. 2** presents an example of the three-dimensional point crowd obtained by this method. It is currently possible to measure a standing tree position within an error range of 4 cm or less, a diameter at breast height of 2 cm or less, an average tree height of 1 m or less, an average crown height of 1 m or less, and an average inclination of 3° or less [27]. A measurement value obtained in such a manner is comparable to conventional ones that are manually obtained. Moreover, as a practical matter, it is capable of saving labor, as a single person can carry out a measurement, the device can be used in, e.g., a slope with poor footing, and the necessary information is obtained.

Because measurement by OWL requires repeated movements and fixed measurements, the authors have also attempted to determine if a similar measurement is possible by simply continuously moving in the forest on foot. For this reason, they have also made an attempt at applying the method proposed by Zhang and Singh [29] to forest measurement [30]. However, they have not yet obtained a performance comparable to the measurement error accuracy of the OWL, indicating that further improvement is necessary.

Fig. 3. A pair of the stereo camera and prism for tracking on a cart.

Fig. 4. Environment and trajectory of the experiment.

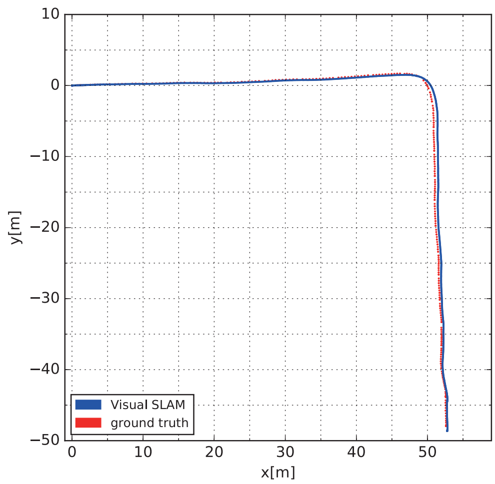

Fig. 5. Trajectory based on ORB-SLAM2 compared with ground truth.

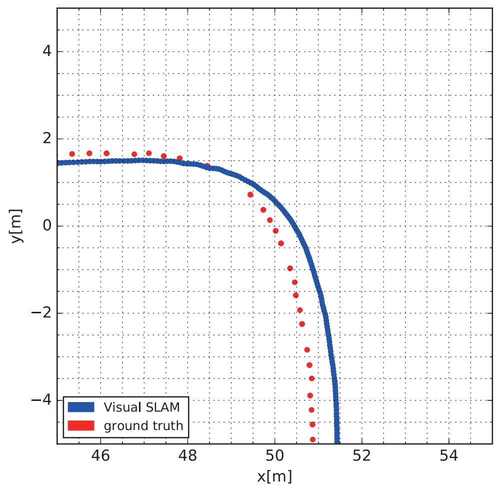

Fig. 6. Trajectory based on ORB-SLAM2 compared with ground truth (magnified).

3.2. Performance of ORB SLAM

Lastly, an experiment is introduced using an example of so-called "Visual SLAM," which is SLAM carried out using only a camera, and which is not dependent of self-location measurement means such as odometry. The example introduced here is an implement called ORB-SLAM2, by Mur-Artal et al. [b]. The algorithm has been proposed in previous studies [20, 31]. Feature points in an image are detected by the ORB feature amount [32], and this is used for a correspondence of feature points in an image captured by a monocular camera or a pair of stereo cameras. As the origin of the name ORB suggests, the advantages of FAST feature amounts [33] and BRIEF feature amounts [34] are combined, for better correspondence.

For the experiment introduced here and presented in **Fig. 3**, a prism for tracking with a geodetic total station (Topcon Corporation) is placed between the two cameras for stereo vision, and this arrangement is placed on a cart. A camera (GS3-U3-23S6M-C, Point Grey Research, Inc.) and lens (HS0818V, Myutron Co., Ltd.) are used, and the baseline length is 450 mm. The interface between a PC and the camera is a USB. The resolution of the obtained image is 1920×1200, and the shutter speed is fixed at 1 ms. This was obtained in the PC at 15 fps. Using the obtained image column, an attempt of self-location estimation based on ORB-SLAM2 [b] was made with offline processing. However, when executing SLAM, the image was reduced to 960×600.

