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Sensor Fusion for Localization, Mapping and Navigation in an Indoor Environment

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***Abstract*—This paper describes localization and navigation in an indoor environment with transparent objects. Although LIDAR proved to be a popular choice, its inability to detect glass surface requires another sensor to ensure navigation capability will work in all kind of environment. In this paper, sonar sensor is used in complement to laser due to its capability to detect hard surfaces and low cost. The experiment shows that a better map can be achieved when these two sensors are used.**

***Index Terms*—Sensor fusion, Laser-based 2D SLAM technique, AMCL, Sonar Ring, ROS, Transparent objects.**

I. Introduction

NOWADAYS , the Global Positivity System (GPS) technology can achieve accurate position in the outdoor and it is used in a wide variety of products. However, the signal attenuation influenced by the construction materials of buildings means that indoor positioning systems cannot rely on this technology. Hence, there are several indoor positioning systems developed over the last decade, relying on a wide variety of technologies, including WLAN, LARDAR, Infrared and Ultrasound and others [1].

Simultaneous Localization and Mapping (SLAM) has been one of the most fundamental principles in Robotics. SLAM is essential and popular technique for autonomous mobile robots to accomplish useful tasks without a priori information about the environment given space [2]. In mobile robot, in order to collect massive information from the sensorial reading, different sensors fusion is a way to allow the extraction of information that cannot be achieved by one type of sensor. Different type of sensors work differently and meanwhile they reflect both their advantages and disadvantages. Hence, Sensor fusion is a technique to enhance the strength of different sensor to compliment the shortcoming of the other space [3].

The paper focus on localization and mapping of a mobile robot in environment with transparent objects. After which, SLAM technique is presented in scenarios where the environment has transparent objects, also describes the algorithms and implementation of the proposed methods for non-reflective objective scenarios. Several experiments are evaluated and their results carried out are discussed.

II. Sonar Ring Implementation and Design

In order to achieve the suitable Sonar ring building, the sonar beam pattern and sonar reading error along different distance

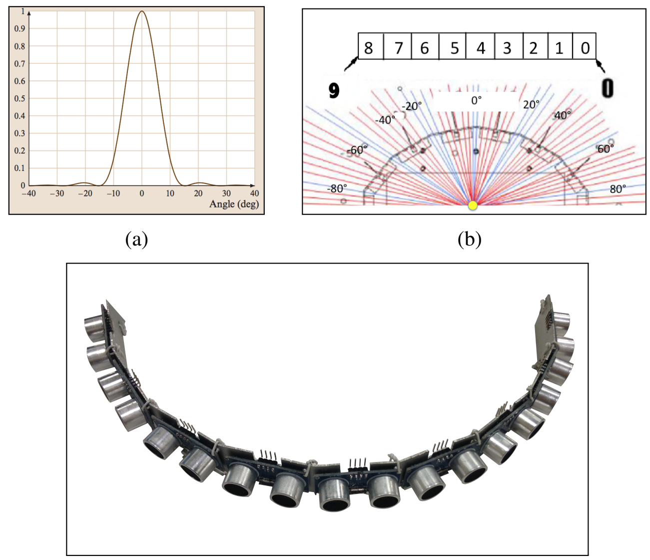

Fig. 1: *Sonar Ring Implementation: (a) Normalised amplitude of echo from small object predicted by the piston model as a function of angle [4]. (b) Sonar Ring design (c) Sonar Ring real Implementation*

are mainly evaluated in this section due to the requirement of sonar ring building mentioned before. For sonar beam pattern, we apply fundamental acoustics theory to build model in a qualitative description of the sonar transducer [4].

According to this model, it illustrated the echo amplitude from a small object located in the far field as a function of angle detected by the electrostatic instrument grade transducer. Figure 1(a) shows normalised echo amplitude curve depending on different angles. The figure shows that ultrasonic sensors usually have relatively wide sensitivity cones. This means that obstacles separated up to an angle of 10 degree from frontal orientation of the sensor contribute the proper amplitudes in the received echo. In [5], it is shown that there is no distortion when the minimum angle between two sonars is 20 degree. This means that the maximum value between these registered peaks will correspond with the frontal orientation between transducers and object.

