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SLAM based Autonomous Navigating Object Identifier for an Indoor Environment using 3D - LiDAR and MoBiNet

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Abstract:

This research work focuses on design and development of a mobile object identifying system for an indoor environment. A robot is designed that maps the entire indoor environment and identifies the objects that are present within the destination location. The developed embedded module uses 3D-LIDAR (Light Imaging Detection and Ranging) to map the environment and Software namely MATLab, Robot Operating System (ROS) and Python for platform development. It also uses SLAM (Simultaneous Localization And Mapping) and PRM (Probabilistic Roadmap) algorithms to perform localization, mapping and path planning.

Keywords **—Robot, LIDAR, MATLab, SLAM and PRM.**

I. INTRODUCTION

Autonomous navigation is the future of robotics and object recognition is one of the vital activities that need to be performed by robots. Autonomous robots are used in various applications namely household cleaning, Goods delivery, factory automation and safety measures [1]. Autonomous navigation is a complex task that involves localization, mapping and path planning. Localization is the basic step in autonomous navigation since the robot has to know or identify the position of itself in an environment. Localization is performed by triangulation method. Mapping involves associating the scanned data set obtained from each environment to derive overview topography of the scenario [2].

LIDAR (Light Imaging Detection and Ranging) is used in the developed robot to detect all fine objects present in the indoor environment precisely, based on which the three dimensional (3-D) map of the environment is constructed. The 3-D LIDAR consist of a transmitting laser and a receiver. LIDAR emits laser signals in 360 degrees, whenever this signal hits an obstacles, it gets reflected and received by the receiver present in LIDAR. From the reflected signal, the meta data namely position, height and distance of the object is computed. In simple terms LIDAR is a scanner that could create an exact digital copy of all the physical objects present in the considered environment with precise measurements.

The mobile object identifier first builds a virtual map in which it could travel by combining various LIDAR scan results of the environment. This robot uses the SLAM algorithm for localization and mapping activities, the PRM is used to create the possible navigation path for the robot from source to destination. The mobile object identifier identifies the object's material with computer vision and machine learning in its route to the destination.

The contents of the paper are organized as following. Section II describes the literature of related works. Section III defines the proposed work. Section IV details the experimental outputs. Finally, the conclusion of this work is summarized in Section V.

II. LITERATURE SURVEY

In [1], author has mentioned the various fields in which the autonomous navigation system is in use and provides an overview of the researches in the past decade about autonomous navigation in human environments by mobile robots. It is recommended to consider execution time, trajectory length, free collision with static obstacles and human factors.

In [2], author implements automatic parking system based on laser SLAM by B-Spline path planning algorithm and elaborates the research method of laser-based SLAM parking space environment reconstruction. This approach selects short range LiDAR to enlarge its perception on parking environment and senses available parking.

In [3], author implements fast SLAM technique. The accuracy of the localization of the robot's position was achieved by placing long range sensors in the environment and the data from these sensors are combined to detect the position of the robot more accurately than the normal slam and navigation was performed in the mapped environment.

In [4], author proposes monocular SLAM using 2d LiDAR to scan the environment. Then a two dimension (2D) map is built using the laser data and localized in six dimensions (6D), so that the robot's position from the ground level is obtained. This localization technique is used to analyze different terrains like stairs, slopes.

In [5], author presents a simple and cost - effective 3-dimensional (3D) mapping of internal structures using Light Detection and Ranging (LIDAR). LIDAR is being controlled in such a way to measures the distance and angles from both servo motors simultaneously on which LIDAR is mounted.3D mapping using photogrammetry technique is very sophisticated, time consuming and costly. 3D mapping provides a very realistic view that enhances the visualization.

In [6], author presents a novel robot system for cleaning the garbage on the grass automatically. Based on the powerful deep neural networks, the proposed robot can recognize and pick up the garbage without any human assistance. Through the manipulator, relatively large garbage on the grass can be picked up. This cleaning mechanism is more suitable for cleaning the garbage on the grass than the one used by the existing road sweeper truck or vacuum cleaning robot.

