

## FEASIBILITY ANALYSIS OF 2D-SLAM USING COMBINATION OF KINECT AND LASER SCANNER

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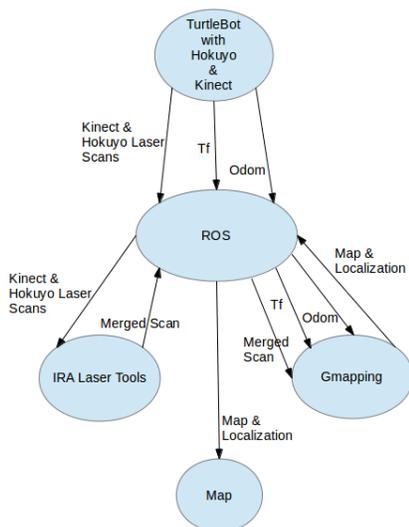
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### Graphical abstract



### Abstract

Both laser scanner and Kinect has been widely used in robotic application for simultaneous localization and mapping (SLAM). However, each sensor has its own limitations. For example, Kinect does not have a wide range field of view and laser scanner could not detect obstacles beyond its scanning plane. The paper proposes a method to combine the data from Kinect and laser scanner to perform a 2D-SLAM. The sensors will be mounted in different types of configurations; both facing forward and facing in opposite directions. This system is able to detect complex surrounding features for better mapping and obstacle avoidance.

Keywords: 2D, SLAM, kinect, laser scanner

### Abstrak

Kedua-dua pengimbas laser dan juga Kinect telah digunakan secara meluas untuk aplikasi robotik terutamanya untuk penyetempatan dan pemetaan secara serentak (SLAM). Tetapi, setiap sensor tersebut mempunyai kelemahan tersendiri. Contohnya, Kinect tidak mempunyai kelebaran penglihatan yang meluas dan pengimbas laser pula tidak dapat mengenal pasti objek yang tidak berada di paksi imbasannya. Kertas kerja ini mencadangkan satu kaedah untuk menggabungkan data yang diperolehi daripada Kinect dan pengimbas laser untuk melaksanakan 2D-SLAM. Kedua-dua sensor tersebut dipasang dengan konfigurasi yang berlainan; kedua-dua memandang kearah hadapan dan juga memandang ke arah yang bertentangan antara satu sama lain. Sistem ini mampu untuk mengesan ciri-ciri persekitaran yang kompleks untuk pemetaan dan pengesanan halangan yang lebih baik.

Kata kunci: 2D, SLAM, kinect, pengimbas laser

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## 1.0 INTRODUCTION

The SLAM problem has been substantially researched theoretically and has been successfully implemented on mobile robots in 2D and 3D environments [1, 2, 6, 7, 8, 9, 10]. To implement SLAM, the robot needs to localize itself and map the environment which makes it a challenging problem to solve because of the

mutual dependency of the map and robot's pose. In order to localize the robot in the real world would require the map of the environment and in order to build the map, localization of the robot is required. Due to this, mobile robots now carry precise sensors such as wheel encoders, gyroscopes, accelerometers, ultrasonic sensors and laser scanners. Measurements from these sensors are vital for solving

the SLAM problem. Most of the researches that have been done were using a single range measurement sensor for mapping such as the laser scanner [1] or ultrasonic sensors [18] or the Xbox Kinect [6, 7, 10, 11, 13]. Multiple sensors were also used in past researches but with each sensor to its own specific task such as the laser scanner for mapping, Kinect for obstacle avoidance and a GPS to aid localization [2, 12].

Our motivation for this paper is that first, the real world environments are not smooth and flat. It is filled with various sized of obstacles. Previous works on SLAM have been neglecting the need for mapping small obstacles. The resulting maps can be deemed inaccurate thus disabling them for future autonomous navigation use. Secondly, using the Kinect alone to perform SLAM is achievable but the quality of the map is usually unsatisfactory as we will show in section 4. In this paper, we merged the range measurement data from both the Kinect and a laser scanner to be specifically used for mapping. The utilized Gmapping algorithm is a highly efficient Rao-Blackwellized particle filter to learn grid maps from range measurement data [5, 15]. The aim of this paper is to highlight the ability of the merged range measurement data to detect small obstacles and to construct an accurate map of the environment including the mapping of small obstacles.