To match with the 180 degrees field of view of laser sensor, The design diagram is shown as figure that each sensor is arranged at an angle of: -80,-60,-40,-20,0,20,40,60,80 degree.

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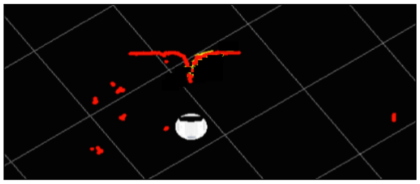
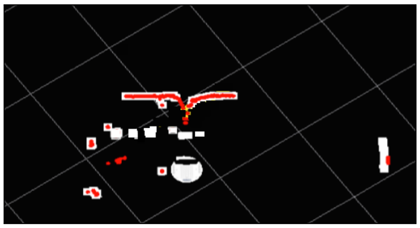


(a)



(b)

Fig. 2: *Behaviour of sonar ring of the Turtlebot with glass surfaces: (a) Laser-scan (Red dot). (b) Sonar-scan (White dot).*

Figure 1(b) and Figure1(c) illustrates the arrangement in the robot.

III. Limitations of Application of Single Sensor

Usually, indoor mobile robot equipped with a LIDAR Hokuyo URG-04LX-UG01 for navigation purpose in indoor environment that has detection range from 20mm to 5600mm [8]. But it cannot recognise transparent objects. Sonar sensing is one of the most useful and cost-effective methods of sensing. These reasons have led to their widespread use in applications such as navigation of autonomous robots, map building, and obstacle avoidance. The behaviour of sonar ring is compared with the LRFs in this same situation. Noted that, in Figure 2(b), the behaviour of sonar ring of the Turtlebot facing glass surfaces can detect the glass as shown in white dot while Figure 2(a) shows that the red dot is misreading of LRFs in glass detection.

Although the sonar has the ability to detect the glass surface, the sonar readings with low resolution and larger error ranges from environment is unreliable into 2D SLAM technique in generating the map referring to the environment.

IV. The Algorithm of Two Approaches in Dealing With Transparent Objects

Sensor fusion is an important technique in smart robots operation. There are two approaches depicted in this paper. One is sensor fusion map that the fusing sensory data provided by both laser sensory data and sonar sensory data flowing into SLAM to generate the map regarding the transparent objects. The other is the maps overlapping that depends on the map provided by laser sensory data fusing with sonar sensory data to generate another map. But it firstly generates a pure 2D laser-based SLAM map. And regarding the transparent objects, its sonar sensory data adds on the map that means this map is two-layer maps after SLAM technique.

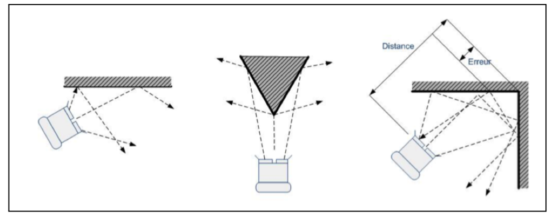


Fig. 3: *Reflector models. (a) Plane. (b) Edge. (c) Corner.[6]*

A. SLAM based on Monte Carlo Methods

In the beginning, Particles filters (PF) are application of Bayes filter. And then, it is a popular platform of Monte Carlo Localization Methods (MCL) and its algorithm is very different from Kalman filter technique.

Before navigating reliably in indoor environments, a mobile robot must know where it is. Thus, reliable position estimation is a key problem in mobile robotics. AMCL theory is an application of PF method using fro robot localization. Despite its relatively young age, MCL has already become one of the most popular localization algorithms in robotics [11]. It is easy to implement and tends to work well across a broad range of localization problems. However, a shortcoming of the naive implementation of MCL happens in a situation where a robot locates at one spot and repeatedly feel the environment without moving. Moreover, as particles far away from the converged state are rarely selected for the next iteration, they become scarcer on each iteration until they disappear altogether. At this point, the algorithm is too difficult to recover[12] as this problem is more likely to occur for small number of particles when M¡50.

B. Environmental modelling

Modelling the sonar measuring processes is useful in interpreting echo information. In this section, three simple reflector models are considered in common office environment: planes, corners, and edges, shown in Figure 3[6].

