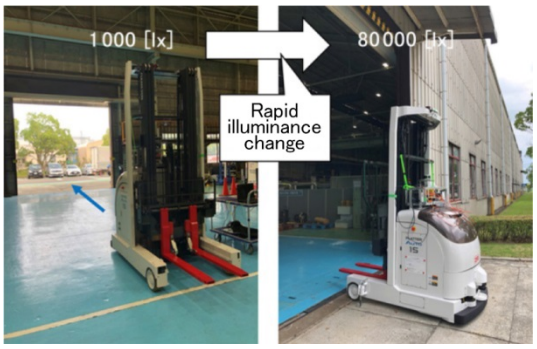
Robust and Accurate Self-Localization Method under Varying Lighting Conditions



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For guiding industrial AGVs (Automatic Guided Vehicle), robust self-localization method is indispensable. Visual SLAM (Visual Simultaneous Localization And Mapping, hereafter V-SLAM) using a camera is one of the self-localization methods that can be used indoors and does not depend on artificial landmarks. However, in a semi-outdoor environment affected by sunlight, since the lighting conditions fluctuate rapidly, the self-localization methods process using V-SLAM may become unstable. Therefore, Mitsubishi Heavy Industries, Ltd. (MHI) has developed a robust and accurate self-localization method for operation under varying lightning conditions, by combining 2D LiDAR, standard equipment of many industrial AGVs, with V-SLAM, and also integrating internal sensors using extended Kalman filter.

1. Introduction

MHI Group is developing mobile robot products such as disaster response robots,[(1)] plant patrol inspection robots[(2)] and unmanned forklifts.[(3)] Commonly for these products, self-localization method method, which estimates the position and orientation of the robot in real time, is indispensable.

In GNSS（Global Navigation Satellite System）-denied indoor environments, one of the most common approach is using artificial landmarks (beacons, reflectors, image markers, etc.). However, there are challenges associated with operability because such approaches require system re-construction after changing the equipment layout.

In recent years, SLAM has been attracting attention as a self-localization method that can be used indoors without artificial landmarks. SLAM is a method that simultaneously estimates self-pose and constructs a map, and its mainstream approach is to use topographical features that exist naturally and image features. In order to apply SLAM to navigation of industrial AGVs operating under environments such as factories or warehouses, it is important to ensure robustness to environmental changes. Industrial AGVs basically move indoors, but stable self-localization needs to be possible even in areas that are strongly affected by sunlight (semi-outdoor environments).

This report outlines a SLAM design that realizes accurate and robust self-localization for operation under varying lighting conditions, by combining 2D LiDAR, standard equipment of many industrial AGVs, with V-SLAM, while also integrating internal sensors using extended Kalman filter.

2. Realization of robust self-localization process by integrating multiple sensors

2.1 Functional configuration

This technology uses a wheel encoder and an inertial measurement unit (IMU) as the internal sensors, and a monocular camera and 2D LiDAR as the external sensors (**Figure 1**). The internal sensors and 2D LiDAR are not affected by lighting conditions. Therefore, even in situations where

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the lighting conditions fluctuate rapidly, the self-localization performance can be maintained by the internal sensors and 2D LiDAR. The components of this technology, V-SLAM, LiDAR SLAM and extended Kalman filter (EKF), are described in detail in Section 2.2, Section 2.3 and Section 2.4, respectively.