In [7], author has used the latest technologies in computer vision, robot control and other fields and taking advantage of their maturity, a system has been built that makes it possible to visually classify and separate different types of waste effectively, a task that would normally require manual work.

In [8], author designed a system which can separate inorganic waste like plastic bottles, aluminum cans, plastic cutlery, and other kinds of waste. It uses knowledge from different areas like computer sciences, optics, mechanics, and electronics. The specific topics that we have focused on are image processing, computer vision, machine learning, pattern recognition, embedded systems, and circuit design.

In [9], the authors talk about an effective liberation of various materials like metals and plastics is a crucial step towards mechanical separation. Classification of electronic scrap is also important to be able to provide an appropriate feed material for the subsequent separation process. In the study, liberation and its impact on the separation of personal computer PC scrap and printed circuit board PCB scrap has been investigated in detail.

In [10], author augmented Latent Dirichlet Allocation (aLDA) model to combine these features under a Bayesian generative framework and learn an optimal combination of features. Experimental results of the paper show that the system performs material recognition reasonably well on a challenging material database.

In [11], author studied rectifier neural networks for image classification. Author proposed a Parametric Rectified Linear Unit (PReLU) that generalizes the traditional rectified unit. PReLU improves model fitting with nearly zero extra computational cost and little overfitting risk. Based on the learnable activation and advanced initialization the paper achieves 4.94% top-5 test error on the ImageNet 2012 classification dataset.

In [12], author trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, this model achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art.

III. PROPOSED METHODOLOGY

The Autonomous Navigating Object Identifier robot has three main modules, they are Path planning module, object classification module and action module. The explanation for each modules are given below.

A. Path Planning Module

The path planning consists of a robotic system and an external processing unit. The robotic system consists of hardware parts such as sensors, motors, Wi-Fi, Bluetooth modules, and a local processing unit. The Robotic system acts as the master and the external processing unit acts as the slave. The Robot sends the scanned sensor data obtained from the LiDAR to the external processing unit through a Wi-Fi medium. These data are further processed in MATLab. The sensor data is processed and stored for future calculations.

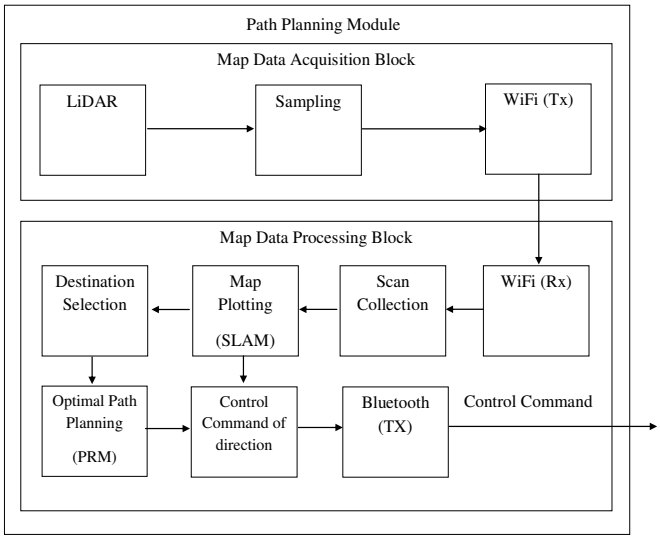


Figure 3.1 Path Planning Module

Then, the robot is moved gradually and the scans are collected. On the collection of sufficient scans, the scanning process is over and now the collected values are processed to plot the graph of the environment. The next step is to select the destination in the built map. Once a destination is fixed an optimal path is constructed in the external processing unit and it directs the robotic system to follow that path. The current position and the trajectory of the robotic system are monitored by the external processing unit. Whenever the robotic system tends to deviate from the path its movement is altered by the commands that are received by the Bluetooth module from the external processing unit

1. SLAM

Simultaneous Localization And Mapping (SLAM) is the computational problem of constructing or updating a map of an unknown environment while simultaneously keeping track of the robot location within it.