A plane model is a smooth surface such as smooth walls and door surfaces like planar reflectors. A wall is relatively easy to detect if the incident angle between wall and sonar is about right angle to indicate an accurate measurement. The edge in models as convex corners and high curvature surfaces (posts), where the reflection point is independent of transducer position. Edges have the worst situation in sonar detection due to its few reflection and narrow surfaces. The concave right-angle intersection of two surfaces forms a corner. Corners formed by intersecting walls such as the sides of file cabinets, and door jambs are commonly- observed corner reflectors in indoor environments. The corner is a situation waves reflect back in the same direction from which the sources originate.

C. Approach A: Sensor Fusion

ROS Arduino publishes the sonar information in Float32MultiArray message type that is a dot sensor message. However, Gmapping who is capable of dealing with laser scan data was concentrated on the message of LRFs. The code of the Gmapping algorithm may not eventually be changed to

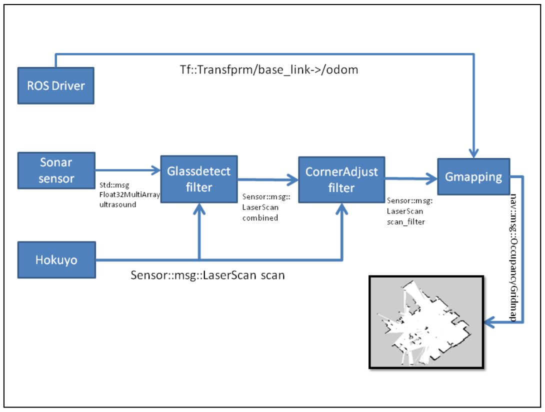
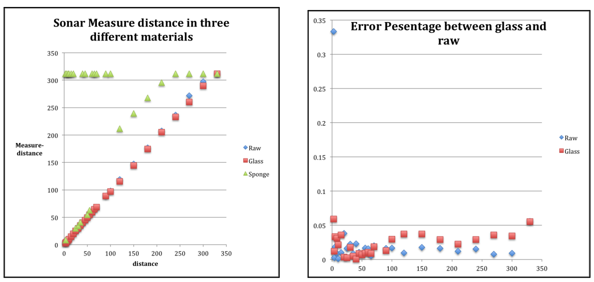


Fig. 4: *Overview of sensor fusing filter integration*



(a) (b)

Fig. 5: *Sonar property: (a) Sonar Measure distance in three different materials. (b) Error Pesentage between glass and raw*

accept both types of messages. As consequence, the idea of this approach is to design two intelligent layers filter, denoted as GlassDectect layer and CornerAdjust layer, which concentrate on the output of each sensor and adjusts, modifies or ignores that information according to different situations as shown in Figure 4. These two layers adapt to any set of range sensing data and provide filtered data to potentially any generic 2D SLAM algorithm in environment with transparent objects.

In the first place, to differentiate whether the objective is glass or not is the main and difficult target in this section as the different scenarios cause biased reading. Due to cone of angle, it is possibly not directly to replace, or compare the sonars data and lasers data [7]. In order to solve this problem, several tests have been conducted in measuring the sonar's reading at different distance in facing these materials that are glass, smooth wood and sponge which commonly found in indoor environment. And their corresponding plots are illustrated in Figure 5. They provides an evident reading error percentage graph at different distances and supportably shows entire reading error percentage below 5% in terms of 11cm maximum error reading.

The Algorithm 1 presents a high-level code of the implemented checking from sonar readings to laser readings.

