Practical Implementation of FastSLAM for Forestry Robot

Sylvain Geiser*
Department of Interdisciplinary Informatics, Graduate School of Computer Science and Systems Engineering, Kyushu Institute of Technology
680-4, Kawazu, Iizuka-City, Fukuoka, 820-8502, Japan

Sakmongkon Chumkamon
Department of Mechanical Information Science and Technology, Kyushu Institute of Technology
680-4, Kawazu, Iizuka-City, Fukuoka, 820-8502, Japan

Ayumu Tominaga
National Institute of Technology, Kitakyushu College
5-20-1 Shii, Kokuraminamiku, Kitakyushu, Fukuoka, 802-0985 Japan

Takumi Tomokawa
Department of Mechanical Information Science and Technology, Kyushu Institute of Technology
680-4, Kawazu, Iizuka-City, Fukuoka, 820-8502, Japan

Tan Chi Jie
Department of Mechanical Information Science and Technology, Kyushu Institute of Technology
680-4, Kawazu, Iizuka-City, Fukuoka, 820-8502, Japan

Eiji Hayashi
Department of Mechanical Information Science and Technology, Kyushu Institute of Technology
680-4, Kawazu, Iizuka-City, Fukuoka, 820-8502, Japan
E-mail: geiser.nathan-sylvain778@mail.kyutech.jp, m-san@mmcs.mse.kyutech.ac.jp, tominaga@kct.ac.jp, tomokawa.takumi163@mail.kyutech.jp, tan.jie-chi339@mail.kyutech.jp, haya@.mse.kyutech.ac.jp,
http://www.kyutech.ac.jp/

Abstract

As the Japanese forestry workforce is shrinking, field robots are gaining interest in performing dangerous tasks. This paper presents research conducted on the SOMA robot designed at Hayashi Laboratory. It focuses on issues encountered through the implementation of FastSLAM algorithm on this robot. In particular, the determination of the positions of trees from the raw pointcloud of the lidar, side effects occurring at the boundary of the lidar visibility scope, and the modelling of motion and observation noises are discussed.

Keywords: Field Robot, online SLAM, Forestry, Particle Filter

1. Introduction

In Japan, the decline of the number of workers in the forestry sector urges to use robots, especially for perilous tasks. The SOMA robot is a prototype developed at Hayashi Laboratory in order to address this need[1].

Since the ability of Simultaneous Localization and Mapping (SLAM) is essential for a mobile robot,

*7 rue Peyron, Vienne (38200), France

FastSLAM is under implementation on it[2]. This online algorithm is based on a particle filter whose particles represent joint hypothesis of the pose of the robot and the feature map of the environment. Employing this solver in the forestry context requires many adjustments and this article shed light on the encountered issues and the remedies which help fixing them.

The first part of this article deals with the process needed to extract the coordinates of the trees relative to the robot from the raw pointcloud of the lidar. Then, the side effects occurring at the boundary of the visibility scope of the sensor are described and a solution is proposed. Thirdly, the characterization of motion and observation noises through statistical analysis of simulation data is detailed. Finally, a conclusion gives an insight of the remaining topics to be investigated.

2. Observation of trees

Since the SOMA robot evolves in the forest, trees fulfill the role of landmarks. The feature maps of the particles are made of a collection of the positions of these easily distinguishable objects.

In order to get their coordinates, trees must be found in the pointclouds generated by the lidar mounted on the robot. This first part of the process is performed by clipping the pointcloud in height to remove the ground and the canopy and then using euclidian clustering (Fig. 1). Once trunks are uniquely identified, a point has to be defined for each of them, involving polar coordinates in the local coordinate frame of the robot.

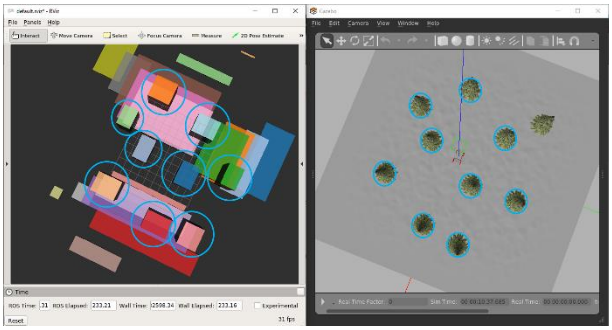

Fig. 1. Clusters made from lidar pointcloud (RViz on the left, Gazebo on the right)

2.1. *Centroids of clusters*

At first, the centroids of the clusters were chosen as the positions of the trees. However, a tree is never entirely captured by the lidar. In fact, only half of its perimeter is represented at the most. This leads to a mismatch between the geometric center of the points and the center of the tree projected on the plane. In addition, due to its dependence on the viewed part of the tree, the centroid varies with the pose of the robot relative to it[3]. This breaks the fundamental static world assumption, on which FastSLAM rests.

