Robotics and Autonomous Systems 88 (2017) 97–103

Contents lists available at ScienceDirect

Robotics and Autonomous Systems

journal homepage: www.elsevier.com/locate/robot

Detecting glass in Simultaneous Localisation and Mapping

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ARTICLE INFO

Article history:
Available online 5 November 2016

Keywords:
Glass detection
SLAM

ABSTRACT

Simultaneous Localisation and Mapping (SLAM) has become one of key technologies used in advanced robot platform. The current state-of-art indoor SLAM with laser scanning rangefinders can provide accurate realtime localisation and mapping service to mobile robotic platforms such as PR2 robot. In recent years, many modern building designs feature large glass panels as one of the key interior fitting elements, e.g. large glass walls. Due to the transparent nature of glass panels, laser rangefinders are unable to produce accurate readings which causes SLAM functioning incorrectly in these environments. In this paper, we propose a simple and effective solution to identify glass panels based on the specular reflection of laser beams from the glass. Specifically, we use a simple technique to detect the reflected light intensity profile around the normal incident angle to the glass panel. Integrating this glass detection method with an existing SLAM algorithm, our SLAM system is able to detect and localise glass obstacles in realtime. Furthermore, the tests we conducted in two office buildings with a PR2 robot show the proposed method can detect ∼95% of all glass panels with no false positive detection. The source code of the modified SLAM with glass detection is released as a open source ROS package along with this paper.

1. Introduction

Simultaneous Localisation and Mapping, or SLAM, has become an essential component for a modern mobile robotic platform to build map of its surrounding environment, locate and navigate itself within the environment [1]. In recent years, most of state-of-art mobile robotic platforms are equipped with laser ranger finders to provide highly accurate inputs to SLAM algorithms. Together with sufficient computing power, mobile robots such as PR2 robot can now generate accurate mapping and localisation information in realtime [2]. Because laser range finders measure the distance to an object through reflected laser signals from the object, they are inherently ineffective in dealing with transparent objects such as glass panels. Most of laser signals from a laser range finder pass through glass panels without being reflected back to the sensor. The modern building designs feature more and more large glass elements in both exterior and interior of the buildings (Fig. 1(a)). Current implementations of SLAM with laser range data cannot produce correct results and our robot, therefore, cannot navigate and operate safely in such an environment (Fig. 1(b)). Being able to detect large glass panels that have been installed ubiquitously around office buildings has become a must solve problem before we can allow our service robots move around in these modern buildings. In addition to solving the navigation problem, being able to identify large glass panels also brings other important benefits. For example, under certain lighting conditions, glass panels will mimic large mirrors. This will confuse a robot perception system that is largely based on computer image processing. With the knowledge of glass panel locations, a robot should be able to distinguish whether an object appears in front of the robot is real or a more reflection.

Most existing approaches in addressing the limitation of laser rangefinders involve additional sensors such as ultrasonic sensors to provide complementary sensing information and employ sophisticated sensor/data fusion techniques [3–6]. We propose a simple and robust method to detect glass by measuring the intensity of reflected laser signals from the *normal* incident angle to the panels (Fig. 3). This method is based on the standard optical physics that highly polished materials such as glass specular reflects (most of) light. Glass detection using scanning laser rangefinders is only feasible in a small range of view angles directly towards the glass from where the reflected laser light is strongest. Several recent works used the same observation to develop sensor models and sophisticate algorithms to detect glass based on view angles [7,8]. In comparison, our detection method directly uses the intensity of the reflected light as the physical property to determined the presence of glass. It suffers less from uncertainties in sensor models and environmental noises.

We incorporated our detection method in an existing SLAM implementation GMapping and tested the modified SLAM algorithm

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http://dx.doi.org/10.1016/j.robot.2016.11.003
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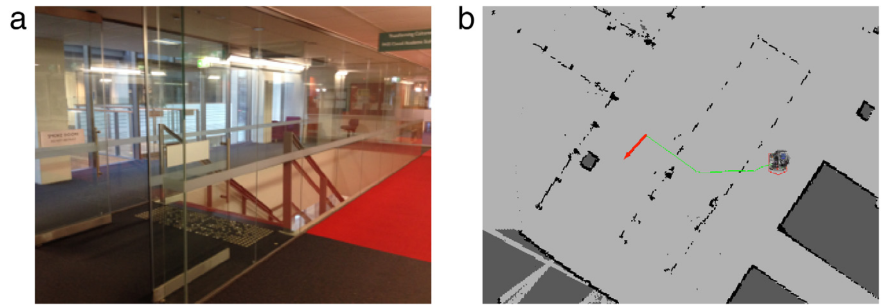