In the second place, after detecting the difference between sonar and laser "check[]" array variable carries information of the real measuring difference in meter scale shows high probability of exiting glass in certain section. The Algorithm 2 presents a glass drawing algorithm and the implements

Algorithm 1: Algorithm Check Difference

input : UltrasoundArray sonar, LaserScanArray scan
output: ArrayCheck[ ], Array$side_n$umber[ ]

for $i \leftarrow 0$ **to** $\frac{laser.ranges.size()}{number\_sonar}$ **do**
    if laser.ranges[i] >= (sonar[reading] + 0.3) **then**
        $store_index[reading] + 1;;$
end
if sonar[reading is valid] **then**
    $\mathbf{r_n}[i] \leftarrow 0;$
else if $\frac{store_index[sonar]}{ls_index[sonar]} >= 50\%$ **then**
    for $i \leftarrow 0$ **to** $\frac{laser.ranges.size()}{number\_sonar}$ **do**
        $check[reading] = difference \times percentage;;$
        $percentage = -0.0008618 \times i_2 + 0.0491 \times i + 0.3;;$
        if laser.ranges[i] >= (sonar[reading] + 0.3) **then**
            $store_index[reading] + 1;;$
    end
else
    Keep check[reading] = 0;
end
return Array Check[ ], Array $side_n$umber[ ]

Algorithm 2: Algorithm GlassDetection Layer Filter—Drawing Glass

input : Array Check[ ], Array_$side_n$umber[ ], UltrasoundArrayultrasound, LaserScanArrayscan
output: sensor :: msg :: LaserScan$scan_f$ilter, recorder_change[ ]

for reading ← 0 **to** number_sonar **do**
    if Array_Check[current] >= 0.08 **then**
        if Array_Check[ ] >= 0.08 **then**
            Two check[ ] difference;
            for piece ← 0 **to** opp_large_side **do**
                $scan_f$ilter.ranges = laser.ranges;
            end
        else if Array_Check[ ] < 0.08 **then**
            if reading equalsonar_namber **then**
                Checkprevioussonar[reading − 1];
            else
                One check[ ] difference;
                for piece ← piece **to** opp_side **do**
                    $scan_f$ilter.ranges = laser.ranges;
                    recorder_change[reading] = 1;
                end
            end
        else
            $scan_f$ilter = scan;
        end
    else
        $scan_f$ilter = scan;
    end
end
return sensor :: msg :: LaserScan$scan_f$ilter, recorder_change[ ]

conversion of sonar readings to each point of LaserScan message according to angle theta and side-length. According check[] array variable, it uses to compare with the 8cm threshold that is reading error combined from maximum 5cm of sonar reading error measuring and accuracy: 6—100cm—30mm,

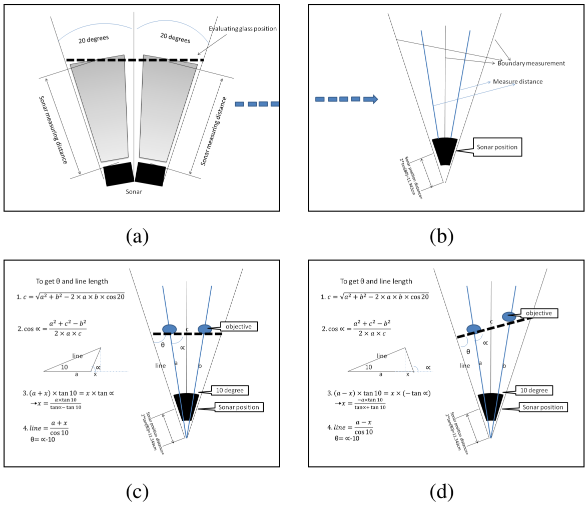


Fig. 6: *Approach One Design diagram: (a) Sonar Measure distance in two different sections. (b) Abstract Sonar Measure distance diagram (c) Mathematical structure of Obtuse Angle (d) Mathematical structure of Acute Angle*

$100 - 409cm - 3\%$; of Hokuyo laser [9]. There are three scenarios: One is that at least two check[] array parameters continuously show the difference beyond 8cm; the other one is only on check[] array parameter discretely show the difference; another is none of them showing difference.

In the third place, the second intelligent layer filter named CornerAdjust layer is designed to detect the error reading from corner situation in order to deal with the previous issue. In this scenario, the reading difference between sonar data and laser data causes a misunderstanding from previous algorithm that may believe there has a probability of existing a glass. The reading message from laser data is the distance from Turtlebot to objective. The corner analysis is a way to achieve the slope between each reading message by differentiating the reading message. If a corner happens, there is one large slope whose value should exceed certain threshold [10]. Thus, if there is only one or two large slope that mean one or two corner, the reading of laser data replaces back from frontal line drew from sonar data. If many corners detect by using corner analysis, it seems that this issue may be caused by other reasons such as small glass, error reading from edge situation so that the frontal line remains.