First step is to scan the environment. Once the scan is obtained it has to be plotted. When the current scan matches with the earlier scan data, then it is called loop closure.

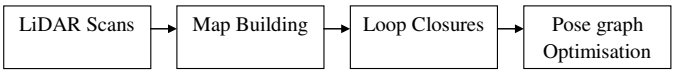


Figure 3.2: SLAM Algorithm

Loop closures are then identified. Pose graph optimization is performed whenever loop closure is identified. Completion of map by returning to the initial position which forms a complete loop, this is the final pose graph optimization that is performed in the algorithm during the construction of map. At last occupancy grid is constructed.

2. PRM

The Probabilistic Road Map (PRM) planner is a motion planning algorithm in robotics, which solves the problem of determining a path between a starting configuration of the robot and a goal configuration while avoiding collisions.

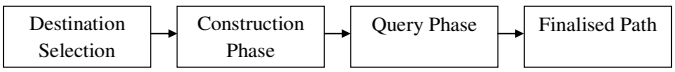


Figure 3.3: PRM Algorithm

The destination is selected from the map built by the SLAM algorithm. Then in the construction phase the map is allotted with x number of nodes, a random path is created and all the distance needed to reach the destination node are calculated by contacting with the neighbouring nodes in the query phase.The finalised path is obtained by Dijikstra's shortest path query.

B. Object Classification Module

The Object Classification Module consists of an Image acquisition module in the robotic system and an external processing unit. Since the processing of an image is a complex process, it requires a better processor. Hence the processing is carried out in an external processing unit. The image acquisition block acquires an image through raspberry pi camera of 8mega pixels. It is sent to an external processing unit through the Wi-Fi interface in the raspberry pi of the acquisition module. A Wi-Fi link is established between the image acquisition module and the external processing unit. Then after receiving the image, it is processed by an image

processing algorithm named MoBiNet in the external processing unit.

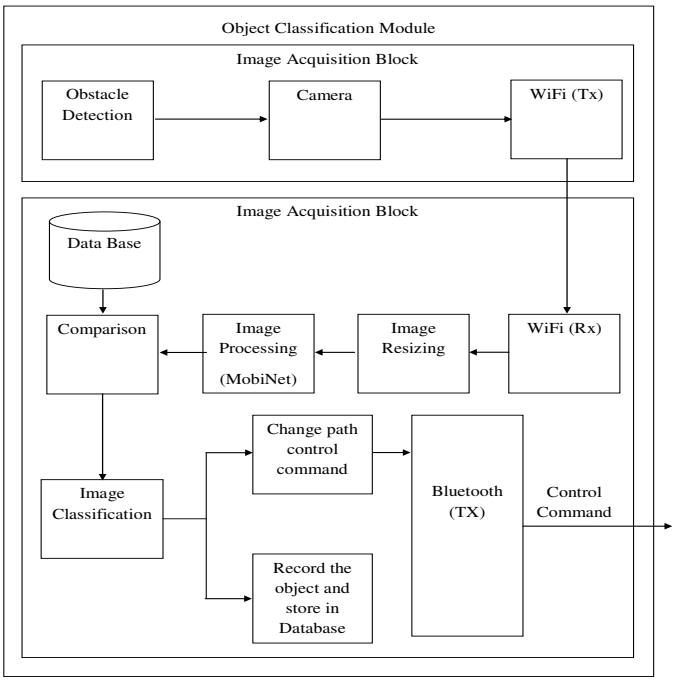


Figure 3.4 Object Classification module

The Image is processed and after the classification of the object, the control command is sent to the robotic system. If the image is observed to be Object, the robotic system records the object else if it is a human or a bigger obstacle, it would take another path.