Pushed by hand, the cart went straight on a path of an on-campus parking lot, as shown in **Fig. 4**, and subsequently turned right and straight further. The distance of the straight travel before and after the right turn was approximately 50 m each. At this instant, the camera position actually obtained with ORB-SLAM method was compared with the position on the cart actually obtained by tracking with the total station. Here, the position actually obtained with the total station is considered to be the true value. The experiment results are presented in **Figs. 5** and **6**. **Fig. 5** presents the entire trajectory, and **Fig. 6**

Fig. 7. An image example and ORB feature points (1).

Fig. 8. An image example and ORB feature points (2).

Fig. 9. An image example and ORB feature points (3).

presents an enlarged view of the vicinity of the point of the right turn. As a whole, although the number of positional errors increased when the camera had a rotation angle speed before and after the right turn as compared to when going straight, it still indicated that the self-location was successfully measured, with a difference of approximately 500 mm as a vertical distance between the trajectories. **Figs. 7–9** present feature points detected in the image at this instant, indicating the ability of SLAM using the ORB feature amounts.

4. Conclusions

This article has given a simple overview of the history of technological developments related to SLAM. As described, the essence of SLAM lies in the paradigm of simultaneously estimating the probability distributions of the both the self-location and map of the mobile robot. In addition, this article has presented two application examples of SLAM recently experienced by the authors. These are examples of use of the technology fostered in SLAM, and application of the same to mapping and localization. Both are scenes that required not simply mapping or localization, but application of SLAM where measurements have to be started without being given the position and map of the measurement device in advance before starting the measurement. The authors are grateful that this article could be of assistance in the understanding of a brief overview of the SLAM technology.

Acknowledgements

The author appreciate Mr. Tomofumi Yamada of a graduate student of the Intelligent Robot Laboratory with production of the pictures and results of **Figs. 3–9**.

References:

[1] H. Durrant-Whyte and T. Bailey, "Simultaneous Localization and Mapping (SLAM): Part I," IEEE Robotics & Automation Magazine, pp. 99-108, June 2006.

[2] T. Bailey and H. Durrant-Whyte, "Simultaneous Localization and Mapping (SLAM): Part II," IEEE Robotics & Automation Magazine, pp. 108-117, September 2006.

[3] S. Thrun and J. J. Leonard, "Simultaneous Localization and Mapping," B. Siciliano and O. Khatib (Eds.), "Springer Handbook of Robotics," Chapter 37, pp. 871-889, 2008.

[4] M. Tomono, "Simultaneous Localization and Mapping," Ohmsha, 2018 (in Japanese).

[5] H. Durrant-Whyte et al., "Localization of Automatic Guided Vehicles," G. Giralt et al. (Eds.), "Robotics Research," Springer, pp. 613-625, 1996.

[6] R. C. Smith and P. Cheeseman, "On the Representation and Estimation of Spatial Uncertainty," The Int. J. of Robotics Research, Vol.5, No.4, pp. 56-68, 1986.

[7] R. Chatila and J.-P. Laumond, "Position Referencing and Consistent World Modeling for Mobile Robots," Proc. of 1985 IEEE Int. Conf. on Robotics and Automation (ICRA 1985), pp. 138-145, 1985.

[8] N. Ayache and O. D. Faugeras, "Building, Registering, and Fusing Noisy Visual Maps," The Int. J. of Robotics Research, Vol.7, No.6, pp. 45-65, 1988.

[9] W. D. Rencken, "Concurrent Localization and Map Building for Mobile Robots Using Ultrasonic Sensors," Proc. of 1993 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS 1993), pp. 2192-2197, 1993.