D. Approach B: Sonar-Map overlapping Laser-Map

The proposed method concentrates on a new map came from adding the sonar original data on the map achieved from the 2D laser-based SLAM. Since Gmapping who is capable of dealing with laser scan data was concentrated on the message of LRFs, this approach is a way to avoid the limitation of the Gmapping algorithm to accept both types of messages.

In order to add the sonar data on the map, ROS driver convert the sonar information from Float32MultiArray message to PointCloud message that also is a dot sensor message as only PointCloud message can integrate with occupancy grid map message. As consequence, the idea of this approach is to design a intelligent over-layer map, denoted as sonar map layer,

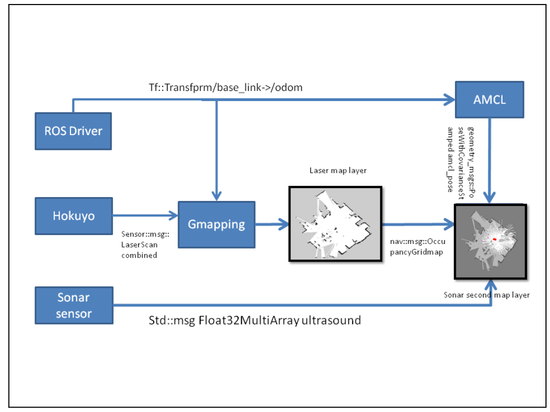


Fig. 7: *Sonar-Map overlapping Laser-Map*

Algorithm 3: Algorithm Maps Fusing

input : $UltrasoundArrayultrasound$, $PoseWithCovarianceStampedamcl_pose$, $createCloudOverlaymap$
output: $ccupancyGridsonar_map$

```
PointCloudsonar_pts;
Pointrobot_pose (AMCLpositionmessage);
Convert to PointCloud
for i ← 0 to sonar_number do
    sonar_pts.points[i].x = sonar[i] × sin(angle);
    sonar_pts.points[i].y = sonar[i] × cos(angle);
    sonar_pts.points[i].z = 0.22;
    sonar_pts.channels[0].values[i] = 100 + sonar[i];
    angle = angle + π/9;
end
Cloudsmessage = Add Point Clouds on map :
robot_pose message, sonar_cloud_point);
SendtoOccupancy(clouds, map_size);
return nav_msgs :: OccupancyGridsonar_map
```

which concentrate on the output of 2D laser-based SLAM map and adds, adjusts or ignores sonar sensory information on the map according to different situations in section 2.2.1. These two over-layer maps adapt to a set of sonar sensing data and provide filtered sonar map to 2D laser-based SLAM map in environment with transparent objects as shown in Figure 7 .

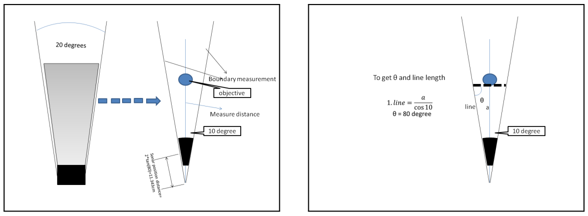
The Algorithm 3 presents a high-level code of adding Poitcloud sonar message on map algorithm. In this code, each point retrieved by the sonar message is added on the over-layer sonar map referring to original laser SLAM map[10].