3. *MoBiNet*

MoBiNet is a streamlined architecture that uses depth wise separable convolutions to construct lightweight deep convolution neural networks and provides an efficient model for mobile and embedded vision applications. The depth wise convolution filter performs a single convolution on each input channel. The point convolution filter combines the output of depth wise convolution linearly with $1 * 1$ convolutions. There are two major steps in the working of MoBiNet. They are training and testing. In Training phase, the images are converted into universal format (Dk x Dk) 224 x 224 and the depth value would be M=3, since it composes of three main colors which are Red, Green, Blue. Then, they are sent first to 5 Depth wise convolution filters with K different kernel size, and passed over to a point wise convolution. In point wise convolution, all the outputs from depth wise convolutions are linearly arranged. The convoluted output is stored as matrix values this is the trained data set. After the training phase, comes testing phase.

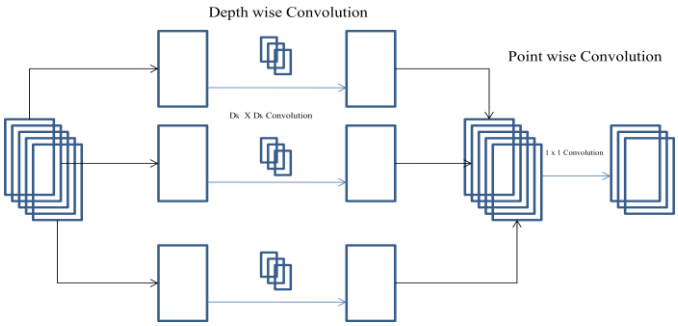


Figure 3.5: MoBiNet Architecture

A raw image is captured and it is converted to universal format passed into 5 depth wise convolution filters followed by a point wise convolution filter, this output is compared directly with the trained data set. The accuracy value depends on how much this testing output matches with the existing trained dataset. When a network is trained with exhaustive number of images the accuracy will be increased.

C. *Action Module*

The action module performs the part which involves mechanical movement of the Object identifying system.

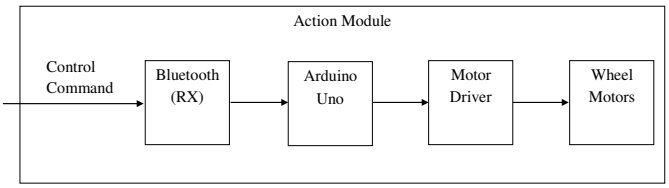


Figure 3.6 Action module

In Figure 3.6, the action module receives different control commands from the path planning module and the Object identification module through Bluetooth and these received signals are processed and sent to the motor driver. These motor drivers serve like an interface between the motors and the processor. Motor drivers use low current control signal and then convert it into higher current control signal which could drive the motor.

IV. EXPERIMENTAL DATA AND RESULTS

A. *Path Planning Module Output:*

First, the Robotic Operating System (Master) is initialized and the LiDAR values are sent from the

robotic system to the external local processing unit as shown in Figure 4.1.

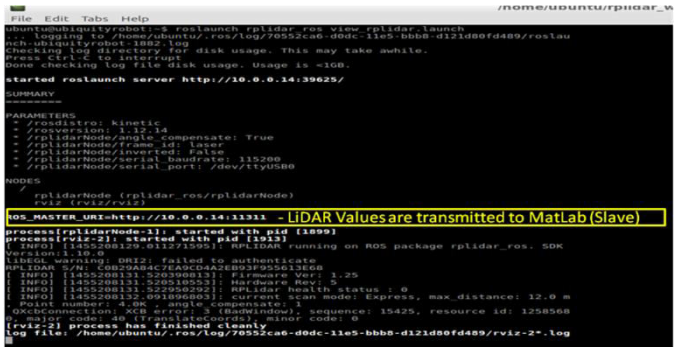


Figure 4.1: ROS initialization and sharing of scans with local processor

The raw LiDAR outputs viewed through ROS running on the robot processor is shown in Figure 4.2. From the experimental result, it is found that maximum distance up to 12 meters can be measured through LiDAR.