Fig. 1. Impact of indoor environment with glass panels on robot localisation, mapping and navigation. (a) A stairwell surrounded by large glass panels; (b) invalid map generated from the SLAM [2] with laser scanning rangefinders showing large gaps that should be marked as glass. Note that the incorrect planning path will guide the robot into the glass panel causing damages.

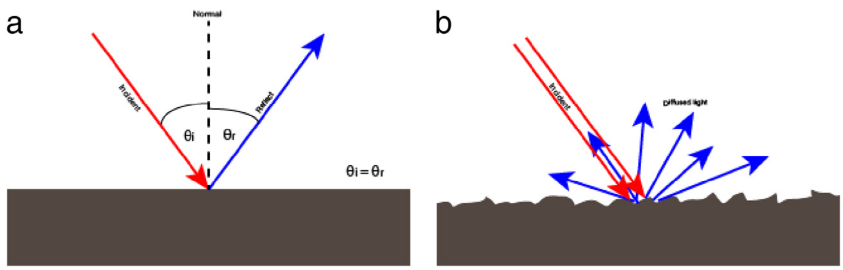


Fig. 2. (a) Specular reflection from a polished surface; (b) diffused reflection from an imperfect surface.

on a PR2 robot in two large office buildings. Our experiments show that accurate mapping and localisation can be generated when glass detection is enabled. In the following sections, we will first review the basic physics that underlies our method and provide a brief technical specification of the PR2 robot relates to our method. We then present an experiment setup and its empirical results that support our glass detection method using reflected laser intensity. This experiment also provides the necessary calibration information to set the detection method parameters. Finally, we will show the SLAM results, i.e. grid maps and localised robot trajectories, from the tests conducted in the two buildings with the PR2 robot and provide a brief discussion.

2. Laser and glass interaction

2.1. Reflections of laser pulses

When light, in our case laser pulses,[1] travel between two different materials, i.e. materials with different refractive indices, certain portion of light will be reflected. There are two types of reflections [9], specular reflection, i.e. light is only reflected at an angle (with respect to the surface normal) that equals the angle of incident, i.e. $\theta_i = \theta_r$ (Fig. 2(a)), and diffuse reflection, light is reflected at many different angles (Fig. 2(b)). Normal environments are dominated by diffuse reflections, because most objects have imperfect surfaces that cause light to reflect in many directions. In fact, this is how we are able to see things. Specular reflection only becomes prominent when the object that light incident on has a highly *polished* surface without irregularities. Large glass panels used in many modern buildings are both highly polished and transparent. Most of light that hits a clean glass panel will either transmit through the panel or specular reflected off the glass. These physical properties of glass panels make them difficult to be detected by robots. Under certain lighting conditions, even people have troubles to see glass panel clearly.

[1] We use light and laser pulses interchangeably in this paper.

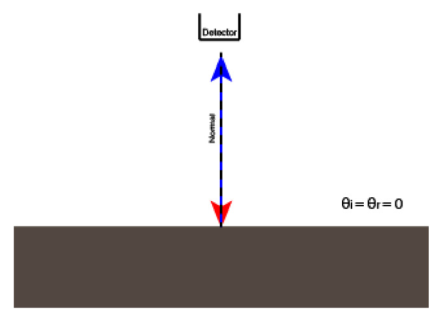


Fig. 3. Specular reflection of laser pulse back to the scanning rangefinder sensor.

A laser (scanning) rangefinder measures its distance to an object by detecting reflected light pulses (emitted by the sensor) from the object. That is, the light pulses must travel directly back to the sensor for them to be measured. In an environment dominated by diffuse reflections, only small percentage of reflected laser pulses that have the right reflected angle travel back to the sensor and consequently the *intensity* or the amount of light pulses collected by the ranger finder sensor remains low. When a laser rangefinder sends its laser to an object with a polished surface as Fig. 2(a), most of its laser pulses are specular reflected and do not return to the sensor. However, when the laser beam is sent along the surface normal (Fig. 3), most of *specular* reflected light will travel back to the sensor and the detected light intensity will be very high. Therefore, we can expect that when a laser scanning rangefinder scans across a polished surface, the sensor should record a sharp increase in reflected light intensity at the angles that are (very) close to the normal to the surface. We will use empirical data collected from the PR2 laser scanning rangefinder to verify our conjecture.