[10] J. Iijima, S. Asaka, and S. Yuta, "Searching Unknown Environment by a Mobile Robot Using Range Sensor – an Algorithm and Experiment," Proc. of 1989 IEEE/RSJ Int. Workshop on Intelligent Robots and Systems (IROS 1989), pp. 46-53, 1989.

[11] J. Iijima and S. Yuta, "Searching Unknown 2-D Environment by a Mobile Robot with a Range Sensor," Computers & Electrical Engineering, Vol.18, No.1, pp. 83-98, 1992.

[12] S. Thrun, W. Burgard, and D. Fox, "Probabilistic Robotics," MIT Press, 2006.

[13] C. M. Bishop, "Pattern Recognition and Machine Learning," Springer, 2006.

[14] Y. Takita, S. Yuta, T. Tsubouchi, and K. Ozaki, "Special Issue on Real World Robot Challenge in Tsukuba," J. Robot. Mechatron., Vol.30, No.4, p. 503, 2018.

[15] N. Akai, L. Y. Morales, and H. Murase, "Teaching-Playback Navigation Without a Consistent Map," J. Robot. Mechatron., Vol.30, No.4, pp. 591-597, 2018.

[16] A. Sujiwo, T. Ando, E. Takeuchi, Y. Ninomiya, and M. Edahiro, "Monocular Vision-Based Localization Using ORB-SLAM with LIDAR-Aided Mapping in Real-World Robot Challenge," J. Robot. Mechatron., Vol.28, No.4, pp. 479-490, 2016.

[17] J. Eguchi and K. Ozaki, "Development of Method Using a Combination of DGPS and Scan Matching for the Making of Occupancy Grid Maps for Localization," J. Robot. Mechatron., Vol.25, No.3, pp. 506-514, 2013.

[18] T. Suzuki, Y. Amano, T. Hashizume, and S. Suzuki, "3D Terrain Reconstruction by Small Unmanned Aerial Vehicle Using SIFT-Based Monocular SLAM," J. Robot. Mechatron., Vol.23, No.2, pp. 292-301, 2011.

[19] A. Sakai, T. Saitoh, and Y. Kuroda, "Robust Landmark Estimation and Unscented Particle Sampling for SLAM in Dynamic Outdoor Environment," J. Robot. Mechatron., Vol.22, No.2, pp. 140-149, 2010.

[20] R. Mur-Artal, J. M. M. Montiel, and J. D. E. Tardós, "ORB-SLAM: a Versatile and Accurate Monocular SLAM System," IEEE Trans. on Robotics, Vol.31, No.5, pp. 1147-1163, doi: 10.1109/TRO.2015.2463671, 2015.

[21] T. Tsubouchi, A. Tanaka, A. Ishioka, and S. Yuta, "A SLAM Based Teleoperation and Interface System for Indoor Environment Reconnaissance in Rescue Activities," Proc. of IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, pp. 1095-1102, 2004.

[22] E. Takeuchi and T. Tsubouchi, "A 3-D Scan Matching using Improved 3-D Normal Distributions Transform for Mobile Robotic Mapping," Proc. of IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, pp. 3068-3073, 2006.

[23] E. Takeuchi and T. Tsubouchi, "Multi Sensor Map Building based on Sparse Linear Equations Solver," Proc. of 2008 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, pp. 2511-2518, 2008.

[24] Y. Hara, S. Bando, T. Tsubouchi, A. Oshima, I. Kitahara, and Y. Kameda, "6DOF iterative closest point matching considering a priori with maximum a posteriori estimation," Proc. of 2013 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, pp. 4172-4179, 2013.

[25] S. Bando, T. Tsubouchi, and S. Yuta, "Scan Matching Method using Projection in Dominant Direction of Indoor Environment," Advanced Robotics, Vol.28, Issue 18, pp. 1243-1251, 2014.

[26] T. Tsubouchi et al., "Forest 3D Mapping and Tree Sizes Measurement for Forest Management based on Sensing Technology for Mobile Robots," K. Yoshida and S. Tadokoro (Eds.), "Filed and Service Robotics," Vol.92, pp. 357-368, 2013.