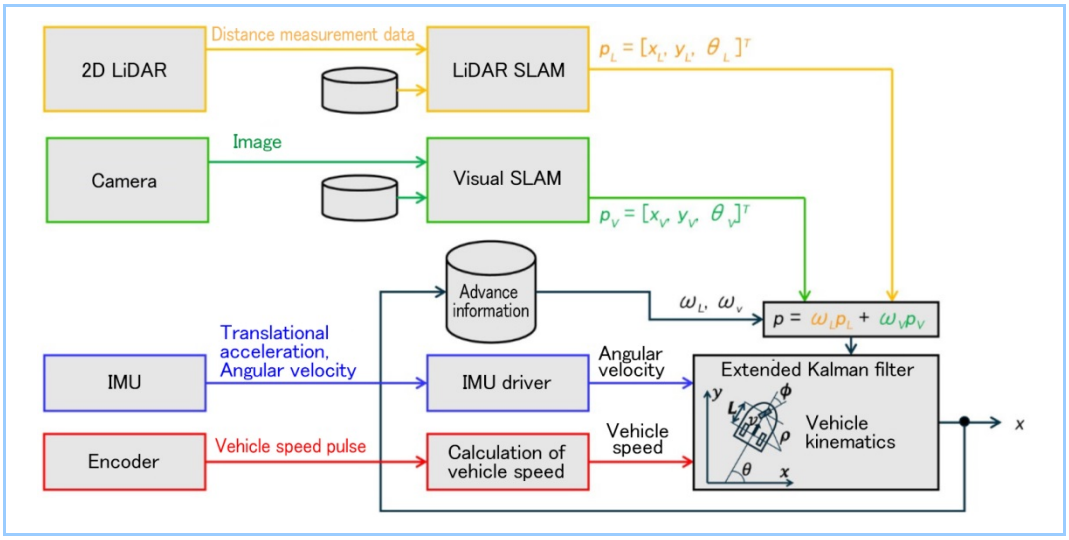

Figure 1 System configuration

2.2 V-SLAM

A monocular camera cannot directly acquire distance information, unlike LiDAR. For this reason, it is difficult for monocular V-SLAM to obtain a map that matches the scale of the real space, which leads to low self-localization accuracy due to the scale drift of the map. Therefore, we have improved the self-localization accuracy by correcting the map using 3D LiDAR. In contrast to monocular cameras, 3D LiDAR can directly acquire distance information, has a wide field of view and also it is robust to fluctuations in lighting conditions. For this reason, in many cases SLAM using 3D LiDAR is capable of more accurate self-localization than monocular V-SLAM. Therefore, by executing both V-SLAM and 3D LiDAR SLAM at the time of map construction and comparing the self-localization results, the amount of error correction for the map constructed by V-SLAM was determined.

Figure 2 shows the relationship between coordinate systems at the time of self-localization. $\{K\}$ represents the self-pose at a certain moment (key frame) estimated by V-SLAM at the time of map construction. $\{L\}$ represents the self-localization result of 3D LiDAR SLAM corresponding to the key frame. The difference between $\{K\}$ and $\{L\}$ is the error of the map constructed by V-SLAM, which is the amount of correction for V-SLAM. $\{C\}$ is the self-pose by V-SLAM based on the relative displacement with the key frame $\{K\}$. By performing correction using the relationship between $\{K\}$ and $\{L\}$, a high-precision self-localization result $\{A\}$ can be obtained with V-SLAM.

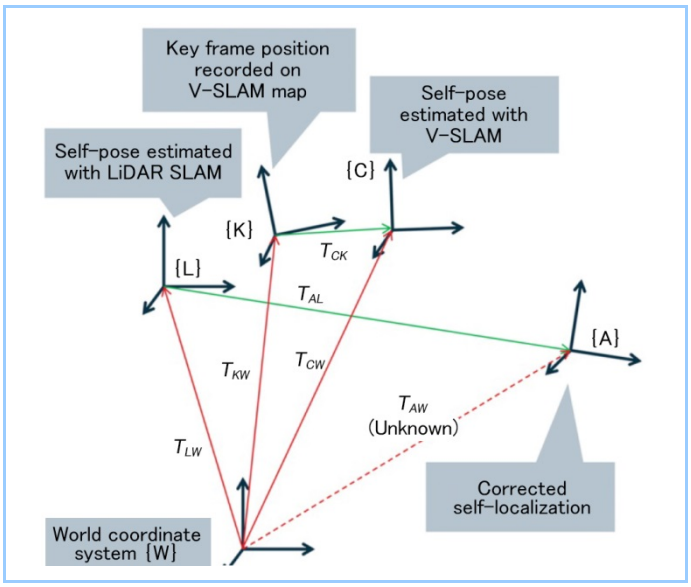

Figure 2 Relationship between coordinate systems

2.3 LiDAR SLAM

Many industrial AGVs are equipped with 2D LiDAR to prevent collisions. Self-localization with 2D LiDAR SLAM was performed using this existing 2D LiDAR. In the case of LiDAR SLAM, similarly to V-SLAM, a method of obtaining the self-pose by collating the data from the sensors with a map constructed in advance is generally used. However, existing 2D LiDAR is often installed in a low position on the vehicle body and the field of view is easily occluded by dynamic obstacles. Since the camera faces toward the ceiling in our design of the V-SLAM, the field of view can always be ensured. However, SLAM using the existing 2D LiDAR cannot always secure the field of view and map matching may fail. Therefore, SLAM using the existing 2D LiDAR was made able to use both a method of using a particle filter on the premise of collation with the known map[(4),(5)] and a scan matching method that aligns terrain patterns by sequential optimization processing without collation with the known map[(6)].

