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RGB-D and Magnetic Sequence-based Graph SLAM with Kidnap Recovery

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Abstract: This paper introduces graph structure-based simultaneous localization and mapping (SLAM) using RGB-D and magnetic sensors. We also propose kidnap recovery with graph SLAM structure. The RGB-D sensor can measure the distance value of the corresponding image pixel and magnetic sensor can measure magnetic field distortion in an indoor environment. Since these two sensors have different characteristics, they have different strengths when performing SLAM. RGB-D sensor-based SLAM is suitable for complex 3D environments, and magnetic sensor-based SLAM provides better performance in feature-poor environments such as corridors. Thus, this paper introduces a robust SLAM system in indoor environment by taking advantages of both sensor characteristics. The proposed algorithm has been tested to verify the superiority of algorithms in indoor environment and kidnapping situations.

Keywords: SLAM, RGB-D sensor, magnetic sensor, kidnapping

1. INTRODUCTION

SLAM technology has been extensively researched in various robotics fields such as mobile robot navigation, autonomous vehicles, and 3D reconstruction for decades [1], [2]. The initial SLAM technology simultaneously corrects current states and updates the surrounding landmark using extended Kalman filter (EKF) method [3], then particle filter-based SLAM [4], [5] is proposed to solve non-linearity problem. Recently, graph structure-based SLAM algorithm [6], [7] is proposed to optimize all trajectories and measurements.

There is a major drawback that camera senors can not measure depth information of each pixel. To overcome this drawback, RGB-D sensors have been introduced that can measure depth information using various systems such as stereo cameras, time-of-flight (ToF), and infrared light approaches. Endres *et al.* introduces RGB-D SLAM algorithm using Kinect style RGB-D sensor [8]. Lee *et al.* proposed a real-time GPU-based 3D SLAM algorithm [10], [11].

Magnetic SLAM has been researched using the field distortions in indoor environments. Jung *et al.* introduces magnetic sequence-based matching for indoor pose graph SLAM [12]. This research proposes to match super nodes contained sequence node data for magnetic loop closing. Lee *et al.* proposes a dual-sensor-based vector-field SLAM (DV-SLAM) to overcome the ambiguity of magnetic sensor characteristics [13].

Since RGB-D sensor and magnetic sensor have different characteristics, this paper proposes a robust SLAM algorithm by taking strengths of these sensor characteristics. The first contribution of this paper is a robust RGB-D sensor matching method using a submap scheme of 3D point descriptions. The second one is a robust magnetic sequence matching using a Gaussian process-based node bundle matcher. The last contribution is a graph structure-based sensor fusion for SLAM, and we also propose a kidnap recovery by retaining the graph structure SLAM.

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2. THE PROPOSED GRAPH SLAM

2.1 RGB-D SLAM

The speeded up robust features (SURF) [14] and Scale Invariant Feature Transform (SIFT) [15] are mainly utilized in the past. Recently, oriented FAST and rotated BRIEF (ORB) feature [18] was introduced for license free and real-time operation. There are many researches using ORB feature for SLAM system [17]. Most researches perform feature extraction and matching on the only keyframe to maintain real-time operation. In this case, the algorithm works well in various feature environments, but it is difficult to apply in insufficient feature environments. Therefore, this paper applies a feature accumulation scheme called submap to overcomes this phenomenon. The submaps are generated by the accumulation of 3D features depending on the reliability of robot odometry. The Fig. 1 shows how it works in insufficient feature environments. The accumulated 3D points of feature, $\mathbf{M}$, in j-th submap, $\mathbf{s}_j$, is presented as follows:

$$\mathbf{M}_{\mathbf{s}_j} = \sum_{i=k\in\mathbf{s}_j}^{l\in\mathbf{s}_j} \mathbf{X}_0^{-1}\mathbf{X}_i T_C^R \mathbf{p}_i \tag{1}$$

where p_i denotes 3D feature points in i-th node, T_C^R is the coordinate transformation from the camera to the robot, and $\mathbf{X}_i$ denotes a transformation expression of i-th odometry. k and l denote the first and last node index of submap, respectively. The correspondence descriptors of ORB features are also accumulated in the submap.

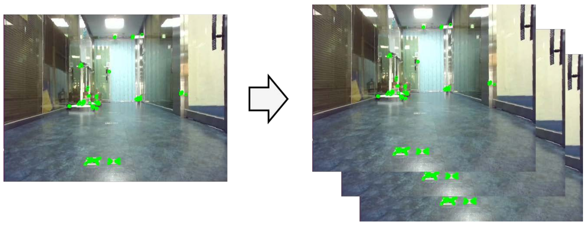

Fig. 1 The concept of submap by accumulating 3D feature point in insufficient environment.