2.2. Laser scanning rangefinders on PR2 robot

PR2 robot is equipped with two Hokuyo Top-URG (UTM-30LX) scanning range finders [10]. One is mounted on the top of the robot

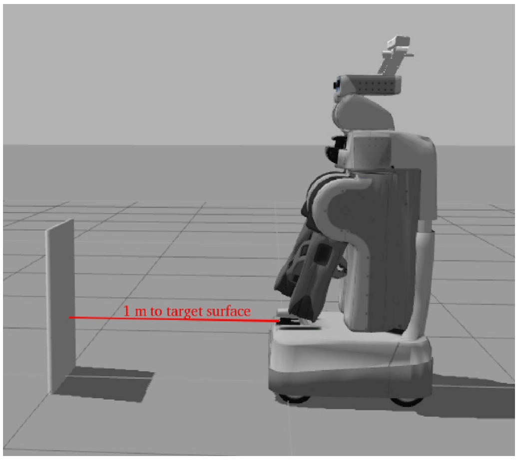


Fig. 4. Experimental setup: testing materials facing the PR2 base laser scanning rangefinder at 1 m distance.

base; the other is mounted on a tilting platform at the upper torso of the robot. We use the laser range finder fixed to the base in this work. The laser rangefinder has a 30 m and 270° scanning range. It can reliably provide both range and intensity[2] data at 10 scans per second. Each scan contains 1040 data points with angle increment of ∼0.25°.

2.3. Experimental data from PR2 laser rangefinder

We set up a experiment to find out the reflected laser intensity responses from different materials when the laser scanning rangefinder from the PR2 robot scans across them. We would like to verify our conjecture stated in Section 2.1. That is, there will be sharp increase of reflected light intensity at the angle along the surface normal to the target object with polished surface. In addition, the results from the experiments help us to determine the parameter values used in the glass detection algorithm.

2.3.1. Experimental setup

We selected a number of materials that are commonly available in our office environment and placed them directly in front of the PR2 base laser sensor at one metre and two metre distances. The base laser sensor was carefully aligned with the targeting material such that the mid point of the sensor was aligned with the surface normal of the target (Fig. 4). The materials used in the experiment are the following:

- **whitefoamboard**: a large white colour foam board.
- **glass**: a single layer toughened glass panel used as transparent office partition wall.
- **blackplastic**: a black colour plastic from a plastic toolbox.
- **mirror**: a large mirror.
- **blackfoam**: a black colour packing foam.
- **concretewall**: bare concrete wall.
- **drywall**: common dry wall that partitions office space.
- **whitereflectivemetal**: a metal file cabinet box with white colour high reflective coating.

Both range and intensity data from the sensor were collected for these materials. The results are shown in Fig. 5(a) and (b). n both plots, the horizontal x-axis shows the midsection of the laser rangefinder scanning range in radian. The zero point is the middle point of the sensor. The vertical y-axis represents the raw intensity values reported by the laser sensor.

The results in Fig. 5 clearly confirm our conjecture that polished surface such as glass panels and polished metal surfaces give very high intensity responses at zero incident angle at which most laser pulses are specular reflected back to the sensor. This sharp increase of intensity quickly disappears when the laser beam is not directly aimed at the target surface. A change in distance between the targets and the sensor does not have significant impact on the intensity response profile. Specifically, the mirror (pink line) and the glass panel (red line) have the two highest intensity responses at the zero point than any other materials used in our trials. They have similar intensity response profiles however the reflected laser intensity given by the mirror is more than twice of the intensity returned by the glass panel. More interestingly, the glass panel produces the sharpest response profile. A single angle change of 0.01 rad causes the intensity value to drop dramatically (>4000 change in intensity values). This result is not surprising since a mirror is basically a glass panel with reflective metal coating to enhance the light reflection. The slightly imperfect metal coating causes a small increase in diffused reflection and the broadening of the intensity response profile. As for the rest of materials used in the trials, the white reflective metal (blue line) gives the third highest intensity response with a considerably broader intensity response profile and the others are practically flat. Therefore, from these results, we are able to develop a simple and effective peak finding procedure to detect the intensity response profile from a glass panel and integrate the glass detection procedure into the existing SLAM algorithm.