## 2.0 RELATED WORK

SLAM has been implemented with various types of mobile robots and other moving vehicles for wide variety of operation. A test-bed vehicle equipped with two SICK laser scanners has been used to perform SLAM to improve the Advance Driver Assistance System (ADAS) technology. It focuses on the detection and tracking of moving objects from the surrounding environment for better intelligence and accuracy of the ADAS [1]. GPS data were also used to help localizing the test-bed vehicle on the real world. Another successful implementation of SLAM in the real world was performed in a crowded urban environment [2]. The robot named Obelix, was equipped with a Hokuyo UTM-30LX for mapping and localization purposes. The robot was also using an extended SLAM routine to successfully navigate through 3 kilometers of path in the urban city of Freiburg, Germany. Besides wheeled robots, SLAM with humanoid robots has also been successful. Humanoid robots possess a large degree of freedom to navigate through areas where wheeled robots find it very difficult. The robot QRIO was successful in environment map-building approach and able to distinguish multiple environment types. Reasonable accuracy of height information was also provided for floors, stairs and obstacles [14].

Instead of the expensive laser scanners, there were also successful implementations of SLAM using the Kinect. Since the introduction of the Microsoft Kinect, extensive analysis of the Kinect for SLAM has been done [3, 11, 19]. In [3], it shows that the estimation of

the local traversability based on a single depth image from the Kinect could lead to an accurate and fast to compute mobile robot system even without a graphical processing unit in the laptop. The system was successful on processing the depth data at 10-25 frames per second on a standard Intel i7 laptop computer. The 3D vision of the Kinect can also be converted into a 2D area map with the method shown in [4]. The 11-bit raw data from the Kinect were converted to depth images and pixels coordinate from the Kinect data were used to publish 2D obstacle locations. It was also mentioned that transparent and highly reflective surfaces could be a problem for the Kinect to detect. Visual SLAM was also successfully implemented using the Kinect with a reasonable degree of accuracy [7] but the resulted 3D map was not suitable for route planning and autonomous navigation. A hand-held Kinect was used to implement a SLAM system called the RGBD-SLAM System [6]. It is now widely used to build 3D occupancy grid maps [11]. It was also mentioned in [11] that the Kinect is a viable option to perform SLAM however the laser scanner is more precise and accurate in terms of 2D mapping which we will show later in this paper. The RGBD-SLAM is also computationally heavy and the integration of the Extended Kalman Filter (EKF) into the system is needed to avoid the time consuming service calls and decrease the time of each algorithm iteration. A more efficient way to do 3D-SLAM is now available with OctoMap. OctoMap is an approach to model the environment in 3D based on octrees using a probabilistic occupancy occupation. It has been successful in modeling non-uniform free and unknown areas [8]. The bounded per-volume confidence approach also allows for a lossless compression scheme which substantially reduces memory usage.

All the mentioned researches above were successful in implementing SLAM but only the humanoid robot QRIO was more focused on mapping small obstacles using the data obtained by its stereo camera. Its floor pattern, tunnel and stair recognition to aid navigation is also notably impressive. With the QRIO as an inspiration, work on this paper then began to focus on mapping low obstacles using the combination of the Xbox Kinect and a laser range finder.

## 3.0 SYSTEM OVERVIEW

### 3.1 TurtleBot

During this research, a custom mobile robot was not built from scratch. A TurtleBot was used and modified instead. The TurtleBot is a robot kit that provides hardware and software for development of robot algorithms. It consists of an iRobot Create, an Xbox Kinect and a single axis gyroscope. A laptop and a Hokuyo UHG-08LX Laser Range Finder were then mounted on the TurtleBot, as shown in Figure 1. Other

differential wheeled robots can also be utilized to replicate this work.

### 3.2 Microsoft Xbox Kinect

The Xbox Kinect camera is a low-cost sensor built for the well-known Xbox game console. It has a 43 degrees vertical and 57 degrees horizontal field of view. The Kinect can provide depth images which then can be converted into point clouds and laser scan data that can be used for SLAM. Another option instead of Kinect would be the Asus Xtion Pro Live Motion Sensor or any other depth camera.

### 3.3 Hokuyo UHG-08LX

The Hokuyo UHG-08LX laser range finder is a suitable alternative so far for mobile robot applications due to its compact size and low power consumption features. Its scanning range is up to 8 meters and a field of view of 270 degrees. The laser range finder can provide us with precise laser scan data which will be useful for SLAM. Any 2D laser scanner could also be utilized.

