Localization Method of Autonomous Moving Robot for Forest Industry

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Abstract
In this study, we are developing an autonomous moving robot for labor-saving in forest industry. Traditional forest management and maintenance consumes excessive labor time. Particularly, the survey and weeding in the forest place large labor burden on the workers. Therefore, the robot which has the weeding mechanism can achieve to reduce the workload. In this paper, we discuss about localize of the robot in the forest. The Monte Carlo is applied for localization, and we are considering basic system.

Keywords: Forest industry, Autonomous moving, Monte Carlo localization, Particle filter

1. Introduction
In this study, we are developing a field robot for labor-saving of forest industry. The robot has a weeding mechanism, and autonomously moves in the forest. The goal is to automate both elimination of the weed plants and observing the growth quality of each tree.

Nowadays, the decrease labor force due to the decline the employment rate and the aging of working population are regarded as problem.1 In the forestry, between from planting to final cutting takes 50 to 60 years, while this time, the workers must do many tasks. Particularly, the weeding that carries out in summer places large labor burden on the workers. In addition, the survey of the forest on mountain and the observing the growth of each tree are also too. As the background to it, it can be said that planting density is high (3000 trees are planting per a hectare) and work on steep grade is forced. As a result, the survey is not sufficiently carried out, the work is delayed and devastation of the forest is occurring at present.

This study is proposing the autonomous moving robot that automates these tasks. The robot recognizes the external environment and avoid the trees (resources) by a depth sensor and a CCD camera.

In this paper, the method call Monte Carlo Localization (MCL) is used in localization system in forest. It is
thought that the localization system is necessary for the following points.
- Ideally, the weeding should be done all over the forest area. In order to move to an unreachable area, it is necessary to track the movement trajectory of the robot.
- When communicate to the user (forestry workers) about the growth of the observed trees, the location information of the tree in the forest is required.

2. System Structure

The robot under development used ATV (All Terrain Vehicle) as a base vehicle in order to cope with rough terrain in the forest. The appearance of the robot is shown in Fig.1. The external environment is recognized by a depth sensor and a CCD camera equipped on the ATV. The brake lever, accelerator lever and steering are controlled by DC motors. The weeding is performed by a multi-blade mechanism attached between the front wheels.

![Fig. 1. Appearance of the robot](image)

3. Autonomous Moving System

In this study, the functions required for the robot are to avoid of contact with the trees and to eliminate of weeds. It is important to have ability to keep moving more than anything else in the dynamic environment due to the growth of plants and so on. Therefore, we developed autonomous moving system that searches gap of trees that can pass through moves, mainly using depth sensor for recognition of external situations.

3.1. Determining of a Trajectory Path Using Depth Sensor

This subsection describes determining of a movement trajectory path using depth sensor. The depth sensor (InfiniSoleil FX8, Nippon Signal, Inc., Co.) installed on the robot is a product assumed for use outdoor by the TOF (Time Of Flight) measure method. The horizontal and vertical components of the viewing angle are 60 and 50 degree, respectively. The maximum measurable distance of the sensor is 15m. The Fig.2 shown flow chart of determining of the trajectory path.

At first, 3 dimensional point cloud data get from the depth sensor, and an image viewed in a bird’s eye view is created. Let this image be an x-z plane image. Next, the location, number and size of the object in front of the robot are recognized by labeling processing on the x-z image. Thus, the gap of each object that the robot can pass through is searched, the center point of the gap is set as the goal position of the robot should go.

![Fig. 2. Flow chart of autonomous moving system](image)

![Fig. 3 Motion model of the robot](image)
At last, calculate the steering angle and the distance to the target position based on motion model of the robot as shown in Fig.3. The actual movement distance is measured by a rotary encoder equipped to the rear wheel, when reach to the calculated distance, the system will return to the process at the top of flow chart.

3.2. Mapping for Depth Information and Color Information

In actual forest, not only the trees, but also weeds are growing. Therefore, the depth sensor will measure the distance of weeds too. As a result, the weeds is treated as an object to avoid target. Therefore, color information obtained from a CCD camera and depth information are integrated to extract three-dimensional distance information of the trees based on image processing.2

The coordinate relationship between the depth sensor and the CCD camera is shown by Fig.4. For simplicity, they are arranged in parallel and same height. \([X_d, Y_d, Z_d]^T\) is the point obtained from depth sensor, \([v, u]^T\) is the coordinate in color image, apply the perspective projection transformation matrix \(K\), the rotation and translation matrix \([R|t]\) between both sensors. Using the Eq. (1), the pixel coordinates in the color image with respect to the three dimensional coordinates are obtained.

\[
\begin{bmatrix}
    u \\
    v \\
    1
\end{bmatrix} = K \begin{bmatrix}
    X_d \\
    Y_d \\
    Z_d
\end{bmatrix} \quad \cdots (1)
\]

\[
K = \begin{bmatrix}
    f_x & 0 & o_x \\
    0 & f_y & o_y \\
    0 & 0 & 1
\end{bmatrix}, \quad [R|t] = \begin{bmatrix}
    1 & 0 & 0 & -b \\
    0 & 0 & 0 & 0 \\
    0 & 0 & 0 & 0
\end{bmatrix}
\]

4. Localization method using the trees as landmark

In this robot, it is thought that the localization system is necessary for the following points.