V. Experiment and Results

A. Approach A

According to algorithm of sensor fusion, two intelligent layer filters are designed into experimental testing. Every time a LaserScan and Float32MultiArray message arrives, their time stamps will be compared using an approximate time policy. After that, the message received will be transferred from sonar frame to LRF frame, to analyse and compare both readings in the same coordinates frame. According to the algorithm 2, 3, their design structure are illustrated in Figure 6

The first GlassDetect layer is used to find the glass in the whole environment. In this case, the mapping task can be done using only sonar ring to draw the position of glass by



(a) (b)

Fig. 8: *Approach One Design diagram: (a) Sonar Measure distance in one section. (b) Abstract Sonar Measure distance diagram*

TABLE I: *Experimental results from different parameters in glass, plane and many corners cases*

Cases	Glass	Plane	Many corner
D_go=10cm	22% glass	glass	glass
D_go=30cm	glass	plane	plane
D_go=50cm	glass	30% glass	30% glass
D_sl=50%	glass	plane	22% glass
D_sl=80%	plane	plane	plane
R_sl=8cm	glass	plane	60% glass
R_sl=15cm	glass	plane	30% glass

converting to LaserScan message. However, the quality of map is expected to be low, due to the low resolution and nature of sonars. In order to decrease the issue of non-normal surfaces, the range of each sonar has been limited to a maximum of 3 meters. Therefore, it is important to verify if this conversion allows Gmapping to successfully map the environment using only sonar data. The second CornerAdjust layer is required to reduce the corner erroneous measures due to nature of sonar according to algorithm 4 as shown in Figure 8. It makes sure that the glass detection is not an erroneous measure due to corner impact. If it is an erroneous measure, the laser readings had belief to retrieve back from sonar data in each sonar section pass to SLAM Gmapping. Besides these scenarios, the laser readings remain same at each sonar section due to low probability of existing glass.

In this section the influence of the temporal thresholds has been tested too and the best results were achieved with the defaulted parameters. Several other parameters were tested, such as distance between glass and objects behind it D_go, the number of difference between sonar and laser D_sl, the reading different threshold among sonar and laser R_sl and corner detecting threshold C_T.

In Table one I, results for D_go set as 10cm, 30cm and 50cm; D_sl set as 50% and 80%; R_sl set as 8cm and 15cm in different trails are shown when the real scenarios are glass, plane and many corners case.

In Table two II, results for C_T set as 2, 10 and 15 in different trails are shown when the real scenario is many corners case.

Finally, these figures show the best results when $D\_go = 30cm$ $D\_sl = 50\%$ $R\_sl = 8cm$ $C\_T = 10$ After the evaluation of all sections, all the gathered information will be used to

TABLE II: *Experimental results from corner parameter in many corners case*

Case	C_T=2	C_T=10	C_T=15
Glass	Many corners	3-5 corners	No corner

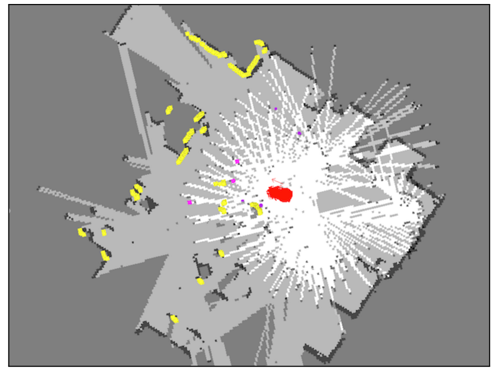


Fig. 9: *Approach Two Experiment in AMCL maps overlapping*

build the new LaserScan message. If glass is detected in a given section, the measurement of the LRF will be corrected if the sonar readings are available.

B. Approach B

According to algorithm of maps overlapping, two maps layer are implemented into experimental testing. The sonar reading is used to find the glass in the whole environment. In this case, the mapping task can be done using only sonar ring to draw the position of glass by adding on the original 2D laser-based SLAM map. Therefore, it is important to verify if this conversion allows Gmapping to successfully map the environment using only sonar data. However, the quality of map is expected to be low, due to the low resolution and nature of sonars. In order to decrease the issue of non-normal surfaces, the range of each sonar has been limited to a maximum of 3 meters. In Figure 9, it was taken when the approach two tested in different trails. The yellow colour is the laser scan dot used for AMCL localization while the pink colour is the sonar Point Cloud message.

In this section the influence of thresholds also were changed in order to achieve the best results. Several other parameters were tested, such as resolution, minimum of occupancy, and maximum of reading range from sensors. Finally, the best layer-map result happens when resolution = 0.1, minimum of occupancy = 0.07, maximum of reading range = 2 where pink colour is the sonar Point Cloud message.