3. DETECTING glass in slam

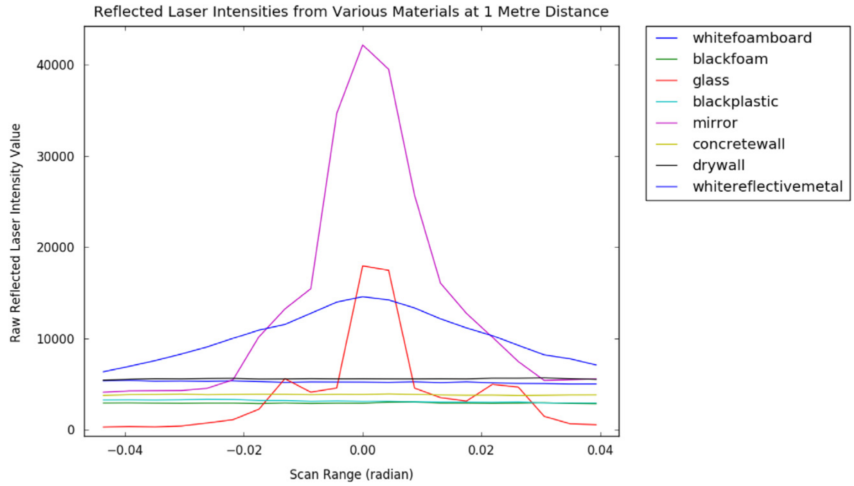
3.1. Detecting intensity response from glass

From the experimental results, a single layered glass panel produces the highest intensity response and the sharpest response profile when it is scanned by a laser scanning rangefinder, compared with other common materials found in an office environment. Through several experimentations, it turned out that the most effective way of finding such intensity response profiles from glass panels is finding peak (and near peak) intensity values within a line of laser scan data and using the adjacent data around the peak intensity value to determine the "gradient" and the width of the profile. The sharpest intensity profiles are those from glass reflections. Specifically, we use the procedure listed in Algorithm 1 to detect glass, in which three parameters are used:

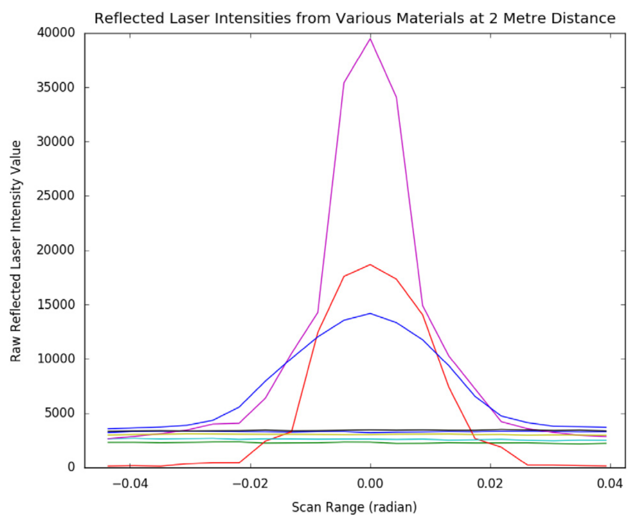
- *glassTrigIntensity* filters out all low intensity data since the intensity from glass must be very high.
- *glassIntensityDelta* filters out any low intensity variations since the intensity variation from the glass must be high.
- *glassProfileWidth* ensures the intensity profile stays narrow.

These three parameters set effective constraints on the intensity response profiles we wish to detect (Fig. 6). Using the experimental data we collected from Section 2.3, we used 8000, 4000 and 5 as the values for the three parameters respectively in the following SLAM with glass detection experiments. Note that, our glass detection procedure relies on a laser scanning rangefinder that can provide distance and intensity data with sufficiently high resolution, i.e. data samples with small angle increments less than 0.01 radian, over a large scanning range. There is a high probability that laser beams from the sensor can scan glass panels across their surface normals, detecting the distinctive light reflection intensity profiles from the glass (as in Fig. 5). A single detection of the intensity profile with the associated distance data represent a cell section on a detected glass object. Combined with a high scanning

[2] The base laser ranger finder on PR2 does not report intensity data by default, we use a custom configuration procedure to enable its reporting.