### 3.4 Robot Operating System

The Robot Operating System or ROS is the base of the TurtleBot system and it defines the means of external communication when building a specialized application. ROS contains stacks and packages where a stack delivers the functionality of the system and a package contains multiple stacks. In this research, a number of stacks and packages namely the IRA Laser Tools [16] for combining multiple laser scans were utilized. Figure 3 roughly explains how the system works. The rosbag [17] package to record and play a bag file which contains all the published data were also utilized.



Figure 1 Modified TurtleBot with mounted Kinect, Hokuyo UHG-08LX and a laptop

## 4.0 OUR APPROACH

The main objective of our work is to produce an accurate map of the environment where even the small obstacles will be included in the map. We focus on the capabilities of the Xbox Kinect to produce a wide vertical depth image so that the small obstacles can be detected and then computed to be included in the final map. A simple test run were done to map our lab's corridor (as shown in Figure 4) using just the Kinect. The test was then repeated using the laser range finder. The quality of the map by using just the Kinect from Figure 5 is much lesser than the quality obtained by using just the laser range finder which can be seen on Figure 6. Because of mapping low obstacles is one of our main objective, we could not afford to discard the Kinect as it has the vertical field of view while the laser range finder does not. To obtain a better map quality and also be able to recognize and map small obstacles, both the Kinect and the laser range finder were opted to be utilized.

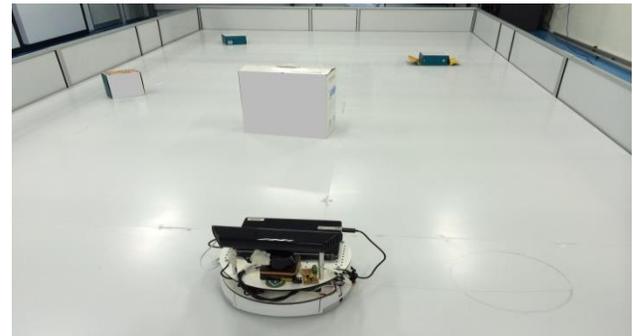


Figure 2 The experimental environment inside the 3.0m times 6.0m robotics platform

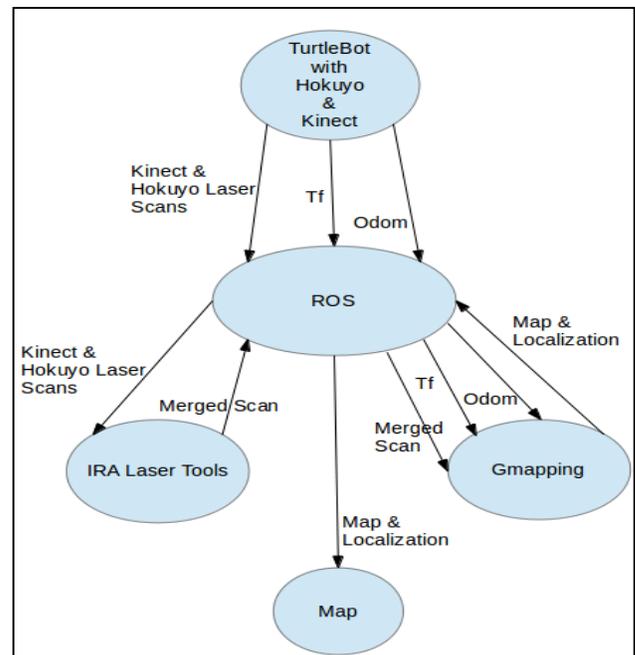


Figure 3 System diagram

Our approach is to merge the laser scan data from multiple sensors into one set of data because most SLAM algorithm can only utilize one laser scan data as input. In order to achieve this, a package in ROS called the IRA Laser Tools were utilized and modified according to our needs. Parts of the pointcloud to laser scan code which are available in ROS were used. The package allows easy, dynamic and simultaneous merging of multiple laser scans into a single scan. The resulting scan will appear generated from a single laser scanner disregarding actual occlusions as seen from the merged scans. A simple laser scan test was done using the sensors on the experimental environment as shown in Figure 2. Figure 7 shows the scan from the Kinect which can detect even the small obstacles. Figure 8 shows the scan from the Hokuyo which can precisely detect the rectangular shape of the 3.0m times 6.0m robot platform arena with four obstacles with various height and width. Figure 9 shows the merged scan. Note that both sensors were facing forward at the time. An open source SLAM algorithm called Gmapping was then utilized to perform SLAM with the newly merged scan from both sensor configurations. Experimental results will be discussed in the next section.