C. Results and Discussion

In all trials, when Gmapping is fed solely with laser data, it cannot detect the glass area. Meanwhile, when Gmapping is fed solely with sonar data, it loses accuracy in the rest of location besides glass and cannot construct the map according to the environment. Hence, the sensor fusion between sonar and laser shows much better results than single sensors.

In the first approach, the results of pure laser mapping picture and both sonar and laser mapping picture in Figure 10 mainly classified the normal environment and glass field, which clearly detected glass and constructed it on map. However, it returns back the error reading due to corner, as well as the narrow edge error still has large influence in map generation that leads to another problem in Turtlebot navigation. For the general

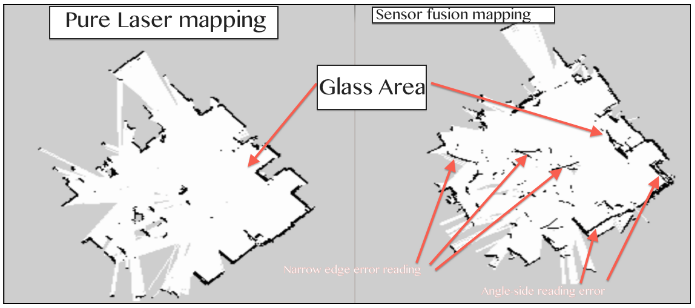


Fig. 10: *Approach One Experimental result in SLAM mapping*

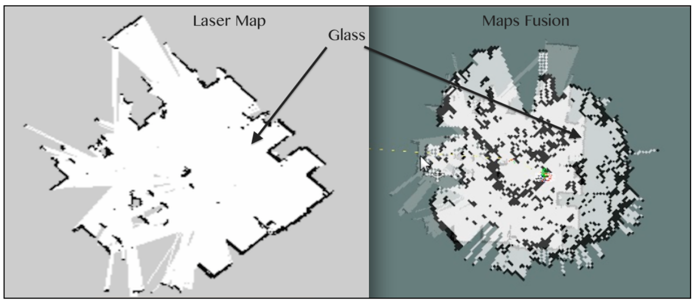


Fig. 11: *Approach one experimental result in SLAM mapping*

scenarios, such as wall or plane glass is clearly recognised from the experimental results which state the approach one is reliable in dealing with the transparent objects problem.

In the second approach, the Figure 11 shows a worst results due to a low quality in overlapping sonar maps. This happens not only because of the low resolution and nature of sonar sensors, but also due to the previous mentioned misbehaviour of the sensors. For this reason, when AMCL is fed with sonar data, that zone was successfully mapped, but the quality of the mapping is quite low. In the general scenarios, such as wall or plane glass also cannot clearly recognised from the experimental results which present the approach two is not useful in dealing with the transparent objects problem.

The main purpose of this thesis is to propose and develop a SLAM approach in achieving a same or better accurate map in such environment. From the results of two approaches, the first approach presents a better performance than the second approach. Yet, the improvements are significant and it has been proved that SLAM in such conditions is possible using a multi-sensor approach. Also, the developed two intelligent layers do not show delays in the system and solution proposed is based on a low-cost philosophy, using only off-the-shelf, fairly cheap sensors. Better results would be obtained using sonars with stable readings. Beyond that, it is the authors belief that a solution based on a radar sensor would be ideal to solve the problem while maintaining maps of high quality, independently of the transparent objects in the environment.

VI. Conclusion and Future Development

In this paper, the primary aim of data fusion is to combine data from multiple sensors to perform inferences that may not be possible with a single sensor. The approach A of using sensor fusion is a simple and easily adaptable approach and its relevant experimental results proved its advantages than the secondary maps overlapping because of low resolution of sonar reading and environmental distortion. A sensor-related issue that requires future work is sensing on various surfaces. The sonar sensors used in experimentation have been shown to be accurate and precise on the plane wall with normal angle. Unfortunately, they do not work well on all surfaces like error reading from edge situation that is complex issue in analysing environmental situation. Hence, replacing the sonar ring by a more reliable range sensor with high resolution would be recommended with integration of a visual Kinect Camera to provide a method to detect glass.

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