(a) A plot of reflected laser intensity responses at 1 m distance from the sensor.



(b) A plot of reflected laser intensity responses at 2 m distance from the sensor.

Fig. 5. Reflected laser intensity from a selection of materials placed in front of PR2 base laser scanning rangefinder. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

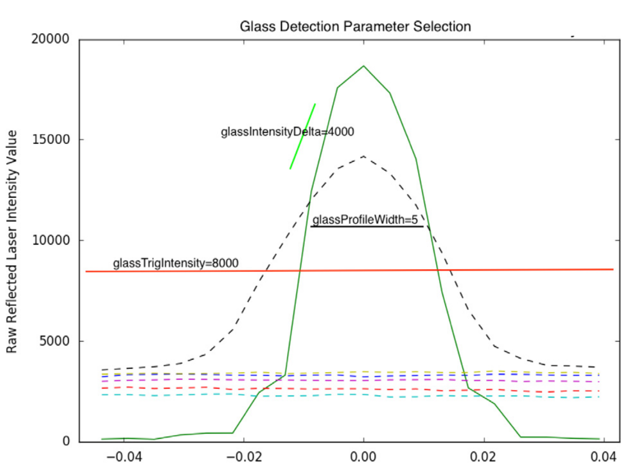


Fig. 6. Determining glass detection parameters from the 2 m single glass reflected intensity profile data.

rate and the fact that the sensor is mounted on a moving platform, this computationally inexpensive glass detection procedure can be easily integrated into an existing SLAM implementation to produce a glass gap-free indoor map of a building.

3.2. Integration with SLAM

We integrated the glass detection procedure described in the previous section with the existing PR2 SLAM implementation that is based on the OpenSLAM GMapping algorithm [2]. GMapping uses Rao-Blackwellized particle filter [11] to produce grid maps from laser range data. We modified the existing implementation to process laser intensity data alongside with the laser range data using Algorithm 1. Outputs from the glass detection are saved in a global *GlassDetectionCache*. After the best particle trajectory is computed and grid map is updated with latest laser range data, we match the raw glass panel positional data (range and angle) saved in *GlassDetectionCache* with the best particle trajectory using the saved timestamps. The raw glass panel position data are corrected using linear interpolation of the odometry correction information derived from the best particles against saved the raw odometry

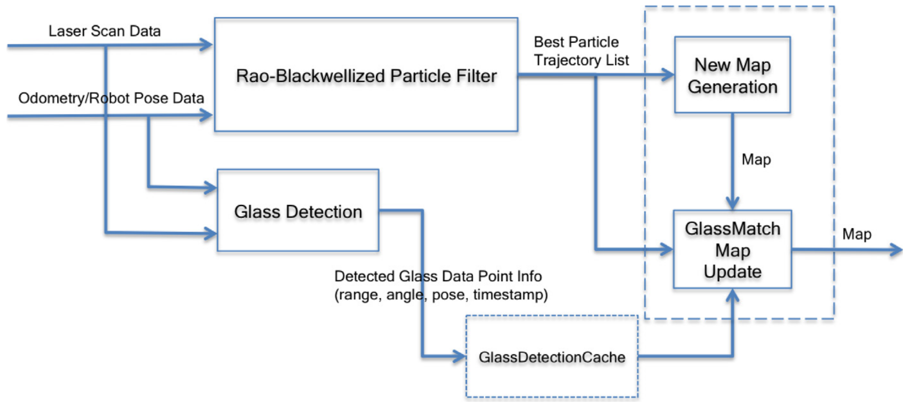


Fig. 7. Modified SLAM with glass detection overview.

Algorithm 1 Detect Laser Intensity Profile from Glass Panel.

Require: A list of laser range and intensity data L from a single laser scan with known angular increment step, robot pose and timestamp.
Ensure: A list of detected glass points with detected peak range, peak angle, timestamp and robot pose.

for all p in L where $p = (range, intensity)$ **do**
  if $intensity_p > triggerIntensity$ **then**
    $p - 1 :=$ previous data point of p if it exists
    if $intensity_p - intensity_{p-1} > intensityDelta$ **then**
      forward search a data point q that has $intensity_{q-1} - intensity_q > intensityDelta$
      if steps between p and q $<$ $profileWidth$ **then**
        $m :=$ middle point between p and q.
        Add range and angle from m, robot pose and timestamp into a *GlassList*
      end if
    end if
  end if
end for
return *GlassList*.

inputs. Finally, the grid map is updated with corrected glass panel position data. The modified SLAM workflow is summarised in Fig. 7.