For robust loop closing, this paper proposes two phases matching method. The first phase is to roughly match with submap. Since submap contains accumulative features, it is more efficient to match them than a normal matching in insufficient feature environments. The matching correspondences are estimated by a ORB-feature matcher. The relative pose with submap is estimated using random sample consensus (RANSAC)-based rigid transformation. In the second phase, the final relative pose between two nodes is estimated for a feature constraint. The rough matching result from the first phase finds the most relative pose of the submap according to the nearest node of the result, then the final relative pose is estimated by performing the rigid transformation again between two nodes.

2.2 Magnetic sequence SLAM

To estimate a distortion of magnetic field, the magnetic data of a single node is ambiguous. Similar to [12], the matching method is based on a super node scheme according to sequence data. Unlike with [12], the supernode is generated overlaid as shown in Fig. 2. According to [12], the matching cost is calculated by Eclidean distance between two vectors **p** and **q** as follows:

$$\text{cost} = \|\mathbf{p} - \mathbf{q}\|_2 \tag{2}$$

where $||\cdot||_2$ indicates L_2-norm. Using (2), each supernode is matched and can be made a connection as shown in Fig. 2. A graph structure is created on these connectivities to find the node bundle match. According to the connections of graph structure, final node bundle matches are estimated by grouping of nodes. Even though the node bundle matching has succeeded, it still has ambiguous matching result. Therefore, we propose a linear correction using Gaussian process (GP) [18]. The GP function is generated by the magnetic data of target bundle node, then the query bundle node matches to target bundle node as follows:

$$x^* = \underset{x}{\operatorname{argmin}} ||GP(\mathbf{q}, T_x\mathbf{p})||_2 \tag{3}$$

where GP denotes GP function and T_x denotes a transformation matrix of x-axis. To optimize (3), a scanning strategy is utilized for the linear correction. The final relative pose between node bundles is estimated from T_x for magnetic constraints.

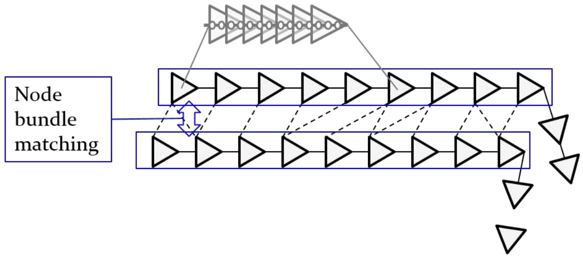

Fig. 2 The concept of node bundle matcher.

2.3 Sensor fusion

This section introduces how to make sensor fusion of RGB-D and magnetic sensors using a graph structure. In the previous sections, image and magnetic-based constraints are generated for pose graph SLAM. Since the magnetic matching is based on sequence data, a small node interval is required. On the other hand, the feature matching needs a certain distance of the node interval for real-time operation. Therefore, this paper introduces a graph structure-based sensor fusion method according to different loop closing update cycle as shown in Fig. 3. Since the node bundle for magnetic matcher contains a drift error, the node bundle match is subdivided according node-to-node constraints as shown in Fig. 3.

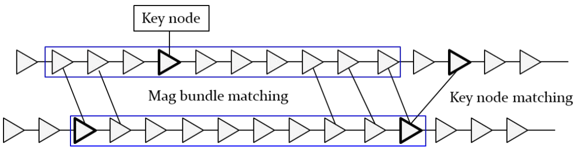

Fig. 3 The concept of sensor fusion using unsynchronized loop closing update.

2.4 Relocation

In the kidnapping situation, the previous graph structure is no longer available because the odometry constraint is invalid. Therefore, this section proposes to maintain graph structure in kidnapping situation. The wheel sensor of robot can recognize the kidnapping. When kidnapping is detected, the odometry constraint is no longer generated, then kidnapping process is performed through the same ways of RGB-D and magnetic matching. Once matching is succeeded, the initial pose is estimated from the matched pose and relative transformation as shown in Fig. 4. After the kidnap recovery, the graph structure is generated in the same way.

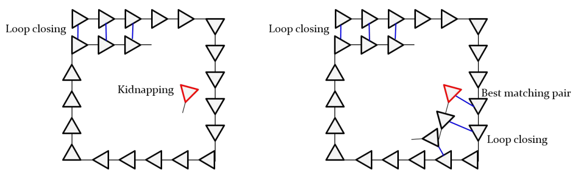

Fig. 4 The concept of kidnap recovery by maintaining the graph structure.

3. EXPERIMENT

The experiment is conducted by a mobile robot, Turtlebot2 Kobuki, as shown in Fig. 5. The equipped sensor system consists of a RGB-D (Asus Xtion) and two magnetic sensors (Xsens MTi-300). The proposed method is processed on real-time with on-board processor (i7 NUC miniPC). The experiment is set to 3 laps and kidnapping situation in the 8.5m $\times$ 13m indoor environment as shown in Fig. 6. Fig. 7 shows all trajectory result. Google Cartographer [19] is utilized for the ground truth using a 2D LiDAR sensor (Hokuyo UST-20LX) and the result is shown in Fig. 8. The root-mean-square deviation error (RMSE) is 0.12m on all the trajectory. Relocation is tested successfully 5 times by maintaining the graph structure. The 3D visualization result of the proposed method is shown in Fig. 9.