2.2. *Cylinder recognition*

In order to improve the accuracy and ensure the consistency of the positions of the trees, the use of pattern recognition has been proposed. The RANSAC algorithm is applied to fit a cylinder to each cluster and take the intersection of the axis of the cylinder and the plane to define the coordinates of the tree. All clusters are processed simultaneously in parallel, the synchronization being handled by the *message_filters* package of ROS.

2.3. *Comparison*

The use of cylinder recognition meets expectations, as it can be seen on Figure 2. Its addition to the poincloud processing leads to much lower final errors, divided by ten for the pose and by more than three for the map.

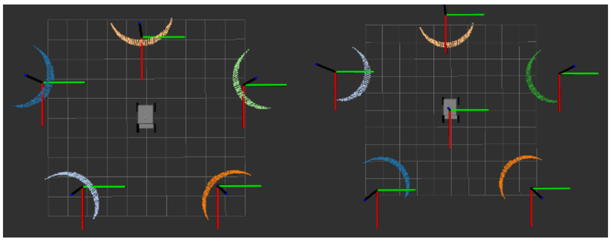

Fig. 2. Positions of trees found by using centroids of clusters (left) and cylinder recognition (right)

3. Side effects of visibility scope

Like every sensor, lidar has a maximum range of operation, which can be roughly defined by a circle of a certain radius around it. This boundary which separates the visible and the invisible is subject to side effects during data association.

Indeed, because of observation noise, the landmark in the map of a particle corresponding to the tree seen by the real robot can be out of the visibility scope but very close to the boundary. On the contrary, the real tree associated to a visible landmark in the map of a particle can be just beyond the limit (Fig. 3). If no action is taken, in the first case, a new landmark is created in the map, and in the second one, the visible landmark is deleted from the map.

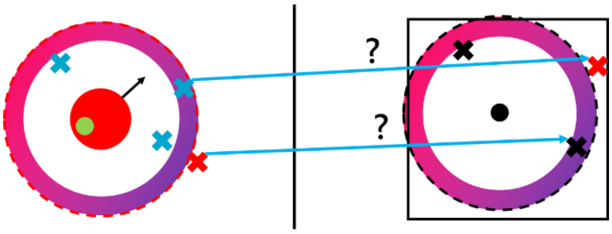

Fig. 3. Side effect occurring at the boundary of the visibility scope of the lidar (real robot on the left, particle on the right)

3.1. *Loose boundary*

One remedy to this issue is to define an area around the visibility boundary in which real trees and map landmarks are not taken into account. Using this conservative approach prevents from improper creations and deletions of features in maps, at the expense of an under-use of observation data.

This airlock area is located between the maximum range circle and a smaller one based on the correspondence threshold. The former is defined such that no tree closer to the robot could be associated with an invisible landmark, and vice versa. The radius of this circle is different for each observation and landmark, because its definition requires a distance to the robot pose to be compared to the maximum range.

More precisely, the procedure applied through multiple data association is the following. Each individual observation situated in the loose boundary or possibly associated with a landmark located in this area is thrown away. Then, the Gale-Shapley algorithm is executed to associate real trees to features in the map[3]. During this step, only visible features outside the airlock zone are considered. Finally, if a tree is not represented, a new landmark is created, and features which are orphan and could not correspond to unprocessed observations are deleted.

This procedure allows the final average map error to be divided by two.

4. Motion and observation modeling

In order to implement the FastSLAM algorithm, motion and observation noises have to be modelled. The movement of the robot is decomposed into three parts: a first rotation, a translation and a second rotation. Regarding observation, it consists of distance and azimuth between the viewed tree and the robot. The noisy values taken by these five variables are assumed to follow a gaussian distribution whose standard deviation is a linear function (Eq. 1).

$$\delta rot1 \sim \mathcal{N}\big(\underbrace{\overline{\delta rot1}}_{\mu_{rot1}}, \underbrace{a_{rot} \cdot |\overline{\delta trans}| + b_{rot} \cdot |\overline{\delta rot1}| + c_{rot}}_{\sigma_{rot1}}\big) \qquad (1)$$

The coefficients of these linear functions need to be adjusted to explain experimental data. As a first step, simulation has been used to characterize them.

4.1. *Statistical analysis*

Since the same procedure has been applied for each variable, its description will only be made for the first rotation of motion.

First of all, the true value of all the parts of motion and the noisy value of first rotation are recorded during a simulation in which the robot is moved in a diversified manner. The time interval used for estimating motion has to be carefully chosen, otherwise the final results would not be usable. As a general rule, it needs to be approximately equal to the time interval between two executions of the FastSLAM algorithm. Similar movements are then grouped to compute the associated variance of the gaussian distribution they are drawn from. This is done for each group by using maximum likelihood estimation. Then, after having removed abnormal values, non-linear least squares are applied on these new points to find the best hyperplane minimizing residuals. The results are graphically represented by Figure 4.