3.3. Grid map with glass detection

We ran the modified SLAM with glass detection on our PR2 robot in two office buildings that use large glass panels. The experiments covered two entire floor levels with complex geometries. No restrictions or controls, e.g. lighting, were administered during the experiments. In both environments, the modified SLAM produced correct grid maps with glass panel properly marked (Fig. 10(a) and (b)). Our results (Table 1) show that the glass detection enabled GMapping was able to mark out ∼95% of all glass panels, whereas only ∼30% of glass panels were marked in the standard implementation using the same dataset. The largest gap in the grid maps caused by missed glass detection was 0.5 m in the modified GMapping and 1.5 m in the standard GMapping. A more detailed analysis of the grid maps against the ground truth indicated that the 30% detected glass in the standard GMapping was largely due to the vertical metal bars and glue materials that support the glass panels. This means that the standard GMapping will have much less success in marking out larger glass panels than the ones in our tested environments.

Table 1
A detailed comparison of glass detection between the standard Gmapping (Gmap) and our modified Gmapping (GmapG).

Mapping areas	Glass wall length (m)	Glass detection (%)		Undetected glass max gap (m)	
		GmapG	Gmap	GmapG	Gmap
B10 stairwell	28.2	95.2	27.6	0.42	1.26
B10 level 5	76.2	94.1	32.3	0.52	1.26
B11 level 7	191.6	95.6	26.8	0.56	1.54

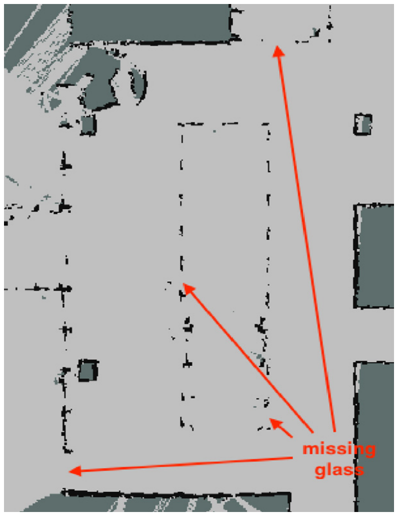
The 5% of missed glass detection in our modified GMapping was due to the scanning laser did not have sufficient opportunities to scan across the section surface around the normal of the glass panels. The main causes for this are the inconsistent (manual) driving of the robot, e.g. quick turns to avoid incoming people or corners; existing obstacles in front of the glass (Fig. 8(b)). The glass detection from the modified GMapping did not produce any false positives in the experiments as we verified the grid maps against the ground truth. This may look suspicious at first, however, it is entirely reasonable because we detect glass by directly measuring the intensity response profile from reflected laser. Laser sensors are highly reliable in terms of providing accurate range and intensity information. The reflected laser intensity profiles from glass panels are highly distinctive compared with other building and office materials (Fig. 5) and they can be detected without any ambiguity.

To highlight the effectiveness of our glass panel detection implementation, Fig. 8 shows a grip map produced at the location shown in Fig. 1(a). where the entire stairwell is surrounded by glass panels. The grid map generated from our modified SLAM clearly marks out every glass panel that is not registered in the grid map produced with the standard SLAM. In addition to accurate map generation, simultaneous robot localisation is also improved considerably with the glass detection. The robot trajectory computed with our modified SLAM (Fig. 9) is smoother, i.e. more valid localisation data points, and more accurate (for example, the orange trajectory in red circled area in Fig. 9 is visibly more reasonable with respect to the blue trajectory) compared with the result from the standard implementation. We include a short video clip showing the realtime generation of grid maps while the robot was (remote controlled) moved around the area.[3]

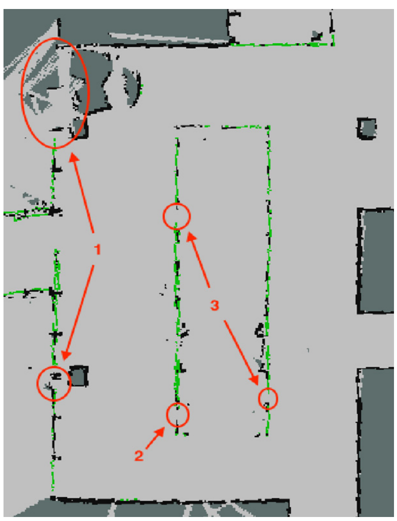
4. Discussion and conclusions

In this paper, we have introduced a highly effective solution to detect glass panels using laser scanning rangefinders without

[3] The video was recorded over the results generated from a cutdown version of dataset for compactness. Hence the results are slightly different from Fig. 8.



