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Sensor fusion-based exploration in home environments using information, driving and localization gains

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ABSTRACT

Exploration is one of the most important functions for a mobile service robot because a map is required to carry out various tasks. A suitable strategy is needed to efficiently explore an environment and to build an accurate map. This study proposed the use of several gains (information, driving, localization) that, if considered during exploration, can simultaneously improve the efficiency of the exploration process and quality of the resulting map. Considering the information and driving gains reduces behavior that leads a robot to explore a previously visited place, and thus the exploration distance is reduced. In addition, the robot can select a favorable path for localization by considering the localization gain during exploration, and the robot can estimate its pose more robustly than other methods that do not consider localizability during exploration. This proposed exploration method was verified by various experiments, which verified that a robot can build an accurate map fully autonomously and efficiently in various home environments using the proposed method.

1. Introduction

In recent years, there have been various trials to extend robotic technology to non-industrial applications such as surgery, cleaning, patrol, and so on. Indoor mobile home service robots are receiving attention especially, because of their economic potential and social expectations [1–3]. In order to make mobile service robots more accessible in home environments, the problem of environmental modeling, which is one of the fundamental problems in mobile robots, should be solved first. This is because a mobile service robot uses a map to carry out various tasks, including navigation, human-robot interaction, and so on. Therefore, the simultaneous localization and mapping (SLAM) community has developed many efficient and highly accurate map-building techniques [4,5], but most of these techniques offer no proposals on how a robot can be made to function autonomously. However, autonomy is an important factor for environmental modeling of service robots. Therefore, various methods of exploration – the name typically given to automated map-building – have been proposed.

Frontier-based exploration, which explores the unknown area in a grid map, was proposed in [6]. In frontier-based exploration, a robot detects the regions between the unexplored area and the open space, designated as the frontier. The robot then moves to the new frontiers to explore them until the entire environment has been explored [7,8]. Frontier-based exploration has the drawback of not being able to use information known about obstacles, which can serve as a guide for the robot to move and correct its localization error. To overcome this problem, an autonomous exploration method using regions of interest was proposed [9,10]. In this research, the view that would result in the sensor data that could be used to maximize exploration efficiency was estimated. While this approach does improve exploration efficiency, it does not address map accuracy at all.

The aforementioned strategies are considered metric-based exploration methods. Another type of exploration method exists, known as topological information-based exploration. The most representative topological information-based exploration strategy is based on the Generalized Voronoi Graph (GVG) representation [11]. In Topological SLAM, developed for exploration of an unknown environment, the robot traces all GVG edges and visits all meet points and boundary points [12]. Additionally the extended Voronoi graph (EVG) was proposed [13]. In this research, both mid-line following and wall-following were used to control the robot motion and to model the environment. This strategy applies to complex indoor environments. However, in order to extract topological information and create a precise map, a robot tend to inefficiently navigate through all GVG edges, so map creation takes a long time. To overcome this inefficiency, thinning-based topological exploration (TTE) was proposed [14]. This scheme is based on

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the position probability of the end nodes of the topological map built in real time. The robot then updates the position probability of each end node sustaining its position at the current location using the range data. By analyzing this probability, the robot can determine whether or not it needs to visit the specific end node to examine the environment around this node. As a result, the TTE scheme can be conducted faster than the GVG-based exploration.

Semantic information-based approaches have also been proposed. This includes the classification of space into different categories such as rooms, corridors, roads, buildings and the addition of objects in a hierarchical map representation [15,16].

Two good criteria by which exploration effectiveness can be measured are the accuracy of the map and the efficiency. The efficiency means how fast the robot can finish the task of mapping with the minimum travel distance required to cover the entire environment. However, none of the above-mentioned approaches address both of these criteria simultaneously. Therefore, this paper proposed a sensor fusion-based exploration method using several gains. The contributions of this research are twofold.

Firstly, a robot can efficiently explore an entire environment using the information and driving gains. The information gain is designed to favor the destination that offers the most information about the unexplored area. This optimal destination is chosen by considering all possible destinations and choosing the best one among the candidates. Choosing destinations based on this gain allows the robot to increase the exploration efficiency. The driving gain was developed by considering traveling distance and direction. Therefore, the proposed method prevents the robot from exploring previously visited places, thus shortening the exploration distance. Secondly, the proposed method improves the accuracy of map building with the localization gain. The robot selects a favorable path for improving localization accuracy by using the localization gain during exploration. Thus, the robot can estimate its pose more robustly than other methods, which do not consider localizability during exploration, and build an accurate map. This paper is organized as follows. Section 2 describes basic techniques for exploration. Section 3 presents the exploration scheme, and experimental results are shown in Section 4. Finally, we present our conclusions in Section 5.