In rough terrain within the actual forest, it is expected that errors will be large with localization using dead reckoning. In addition, the star reckoning by a GPS system will be similar situation because influence of multipass.

We are considering the localization using the tree observed by the robot as landmark, and based on Monte Carlo Localization.

4.1. Expression of the Trees Map

In this study, the trees that the robot should be avoid are used a landmark for localization. The global map for global localization is constructed by the information of trees location. In this time, we made the trees map using data of the trees location measured by laser measuring instrument, and used occupancy grids map with 2 dimension expressed. The three map shown Fig. 5. The grids map’s range is 35 m square area with 0.5 m square grids. Each grid has occupancy value \(m_{xy}\) as shown Eq. (2).

\[
m_{xy} = \begin{cases} 
    0.0 & \text{(not occupied grid)} \\
    1.0 & \text{(occupied grid)}
\end{cases} \quad \cdots (2)
\]

Fig. 5. The tree map and occupancy grid map

4.2. Monte Carlo Localization

Monte Carlo Localization (MCL) is a method of estimating the state of robot by assuming the robot's pose with particles, comparing the results observed by each particle with the actually observed results, calculating the likelihood of the particle.3 It is realize by the following three steps.

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Predict step
\( \mathbf{x}_t = [x_t, y_t, \theta_t]^T \) is the state vector of the robot, and prepare a set of \( N \) particles with weight ( \( \mathbf{X}_t = (\mathbf{x}^{(i)}_t, \mathbf{w}^{(i)}_t), i = 1, 2, \ldots, N \) ). Each particle is transition according to the motion model \( f \) using previous state \( \mathbf{x}_{t-1} \) and the control input \( \mathbf{u}_t = [s \lambda]^T \). In following equation, \( \mathbf{e}_t \) is a noise component according to normal disturbing.

\[
\mathbf{x}_t' = f(\mathbf{x}_{t-1}', \mathbf{u}_t) \tag{3}
\]

\[
\mathbf{u}_t = \mathbf{u} + \mathbf{e}_t \tag{4}
\]

Update step
A likelihood of each particle is calculated by comparing information both of the actual observation data and particle’s observation data. First, a local map expressed by an occupied grids map by data that three-dimensional point cloud obtained from depth sensor is created. The coordinate transformation between the local coordinate and the particle \( \mathbf{x}_t^{(i)} \) in the global map gives the grid in the global map \( m_{x,y} \) corresponding to the grid in the local map \( m_{x,y,\text{local}} \). For each grid in the local map, calculate the correlation value with the global map from the Eq. (5) and (6).

\[
\rho_{m,m_{\text{local}}}^{(i)} = \frac{\sum_{x,y} (m_{x,y} - \bar{m}) (m_{x,y,\text{local}}^{(i)} - \bar{m})}{\sqrt{\sum_{x,y} (m_{x,y} - \bar{m})^2 \sum_{x,y} (m_{x,y,\text{local}}^{(i)} - \bar{m})^2}} \tag{5}
\]

\[
\bar{m} = \frac{1}{2M} \sum_{x,y} (m_{x,y} + m_{x,y,\text{local}}) \tag{6}
\]

The \( M \) is number of the grids corresponding between the local and global map. The correlation value takes a value \( \pm 1 \). The likelihood \( L_t^{(i)} \) of each particle calculates by Eq. (7). The weight of each particle is Eq. (8) with normalized likelihood.

\[
L_t^{(i)}(m_{\text{local}} | \mathbf{x}_{t}^{(i)}, m) = \max(\rho_{m,m_{\text{local}}}^{(i)}, 0) \tag{7}
\]

\[
w_t^{(i)} = \frac{L_t^{(i)}(m_{\text{local}} | \mathbf{x}_{t}^{(i)}, m)}{\sum_{i} L_t^{(i)}(m_{\text{local}} | \mathbf{x}_{t}^{(i)}, m)} \tag{8}
\]

Resampling step
According to the weight of each particle, resampling the particles. We adopted roulette selection algorm for it.

5. Verification Experiment
We experimented the localization mentioned before in test field. Number of the particles is 1000. Fig. 6 shown the result of update step, and the observations of particles with maximum weight in a \( t \). As the result, small diameter trees observed by the robot are contained large diameter trees observed by the particle. Therefore, it is thought that there is a possibility of adversely affecting the likelihood calculation in the updating step.

6. Conclusions
In this paper, we discussed about localization method in the forest. We are constructing the localization system by MCL. In the future, we aim to improve the position estimate accuracy of the robot.

References
   Ministry of Agriculture Forestry and Fisheries, (2016).