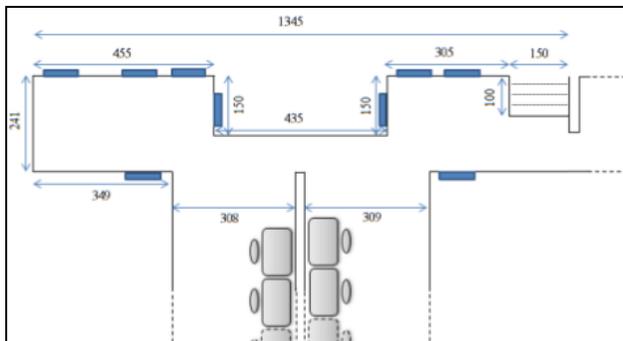


Figure 4 Partial drawing of CEASTech's lab corridor

## 5.0 EXPERIMENTS & RESULTS

After successfully merging the laser scans, we proceed with our experiments. The experiment was split into two shown in Table 1. First, both the sensors were mounted facing forward. Second, the Xbox Kinect was mounted facing forward and the Hokuyo facing backwards. Both experiments were done on a 3.0m times 6.0m robot platform arena with four obstacles with various height and width. From Figure 7 and 8, the fact that three of the obstacles cannot be detected by the Hokuyo while all four of the obstacles can be detected by the Kinect was known.

During the experiment, the TurtleBot was manually controlled with teleoperation randomly without a specific style of movement to replicate an autonomous system performing SLAM in an unknown environment with the presence of obstacles. For each experiment, all the sensor data, robot's movement and transformation were recorded in a bagfile. The

bagfile then was replayed on a different machine to perform an offline SLAM using the Gmapping algorithm.