(a) A grid map from unmodified SLAM. We highlighted few places where glass panel should be marked.



(b) A grid map from modified SLAM with detected glass marked in green. Imperfect glass detections due to 1. obstacles. 2. fast rotation and 3. transient obstructions, i.e. human movements.

Fig. 8. A grid map comparison with glass panel detection and no glass panel detection. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

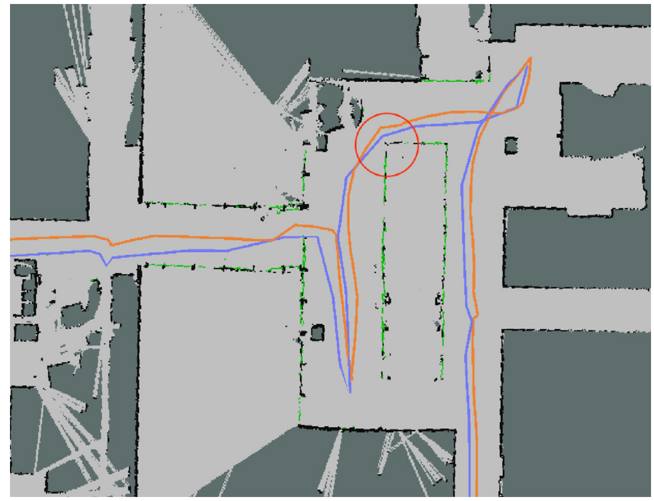


Fig. 9. A comparison between robot trajectories computed under glass detection enabled SLAM (orange) and the standard SLAM (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

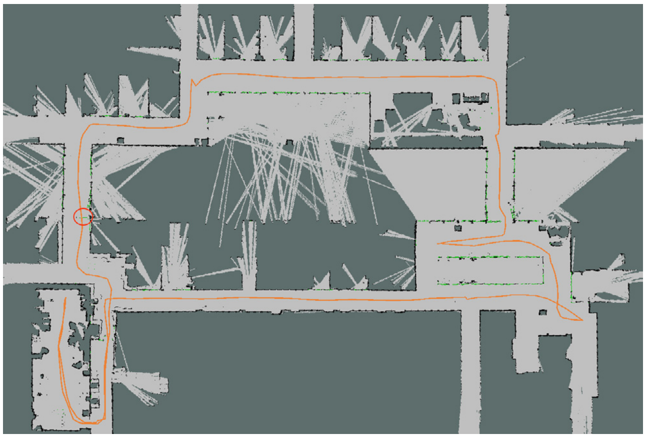
any physical modifications to a standard PR2 robot. Many existing approaches require additional sensor hardwares and advanced sensor data fusion algorithms in order to achieve a similar goal. Some recent works such as Foster et al. [8] used the same idea of glass specular reflection to detect glass as we have in this paper. Their works focused on building sensor models and algorithms that estimate and inference from the small view angles of glass; whereas our glass detection method uses direct measurement on the reflected laser light intensities. This makes our glass detection simple, robust and computationally inexpensive compared with all existing methods as our detection algorithm and empirical results have shown. Our detection method is readily integrated into existing SLAM implementations as we have demonstrated. It can also be directly incorporated into perception subsystems such as object recognition.

Our detection algorithm makes no assumptions about the environment (compared with [6]). The experiments were all conducted in uncontrolled office environments at various times during and after office hours. We have also experimented with applying 10%–20% variations to the control parameters values used in the glass detection procedure. All these variations in experimental conditions and parameters had little effect on the final grid map generated from the modified SLAM algorithm. This means our algorithm is robust and the software can be directly used on PR2 robots in many office environments without further adjustments. When parameter adjustments are required, for example a different laser rangefinder sensor is in use, a calibration based on Section 2.3.1 can be easily performed.