2.4 Integration of sensors using extended Kalman filter

Through movement model calculation (odometry) of an AGV using internal sensors, self-localization results with a short calculation cycle and small variance can be obtained. However, since integration operation is included, error accumulates over time. On the other hand, self-localization using external sensors (V-SLAM and LiDAR SLAM) undergoes only a small effect of the cumulative error, while the calculation cycle is long and the variance is large. Therefore, by integrating the information from the internal and external sensors using EKF (sensor integration) to combine the advantages of both, self-localization with a short calculation cycle, small variance and cumulative error can be realized.

As shown in Figure 1, we calculate linear combination of self-localization results of LiDAR SLAM and V-SLAM using weighting parameters ω_L and ω_V before input to BKF. These weights are set in advance for each location on the map and selected according to the current position of the AGV. This design allows us to robustly localize the vehicle by setting larger values on suitable sensors at each location. For example, in semi-outdoor environments the weight of 2D LIDAR should be larger, while in environments with poor geometrical features the weight of the camera should be larger and sensor integration according to the characteristics of the position can be performed.

3. Verification test

In order to verify the effectiveness of the design, we carried out a self-localization test using an actual AGV. The true pose used for error evaluation was measured by tracking the target marker attached on the AGV with a laser tracker. The test was conducted in an indoor environment and a semi-outdoor environment. The results of each test are described in Section 3.1 and Section 3.2.

3.1 Indoor self-localization test

The results of the indoor self-localization test are shown in **Figure 3** to **Figure 5**. Figure 3 illustrates the movement path of the AGV and the sensing status of the camera and 2D LiDAR during the test. The AGV departed from the starting position, passed through points A and B and traveled back to the original location. While moving, the AGV switched its moving direction multiple times to make the self-localization error of the internal sensors easier to accumulate. For this test, a situation where the field of view of the 2D LiDAR would be frequently obstructed by dynamic obstacles and temporarily placed objects was assumed, so LiDAR SLAM (scan matching), which is not premised on collation with the known map, was used.

The test results indicate that the self-localization result of our method achieved an error of 70 [mm] or less when compared with the true pose measured by the laser tracker (Figure 4). In addition, by comparing the accuracy between V-SLAM and LiDAR SLAM (Figure 5), it was confirmed that when the fluctuation of the lighting conditions is small, the accuracy increasing method with V-SLAM described in Section 2.2 can obtain self-localization accuracy comparable to LiDAR SLAM.

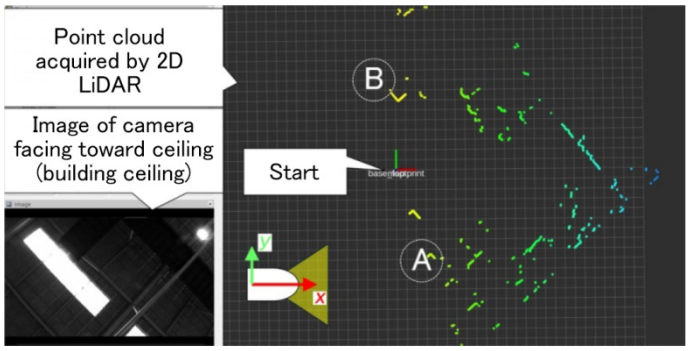

Figure 3 Indoor self-localization test

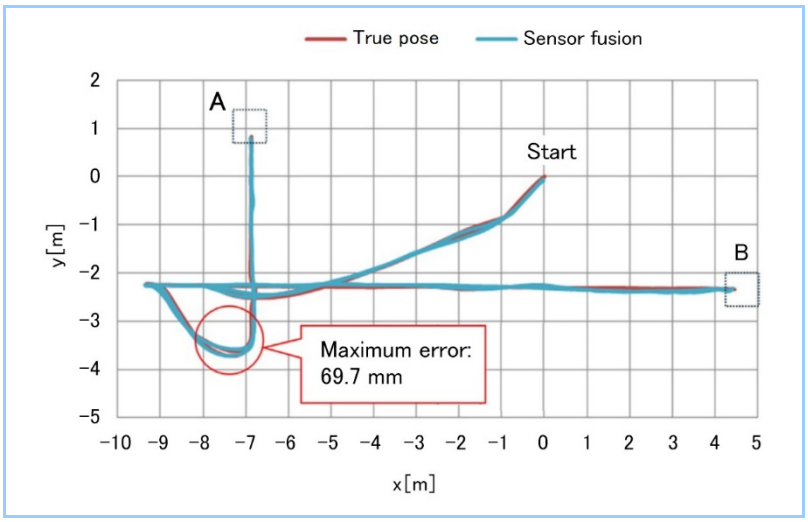

Figure 4 Results of indoor self-localization test (1/2)