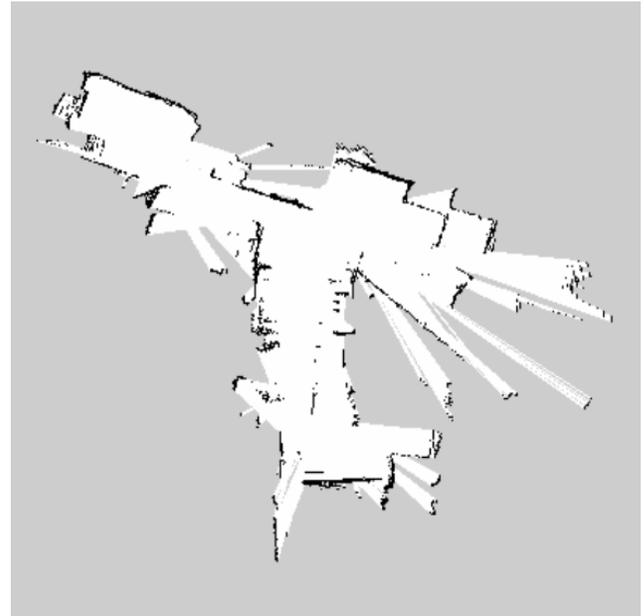


Figure 5 Map of CEASTech's lab corridor using the Xbox Kinect

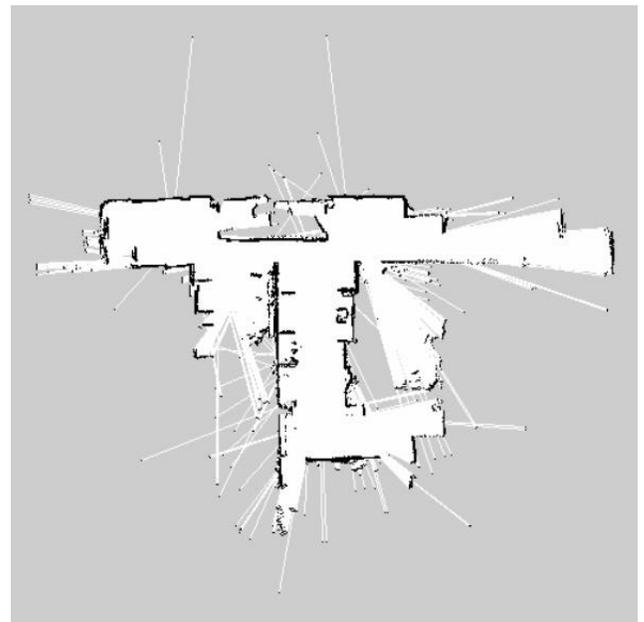


Figure 6 Map of CEASTech's lab corridor using the Hokuyo UHG-08LX

The first experiment results can be seen from Figure 10 and Figure 11. With the Gmapping algorithm, a reasonable map of the robot platform arena was built. Figure 10 shows that early on, all the obstacles including the smaller ones were plotted on the map. Note that the errors are also already visible on the

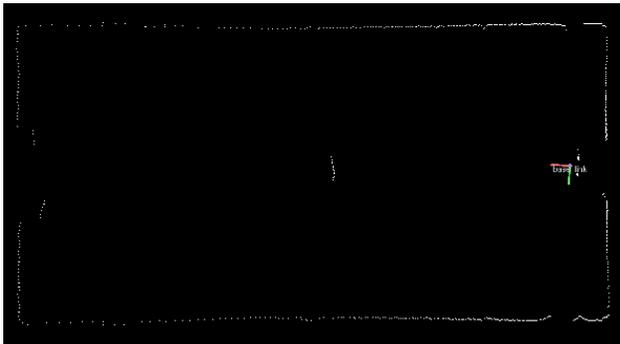
map. The resulted final map was also reasonably accurate with the robot platform arena can be clearly observed. From Figure 11, note that three out of four obstacles are still in the map even though the smaller obstacles are now smaller in scale on the map.

**Table 1** Types of experiments with the duration of the recorded bagfile.

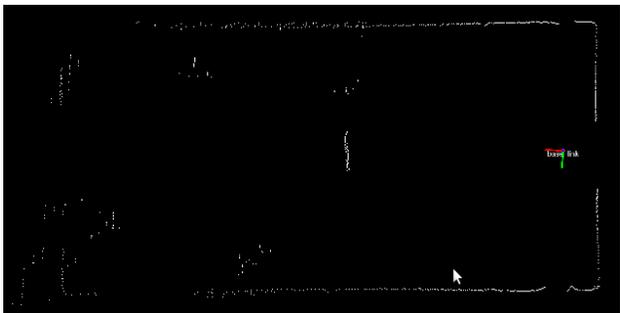
Experiment	Duration / s
1.Sensors facing forward	161
2.Sensors facing opposite direction	242



**Figure 7** Kinect's laser scan of the experimental environment



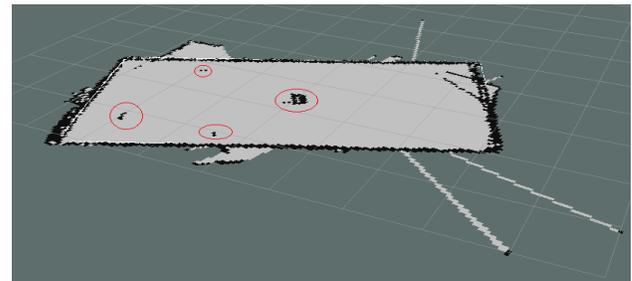
**Figure 8** Hokuyo's laser scan of the experimental environment



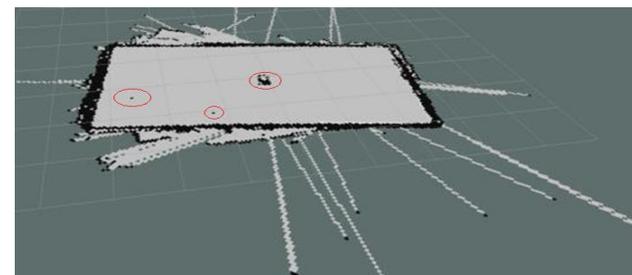
**Figure 9** The merged laser scan of the experimental environment