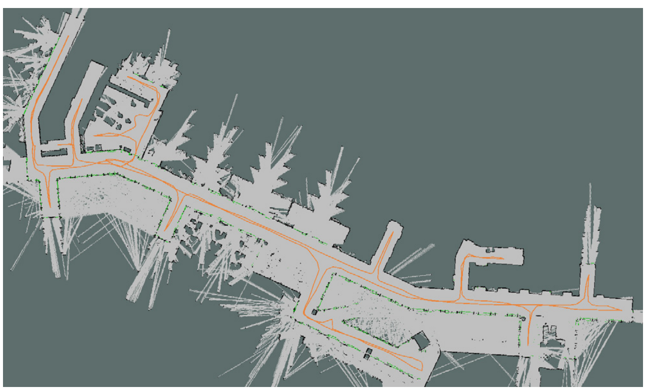
Our glass detection using a laser scanning rangefinder relies on whether the sensor has opportunities to send its laser beam across a target glass surface and receive back the reflected light round the surface normal. This may not occur if the PR2 robot rotates its base too quickly or there are some (permanent or transient) obstacles blocking the laser to the target Fig. 8(b). Consequently, a small section of the glass panel may go undetected. However, this problem can usually solved by slowing down the robot movement and/or allowing the robot to carefully scan the area more than once without any obstructions. It is also possible to apply additional interpolation method to improve the detection.

The glass detection enabled GMapping introduced in the paper works well in mapping out static environments in line with the standard implementation. It does not, however, identify movable glass objects like glass doors. In fact, Fig. 10(a) shows a glass door that was detected and registered in the grid map before it was opened to allow the mapping robot to pass through. This also means that it is possible to further improve the current implement to identify glass doors using temporal information available in the existing data.

This research focused on detecting large glass panels commonly found in office environments. Large mirrors are relatively rare in these environments. Mirror detection and impact of mirror on SLAM with laser rangefinders have not been thoroughly investigated in this paper. However, as the experimental results in Section 2.3.1 have shown, glass panel and mirror can be easily distinguished using the peak intensities. It would be relatively easy to modify the glass detection algorithm presented in this paper to detect mirrors. Mirror detection would be one of our future works.



(a) A grid map of building B10 level 5. Notice that the red circled area is a glass door that was detected and marked on the grid map before it was manually opened to allow the robot to pass through.



(b) A grid map of building B11 level 7.

Fig. 10. Grid maps of two building levels with detected glass marked in green colour and the trajectory of the PR2 robot in orange colour. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Finally, we release the source code of the modified SLAM with glass detection along with this paper as an open source ROS package. Parts of raw laser datasets used in this paper are also included in the release for anyone who wishes to verify our results. Interested readers can find the code repository at http://github.com/uts-magic-lab/slam_glass. We hope the software is useful for the robotic research communities and hopefully, the current work can be further improved by the communities.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.robot.2016.11.003.

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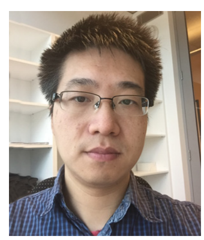

Dr. Xun Wang received his dual bachelor degrees in Computer Science and Advanced Science in Astrophysics from the University of New South Wales, Australia in 2000. He worked as a software engineer in the IT industry, specialised in large-scale distributed system software development, before completing his Ph.D. research in risk modelling and management in intelligent agents at University of Technology Sydney (UTS) from 2008 to 2013. Since then, Dr. Xun Wang is working as Chancellor's postdoctoral research fellow at UTS. His current interests are robotic software development and system integration, human robot interactions and machine learnings. He is currently developing a socially enabled intelligent service robot system based on PR2 robot platform.

Dr. JianGuo Wang received the B.Sc. degree in physics from Nanjing University, Nanjing, China, in 1983, the master's degree in image processing from Sydney University, Sydney, NSW, Australia, in 2001, and the Ph.D. degree in sensor fusion for navigation from the University of New South Wales, Sydney, in 2007. He has been with the University of Technology, Sydney, since 2009, as a Lecturer, and a Research Fellow with the Faculty of Engineering and Information Technology. His current research interests include robotics, navigation, mapping and automation, and in particular, machine vision and sensor fusion.