2. Basic techniques for exploration

In order to conduct exploration, a mobile robot must utilize a model of its environment based on the assumption of perfect localization. In this sense, both the creation of a grid map that is useful for robot operation and localization are the essential components of exploration. Therefore, this section explains two basic techniques necessary for exploration. Firstly, we will introduce occupancy grid mapping, through which we create a map that can be used for essential functions such as motion control and path planning. Then, we explain the extended Kalman filter (EKF) based SLAM method, which maintains and optimizes another map – distinct from the grid map and consisting of landmarks – that is used to localize the robot more precisely.

2.1. Grid mapping

In this section, we briefly introduce the occupancy grid mapping algorithm [17]. In order to build the grid map, a sensor model should be considered. The range data from the sensor possesses some noise. Therefore, the sensor model is designed with Gaussian uncertainty given by

$$p(r|z) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[\frac{-(r-z)^2}{2\sigma^2}\right] \tag{1}$$

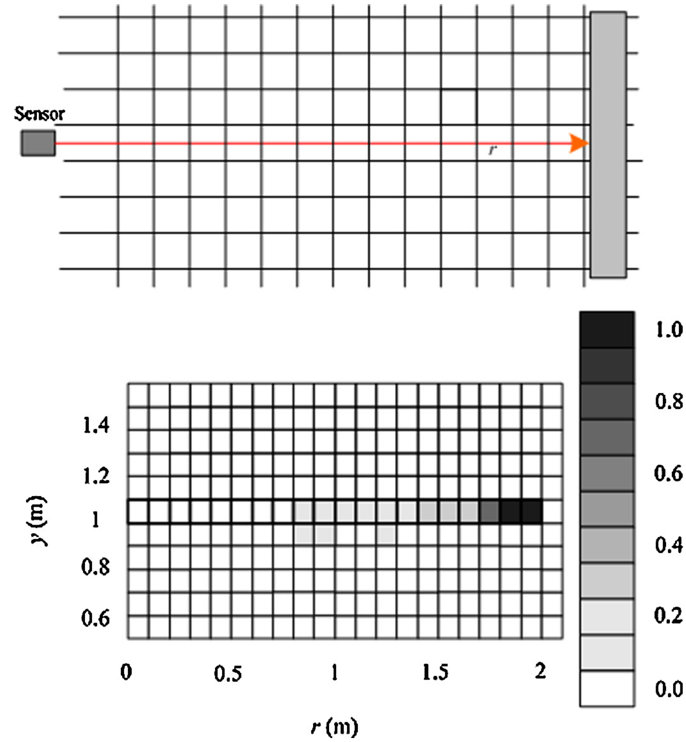

Fig. 1. The process of updating a grid map using range data from range sensors.

where r is a distance measured by a sensor (i.e., a laser scanner), z is the real distance and σ is the standard deviation associated with the uncertainty of both the grid map and the laser scanner. To allow the incremental composition of sensory information, occupancy grid mapping uses the Bayesian update formula in order to determine the cell occupancy probabilities.

$$P[s(C_i) = OCC|\{r\}_{t+1}] = \frac{p[r_{t+1}|s(C_i) = OCC] \cdot P[s(C_i) = OCC|\{r\}_t]}{\sum_{s(C_i)} p[r_{t+1}|s(C_i)] \cdot P[s(C_i)|\{r\}_t]} \tag{2}$$

where $s(C_i)$ is state of cell C_i, and it has two states: occupied (OCC) and empty (EMP). $\{r\}_t$ is the range data at time t and r_{t+1} is the newly measured range data at time $t+1$. Fig. 1 shows the procedure for updating a grid map using range data from range sensors by Eq. (2).

2.2. EKF-based SLAM

During navigation, a robot pose should be corrected continuously because the uncertainty of wheel odometry based on encoder data accumulates and gradually increases as the robot moves. Extended Kalman filter (EKF)-based SLAM is used in this research. The EKF is one of the most popular methods used for mobile robot localization and SLAM. It is an optimal sensor fusion method, which has been investigated for decades. The odometric error caused by an encoder can be compensated for by the EKF, which fuses different types of sensor data with weights proportional to the uncertainty of each sensor.

The EKF is used to handle nonlinearities involved in the motion of the robot and the state vector is defined as follows:

$$X = [X_r^T, X_{L_1}^T, \ldots, X_{L_N}^T]^T \tag{3}$$

where X_r is the robot pose given by $({}^W x_r, {}^W y_r, {}^W \theta_r)$ and X_{Li} is the position of the ith feature denoted by $({}^W r_i, {}^W \alpha_i)$, as shown in Fig. 2. The superscript W is placed before a value to indicate that it is expressed in the world frame. A robot estimates its pose by continuous prediction and update based on the EKF algorithm.