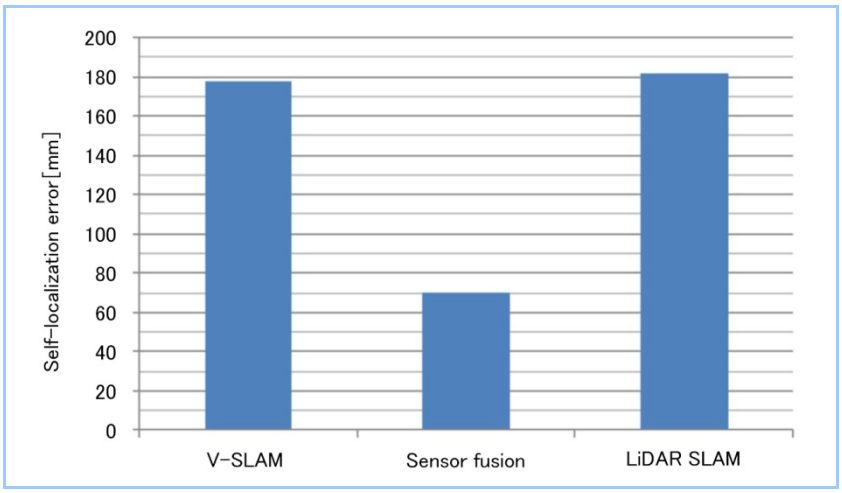

Figure 5 Results of indoor self-localization test (2/2)

3.2 Semi-outdoor self-localization test

Figure 6 to **Figure 8** give the results of the semi-outdoor self-localization test. In this test, a grid map for self-localization with 2D LiDAR (Figure 6) was created in advance and the self-localization was performed by collating it with the obtained map. Figure 7 presents a situation in which the self-localization process is executed in real time by collating the grid map with the laser scan (the colored areas in the figure are the point cloud obtained by laser scanning with 2D LiDAR).

Figure 8 shows the results of evaluating the self-localization accuracy. In this test, the AGV started from indoors and moved to the outdoors and the illuminance changed rapidly from about 1,000 [lx] to 80,000 [lx] due to the influence of sunlight. Even under such conditions, the result of the self-localization using our method achieved an error of 70 [mm] or less.