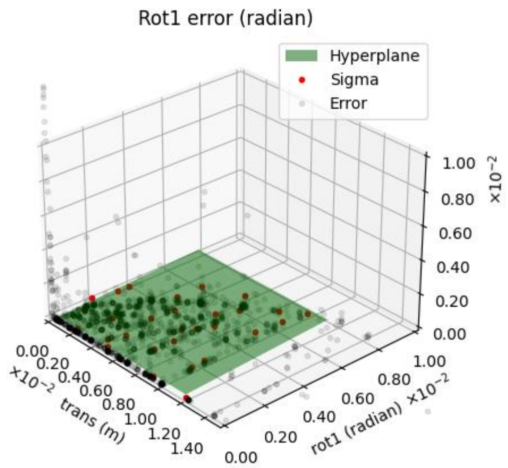

Fig. 4. Non-negative least squares estimation of the parameters of first rotation noise

Globally, the values of the parameters of motion and observation noises derived from simulation data are close to manually tuned ones. They are gathered in Table 1 and Table 2.

Table 1. Estimation of the parameters of motion noise

Errors / Factors	Translation	Rotation	Constant
First rotation	0.0	0.06	0.0002
Translation	0.02	0.006	0.00003
Second rotation	0.0	0.06	0.0003

Table 2. Estimation of the parameters of observation noise

Errors / Factors	Distance	Constant
Distance	0.005	0.0
Azimuth	0.0005	0.0

5. Conclusion

5.1. *Achievements*

Implementing FastSLAM on a real platform arouses numerous issues from which results can suffer.

At the beginning of this article, the localization of trees, essential for the whole algorithm, has been addressed. Centroids of clusters identifying trees have proved to be inconsistent and inaccurate estimates. However, applying RANSAC on these clusters to fit cylinders to them generates satisfactory locations for landmarks.

A sharp boundary for the lidar visibility scope causes side effects at the source of wrong maps with orphan and twin features. In order to limit inopportune creations and deletions of landmarks, an airlock area relative to each observation and feature can be defined according to the correspondence threshold. All trees within this loose boundary are not considered for data association anymore, leading to a wasteful but safe method.

Finally, motion and observation models need to be tuned to reflect the real behavior of actuators and sensors. Instead of manual tuning, which can cause overestimation or underestimation of noise and thus distorts performance, advantage can be taken of simulation or experimental data by using statistical analysis. Non-linear least squares method has been proposed as the core of this approach to find optimized noise parameters for motion and observation.

Providing an answer to these problematics has improved stability and accuracy of pose and map estimates, as it can be seen in Table 3.

Table 3. Quantitative results of successive implementations of FastSLAM

	Centers of clusters	**Cylinders recognition**	**Visibility scope boundary**
Final pose error (m)	2.39	0.21	0.24
Final map average error (m)	0.81	0.25	0.14
Redundant features	5	0	0
Orphan features	1	0	0
Update rate (Hz)	1	1	1

5.2. *Future research*

There are other issues which still need to be handled. Among others, the excellent accuracy of the lidar compared to wheel odometry sometimes leads to divergence of FastSLAM, because particles are generated based on motion only. This is possible that no particles lie within the vicinity of real pose at some point, making observation ineffective at promoting best particles. This drawback can be mitigated by using a mixture approach, where particles are generated by either motion or observation in a fixed or variable ratio.

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Authors Introduction

Mr. Sylvain Geiser

He studied Engineering and Computer Science in Ecole des Mines de Nancy, France, between September 2018 and June 2020. He is currently a Master student at Kyushu Institute of Technology, Japan, and conducts research at Hayashi Laboratory.

Dr. Sakmongkon Chumkamon

Dr. Sakmongkon Chumkamon received Doctor of Engineering degree from Kyushu Institute of Technology in 2017. He was a postdoctoral researcher at Guangdong University of Technology in 2017-2019. Presently he is a postdoctoral researcher in Kyushu Institute of Technology since 2019. His research interests include factory automation robots and social robots.

Projected Assist. Prof. Ayumu Tominaga

Projected Assist. Prof. Ayumu Tominaga is a professor in Department of Creative Engineering Robotics and Mechatronics Course at National Institute of Technology Kitakyushu College. He received the Ph.D. (Dr. Eng.) degree from Kyushu Institute of Technology in 2021. His research interests include Intelligent mechanics, Mechanical systems and Perceptual information processing.

Mr. Takumi Tomokawa

He received bachelor degree in Engineering in 2021 from mechanical system engineering, Kyushu Institute of Technology in Japan. He is aquiring the Master degree in Kyushu Institute of Technology.

Prof. Eiji Hayashi

Prof. Eiji Hayashi is a professor in the Department of Intelligent and Control Systems at Kyushu Institute of Technology. He received the Ph.D. (Dr. Eng.) degree from Waseda University in 1996. His research interests include Intelligent mechanics, Mechanical systems and Perceptual information processing. He is a member of The Institute of Electrical and Electronics Engineers (IEEE) and The Japan Society of Mechanical Engineers (JSME).