## 6.0 DISCUSSIONS

First, the problem of obstacles being cleared out from the map needs to be highlighted. Early on during both experiments, even the smallest obstacles were clearly visible on the map but as the experiments went on and the final maps were published, some of the obstacles went missing from the final map. This is because the smaller obstacles were not in the line of sight of the Hokuyo laser range finder. When the obstacles are no longer in the Kinect's field of view and Hokuyo laser range finder couldn't detect the obstacles but it detects the robot platform arena's wall behind it, the Gmapping algorithm assumed that the earlier plotted areas as errors and then re-marked the areas as free space instead. With the Hokuyo's larger field of view, the probability of the obstacles being cleared from the map is high. This can be clearly seen from Figure 13 where only one obstacle was left on the map. But from Figure 11, when both sensors are facing forward, 57 degrees of the Kinect's field of view were stacked on the Hokuyo's field of view. This lessens the probability of the obstacles being cleared from the map and re-marked as free space thus explaining the resulting map with 3 out of 4 visible obstacles. Furthermore, even if the obstacles were inside the Kinect's horizontal field of view, it could also be too close to the robot and outside of the Kinect's vertical field of view thus the sensors will then detect the walls behind obstacles instead. Modifying the parameters during the conversion of depth images into laser scans could make the minimum distance between the robot and obstacles smaller, but it also resulted in floors being detected as obstacles.



**Figure 10** Map of first experiment on t=48s



**Figure 11** Map of first experiment on t=161s

Secondly, the errors accumulated on the first experiment are visibly larger than the errors from the second experiment. This is because multiple points were detected when the field of views from multiple sensors is stacked on each other. The utilized IRA Laser Tools package during the experiment computed each point, took the lowest range measurement data and published it as a single point. This resulted in a slight delay when the package publishes its merged laser scan data and causing errors. This can especially be seen when the robot is turning as shown in Figure 14 and Figure 15. From Figure 14 a part of the robot platform arena's wall was not updated when the robot is turning can be seen. Figure 15 shows a much clearer example where some points on the robot platform arena's straight wall were updated and the others were not.

Errors from the first experiment could also be interpreted as odometry errors. As we configured both of our sensors facing forward, the maximum field of view is 270 degrees while on the second experiment, we configured our sensors to face the opposite direction which resulted in a total of 330 degrees of field of view. This caused us to turn the robot more during the first experiment to fully map the environment thus resulting in a higher odometry error.

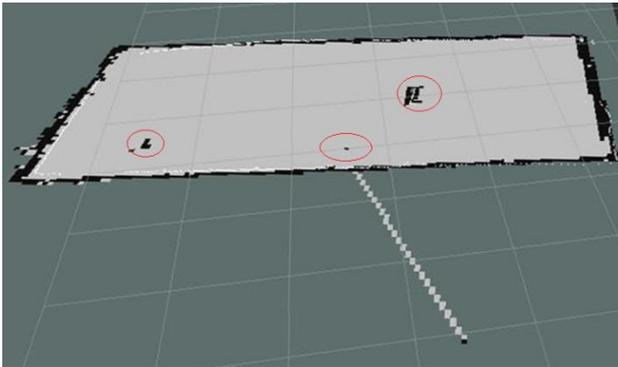


Figure 12 Map of second experiment on t=20s

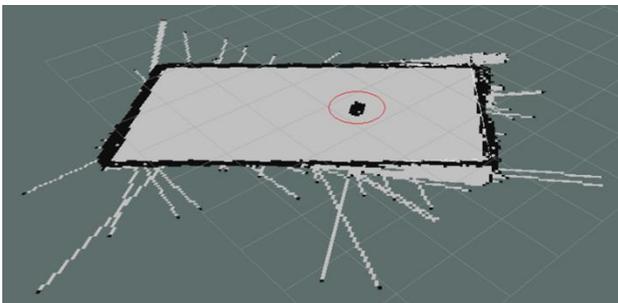


Figure 13 Map of second experiment on t=242s

## 7.0 CONCLUSION AND FUTURE WORK

Solving the issue on obstacles being cleared out from the map and marked as free space will be our future work. We could split the solution into two ways. First,

multiple layer of maps with each map layer will be built by a single specified sensor can be constructed. The multiple maps then can be combined into one complete map from all the sensors. Second, the Gmapping algorithm parameters need further tweaking to lower the probability threshold of a cell being marked as occupied. A lower threshold value can decrease the probability of an obstacle being cleared out from the map but it can also cause a certain degree of errors when the algorithm are not clearing out noises from the map.

Furthermore, errors when merging the scans from the Kinect with other laser scanners can be avoided. We will need to work on a better laser scan merging package for ROS. The package that was utilized is currently not fully optimized for the Xbox Kinect but only for a single plane laser scanner which does not have a vertical field of view.