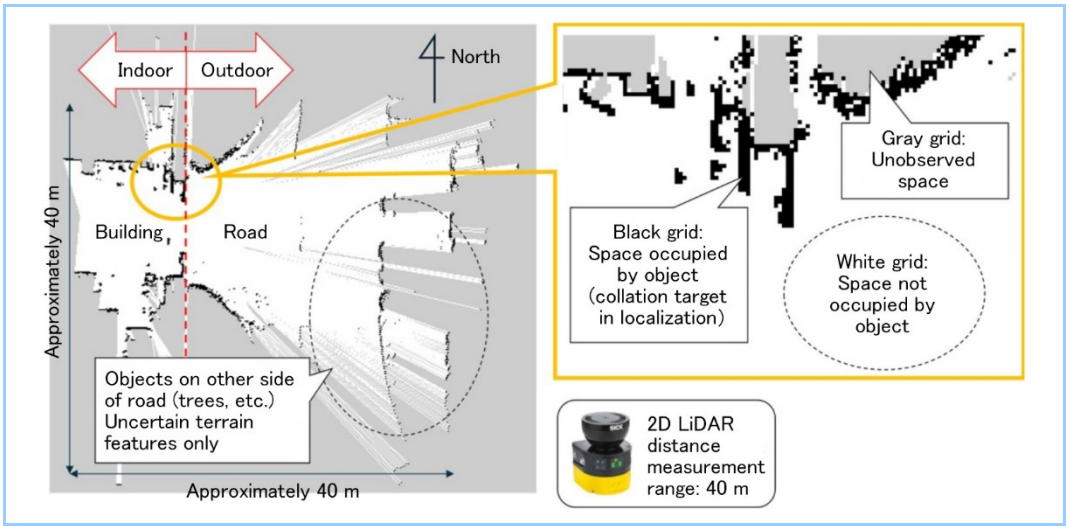

Figure 6 Grid map by LiDAR SLAM

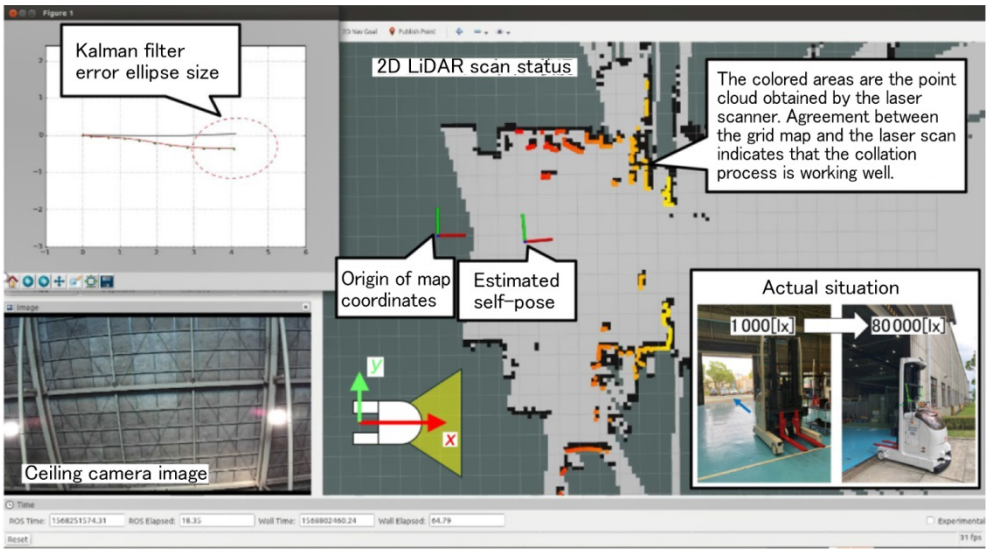

Figure 7 Semi-outdoor self-localization test

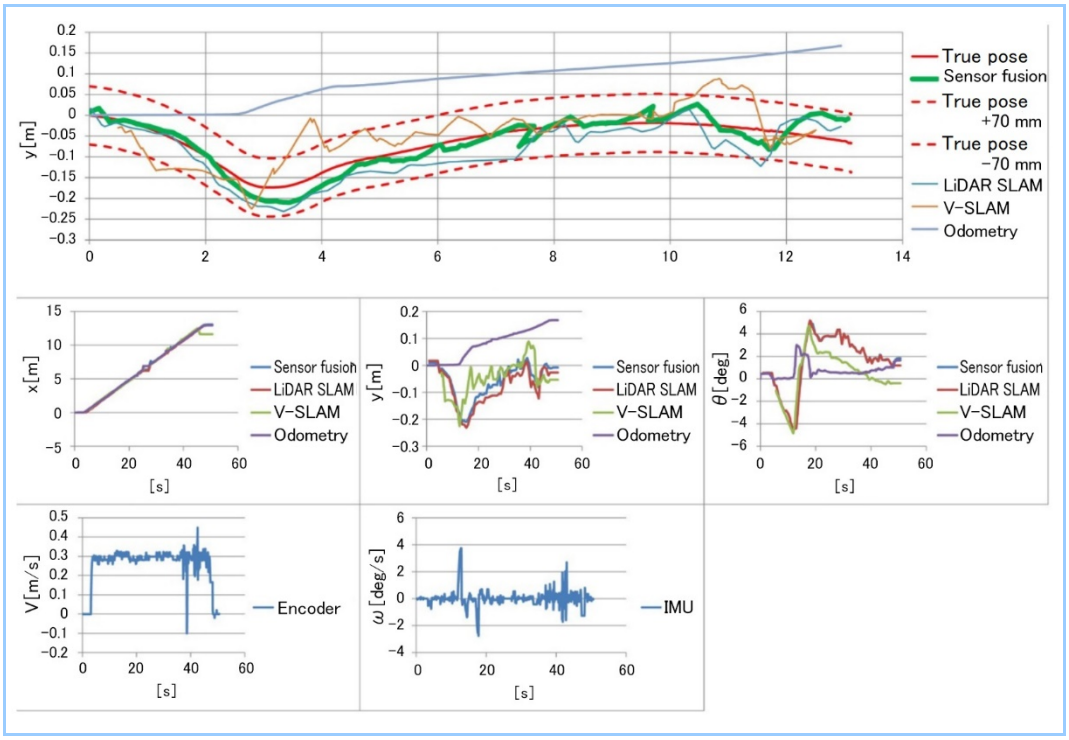

Figure 8 Results of semi-outdoor self-localization test

4. Conclusion

This report outlined SLAM design that realizes accurate and robust self-localization under varying lighting conditions by combining 2D LiDAR, standard equipment of many industrial AGVs, with V-SLAM, while also integrating internal sensors using an extended Kalman filter. We verified the effectiveness of our design through an evaluation test using an actual AGV and confirmed that our method can realize highly accurate and robust self-localization in indoor and semi-outdoor environments.

We will continue to develop sensor integration technologies that can deal with various environmental changes to further improve the reliability of self-localization method.

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