[27] T. Tsubouchi, K. Sasaki, T. Hayami, and Y. Chiba, "Application of Mobile Robot Technology to Forest Measurement," Mokuzai Joho (J. of Japan Wood Products Information and Research Center), pp. 9-13, 2017 (in Japanese).

[28] P. J. Besl and N. D. McKay, "A Method for Registration of 3-D Shapes," IEEE Trans. on Patten Analysis and Machine Intelligence (PAMI), Vol.14, No.2, pp. 239-256, 1992.

[29] J. Zhang and S. Singh, "LOAM: Lidar Odometry and Mapping in Real Time," Proc. on Robotics: Science and Systems 2014, 2014.

[30] S. Seki, T. Tsubouchi, S. Sarata, and Y. Hara, "Forest Mapping and Trunk Parameter Measurement on Slope Using a 3D-Lidar," Proc. of 2017 IEEE/SICE Int. Symp. on System Integration (SII 2017), pp. 380-386, doi: 10.1109/SII.2017.8279242, 2017.

[31] R. Mur-Artal and J. D. E. Tardós, "ORB-SLAM2: an Open-Source SLAM System for Monocular, Stereo and RGB-D Cameras," IEEE Trans. on Robotics, Vol.33, No.5, pp. 1255-1262, doi: 10.1109/TRO.2017.2705103, 2017.

[32] E. Rublee, V. Rabaud, K. Konolige, and G. Bradski, "ORB: An Efficient Alternative to SIFT or SURF," IEEE 2011 Int. Conf. on Computer Vision, pp. 2564-2571, doi: 10.1109/ICCV.2011.6126544, 2011.

[33] E. Rosten and T. Drummond, "Machine Learning for High-Speed Corner Detection," A. Leonardis, H. Bischof, and A. Pinz (Eds.), "Computer Vision – ECCV 2006," Vol.3951, pp. 430-443, Springer, doi: 10.1007/11744023_34, 2006.

[34] M. Calonder, V. Lepetit, C. Strecha, and P. Fua, "BRIEF: Binary Robust Independent Elementary Features," K. Daniilidis, P. Maragos, and N. Paragios (Eds.), "Computer Vision – ECCV 2010," Vol.6314, pp. 778-792, Springer, doi: 10.1007/978-3-642-15561-1_56, 2010.

Supporting Online Materials:

[a] Y. Hara, "Classification of Open Source SLAM" (May 27, 2018, in Japanese). https://www.slideshare.net/hara-y/open-source-slam-3dcvtech [Accessed April 12, 2019]

[b] R. Mur-Artal, J. D. Tardós, J. M. M. Montiel, and D. Galvez-Lopez, "ORB-SLAM2: Real-Time SLAM for Monocular, Stereo and RGB-D Cameras, with Loop Detection and Relocalization Capabilities." https://github.com/raulmur/ORB_SLAM2.git [Accessed March 3, 2019]

Name:
Takashi Tsubouchi

Affiliation:
Professor, Faculty of System and Information Engineering, University of Tsukuba

Address:
1-1-1 Tennodai, Tsukuba, Ibaraki 305-8573, Japan

Brief Biographical History:

1989- Assistant Professor, Utsunomiya University
1991- Assistant Professor, The University of Tokyo
1994- Lecturer, University of Tsukuba
1998- Associate Professor, University of Tsukuba
2006- Professor, University of Tsukuba

Main Works:

• "Forest Mapping and Trunk Parameter Measurement on Slope Using a 3D-LIDAR," 2017 IEEE/SICE Int. Symp. on System Integration, Taipei, 2017.
• "Rock moving operation using a rod-shaped manipulator," J. Robot. Mechatron., Vol.25, No.1, pp. 232-239, 2013.

Membership in Academic Societies:

• The Robotics Society of Japan (RSJ)
• The Institute of Electrical and Electronics Engineers (IEEE)
• The Japan Society of Mechanical Engineers (JSME)