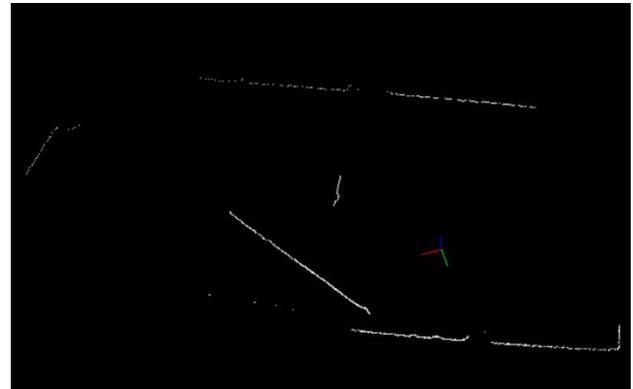


Figure 14 Scan delay while turning

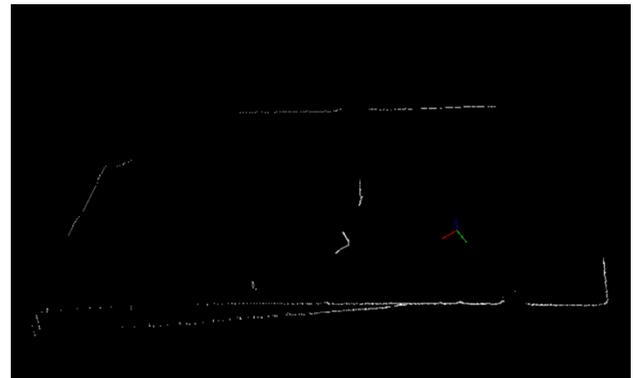


Figure 15 Scan errors while turning

In conclusion, this paper proposed a method to perform SLAM with combined sensors which is the Kinect and a Hokuyo UHG-08LX Laser Range Finder with both sensors were specifically used for mapping. By combining the Xbox Kinect and the Hokuyo UHG-08LX, a wider field of view of the environment were obtained thus managing to perform SLAM better compared to performing SLAM with a single Kinect where the map was inaccurate as can be seen from

Figure 5 or a single Hokuyo UHG-08LX where key features such as small obstacles were missing from the final map. Finally we conclude that this scan merging method is suitable to build a 2D map of the environment including the mapping of small obstacles instead of just detecting the obstacles to perform obstacle avoidance maneuvers.

