Glass and Non-glass Objects Classification Using a Single Laser Rangefinder for Mobile Robots

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***Abstract*— In this paper, we propose a method to classify glass and non-glass objects for mobile robots using a single laser rangefinder (LRF) in indoor environments. The classification results are used to build a glass grid map. Specifically, to classify objects, a mapping from (i) the LRF's received intensity, (ii) measured distance and (iii) corresponding incident angle to material type is proposed. The mapping is built based on a 4-layer neural network. An experiment was performed to verify our method, and results show that our proposed method can successfully classify glass and non-glass objects accurately.**

I. Introduction

In mobile robot localization and mapping using LRFs, objects are assumed to be detectable for all incident angles, but glass cannot be detected for large incident angles. The glass detection failure negatively affects robot localization and mapping accuracy, decreasing the safety of service robots in human environments. In order to solve the problem, a glass grid map showing glass or non-glass objects' positions, is needed. The challenging point in building a glass grid map is to classify glass and non-glass using a single LRF. In previous works, Koch et al. [1] solved it using a multi-echo LRF. However, their method needs a special type of LRFs and does not work on common LRFs. Wang et al. [2] achieved it using intensity features. But their method needs the LRF scan objects at 0 degree of incident angle, which is not always practical for mobile robots.

Our aim is to classify glass and non-glass objects using a common single LRF and relaxing the scan incident angle restriction, then build a glass grid map of the environment.

II. Methodology

According to physical theories, reflected light intensity I is mainly affected by object material type m, distance d and incident angle θ, which means a functional relationship among I, d, θ and m exists. Therefore, we propose to build the following mapping to classify glass and non-glass objects:

$$f(I, d, \theta) \rightarrow m \tag{1}$$

For mobile robots, I, d and θ are obtainable by using a common LRF and a on-line simultaneous localization and mapping (SLAM) algorithm. The output material m is glass or non-glass. We used a 4-layer neural networks to build the mapping. The neural network is trained using manually labeled experimental data, and the cross-validation results shows its successful classification rate is 97.3%.

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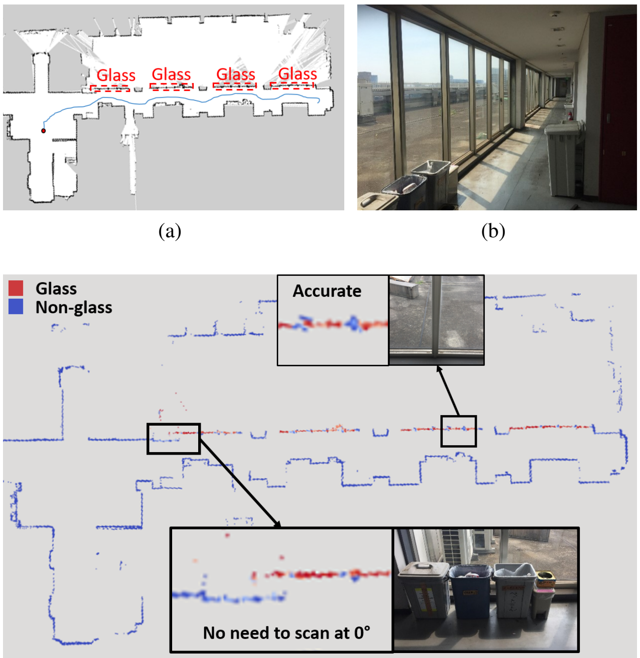

(a) (b)

(c)

Fig. 1. (a), (b) Experiment environment layout and photo. (c) Glass confident grid map generated by our method.

III. Experiment and Results

We performed an experiment to verify our method. Experiment environment is shown in Fig. 1 (a) and (b). We used a Hokuyo LRF and a Pioneer robot, which was tele-operated in the experiment. Figure 1 (c) is the glass grid map generated. As shown in the result, our method is of high accuracy, because even thin metallic frames can be correctly detected. Also, glass located behind several trash bins is also detected, proving that our method does not have to scan objects at 0 degree of incident angle to classify them.

IV. Future Work

Future work includes integrating our method with a localization algorithm and evaluating the improvement of localization and mapping accuracy using or method.

References

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