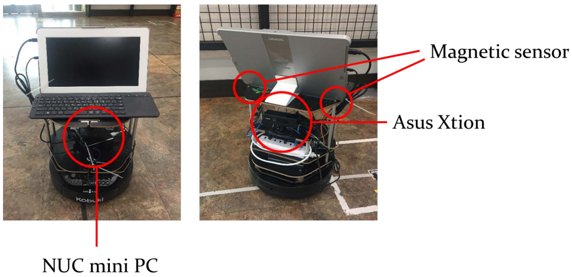

Fig. 5 The robot system for experiment.

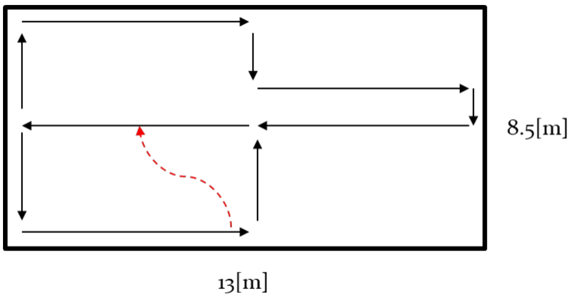

Fig. 6 The experimental method.

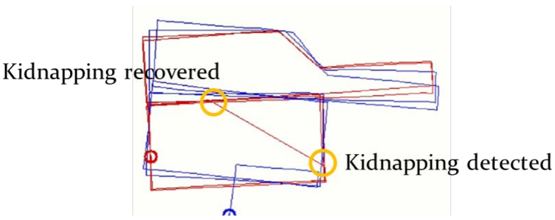

Fig. 7 The all trajectories of SLAM (red) and odometry result (blue).

4. CONCLUSION

This paper introduced RGB-D and magnetic sequence-based graph SLAM with kidnap recovery. The robust RGB-D and magnetic matching methods are proposed using submap scheme and Gaussian process, respectively. This paper also proposed a kidnap recovery algorithm by maintaining the graph structure. The proposed method is verified by testing in indoor environment.

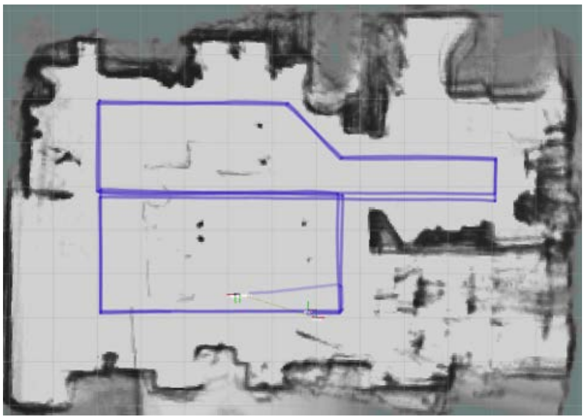

Fig. 8 The result of Google Cartographer algorithm.

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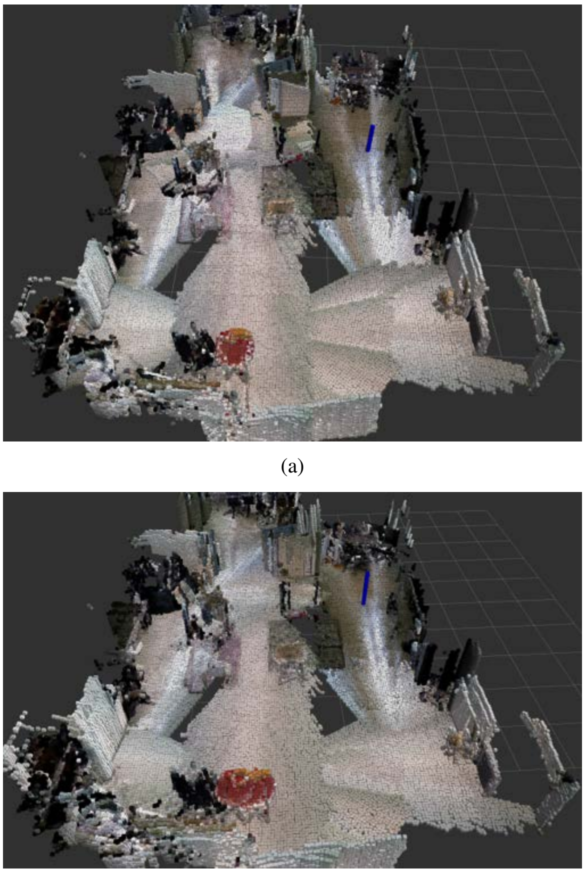

(a)

(b)

Fig. 9 3D visualization result according to the proposed method (a) and odometry (b).

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