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### References

- [1] Zhao, H., M. Chiba, R. Shibasaki, X. Shao, J. Cui, and H. Zha. 2008. SLAM in a Dynamic Large Outdoor Environment Using a Laser Scanner. *Robotics and Automation, 2008. ICRA, 2008. IEEE International Conference on. IEEE, 2008.* Pasadena, CA, United States. 19-23 May 2008. 1455-1462.
- [2] Kummerle, R., M. Ruhnke, B. Steder, C. Stachniss, and W. Burgard. 2013. A Navigation System for Robots Operating in Crowded Urban Environments. *Robotics and Automation (ICRA), 2013 IEEE International Conference on.* Karlsruhe, Germany. 6-10 May 2013. 3225-3232.
- [3] Bogoslavskyi, I., O. Vysotska, J. Serafin, G. Grisetti, and C. Stachniss. 2013. Efficient Traversability Analysis for Mobile Robots Using the Kinect Sensor. *Mobile Robots (ECMR), 2013 European Conference on. IEEE, 2013.* Barcelona, Spain. 25-27 September 2013. 158-163.
- [4] Kamarudin, K., Mamduh S. M., Shakaff A. Y. M., Saad S. M., Zakaria A., Abdullah A. H., and Kamarudin L. M. 2013. Method to Convert Kinect's 3D Depth Data to a 2D Map for Indoor SLAM. *Signal Processing and its Applications (CSPA), 2013 IEEE 9th International Colloquium on.* Kuala Lumpur, Malaysia. 8-10 March 2013. 247-251.
- [5] Grisetti, G., C. Stachniss, and W. Burgard. 2005. Improving Grid-based Slam with Rao-Blackwellized Particle Filters by Adaptive Proposals and Selective Resampling. *Robotics and Automation, 2005. ICRA, 2005. Proceedings of the 2005 IEEE International Conference on. IEEE, 2005.* Barcelona, Spain. 18-22 April 2005. 2432-2437.
- [6] Endres, F., J. Hess, N. Engelhard, J. Sturm, D. Cremers, and W. Burgard. 2012. An Evaluation of the RGB-D SLAM System. *Robotics and Automation (ICRA), 2012 IEEE International Conference on. IEEE, 2012.* Saint Paul, MN, United States. 14-18 May 2012. 1691-1696.
- [7] Hjelmare, F., J. Rangsjö. 2012. *Simultaneous Localization and Mapping Using a Kinect in a Sparse Feature Indoor Environment.* Linköping University Electronic Press.
- [8] Wurm, K. M., A. Hornung, M. Bennewitz, C. Stachniss, and W. Burgard. 2010. OctoMap: A Probabilistic, Flexible, and Compact 3D Map Representation for Robotic Systems. *Proc. of the ICRA 2010 Workshop on Best Practice in 3D Perception and Modeling for Mobile Manipulation.* Anchorage, Alaska, United States. 3-8 May 2010. 2(5).
- [9] Cole, D. M., and P. M. Newman. 2006. Using Laser Range Data for 3D SLAM in Outdoor Environment. *Robotics and Automation, 2006. ICRA 2006. Proceedings 2006 IEEE International Conference on. IEEE, 2006.* Orlando, Florida, United States. 15-19 May 2006. 1556-1563.
- [10] Wulf, O., K. O. Arras, H. I. Christensen, and B. Wagner. 2004. 2D Mapping of Cluttered Indoor Environments by Means of 3D Perception. *Robotics and Automation, 2004. Proceedings, ICRA'04, 2004 IEEE International Conference on. Vol. 4. IEEE, 2004.* New Orleans, LA, United States. 26 April–1 May 2004. 4204-4209.
- [11] Oliver, A., S. Kang, B.C. Wünsche, and B MacDonal. 2012. Using the Kinect as a Navigation Sensor for Mobile Robotics. *Proceedings of the 27th Conference on Image and Vision Computing New Zealand.* Dunedin, New Zealand. 26-28 November 2012. 509-514.
- [12] Srinivasan, K., and J. Gu. 2007. Multiple Sensor Fusion in Mobile Robot Localization. *Electrical and Computer Engineering, 2007. CCECE 2007, Canadian Conference on. IEEE, 2007.* Vancouver, Canada. 22-26 April 2007. 1207-1210.
- [13] Alismail, H., L. D. Baker, and B. Browning. 2014. Continuous Trajectory Estimation for 3D SLAM from Actuated Lidar. *Robotics and Automation (ICRA), 2014 IEEE International Conference on.* Hong Kong. 31 May-7 June. 6096-6101.
- [14] Gutmann, J. S., M. Fukuchi, and M. Fujita. 2008. 3D Perception and Environment Map Generation for Humanoid Robot Navigation. *The International Journal of Robotics Research.* 27(10): 1117-1134.
- [15] Grisetti, G., C. Stachniss, W. Burgard, and B. Gerkey. Gmapping: Package summary. [Online]. From: <http://wiki.ros.org/gmapping>. [Accessed on: 28 September 2014].
- [16] Ballardini, A.L., S. Fontana, A. Furlan, & D.G. Sorrenti. 2014. Ira\_Laser\_Tools: A ROS LaserScan Manipulation Toolbox. *arXiv preprint.* arXiv:1411.1086.
- [17] Leibs, J., J. Bowman, K. Conley, and T. Field. Rosbag: Package summary. [Online]. From: <http://wiki.ros.org/rosbag>. [Accessed on: 28 September 2014].
- [18] Visvanathan, R., S. M. Mamduh, K. Kamarudin, M. H. M. Razali, A. S. A. Yeon, A. Zakaria, L. M. Kamarudin, S. A. A. Shukor, A. Y. M. Shakaff, F. S. A. Saad, and N. A. Rahim. 2014. Multi-channel Ultrasonic Sensing System for Wall Features Extraction. *Electronic Design (ICED), 2014 2nd International Conference on. IEEE, 2014.* Penang, Malaysia. 19-21 August 2014. 351-355.
- [19] Kamarudin, K., S. M. Mamduh, A. Y. M. Shakaff, and A. Zakaria. Performance Analysis of the Microsoft Kinect Sensor for 2D Simultaneous Localization and Mapping (SLAM) Techniques. 2014. *Sensors.* 14(12): 23365-23387.