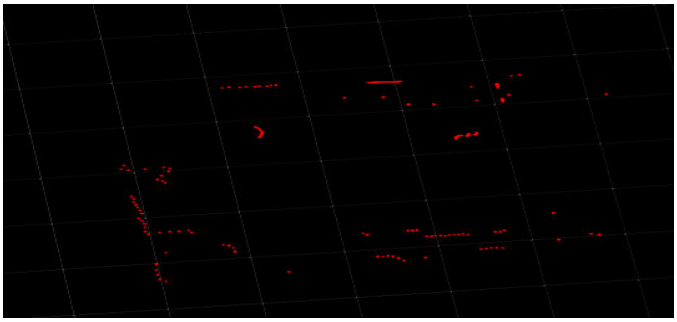


Figure 4.2: Raw LiDAR Scans viewed in ROS

The Figure 4.2 is the live dynamic readings of the environment sensed by LiDAR. These values are framed and sent to local processor as shown in Figure 4.1. The Local processor receives the scanned data set and plot made using MATLab.

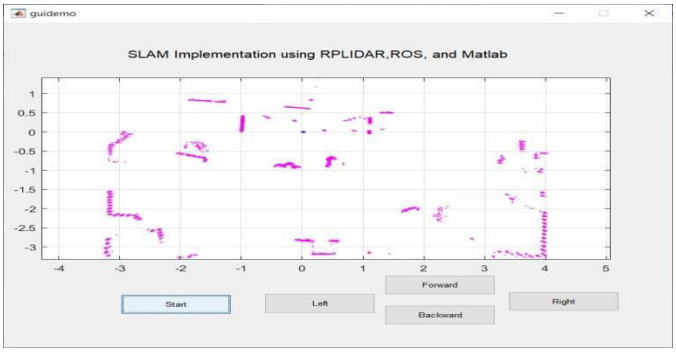


Figure 4.3: Scan Plotted and mapped in MatLab

In Figure 4.3, first set is mapped then after moving the robot to 1 meter, the scans are plotted and the map is again updated in Figure 4.4.

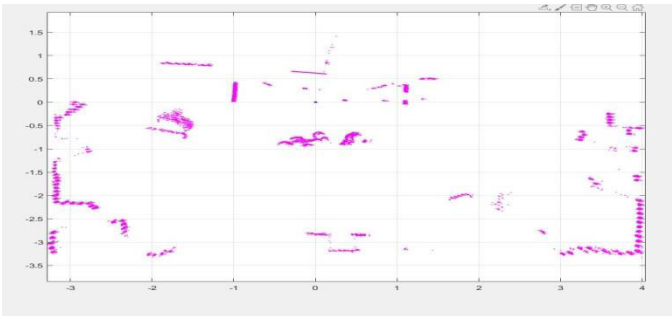


Figure 4.4: Addition of suceeding scans with previous map

The loop closure is identified and pose graph optimization is performed and the white area represent the possible area to move and black dots are the objects in the environment.

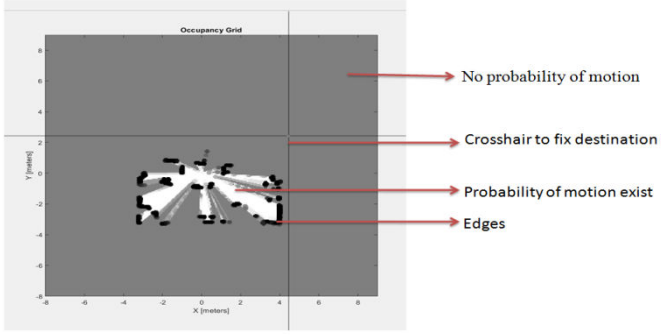
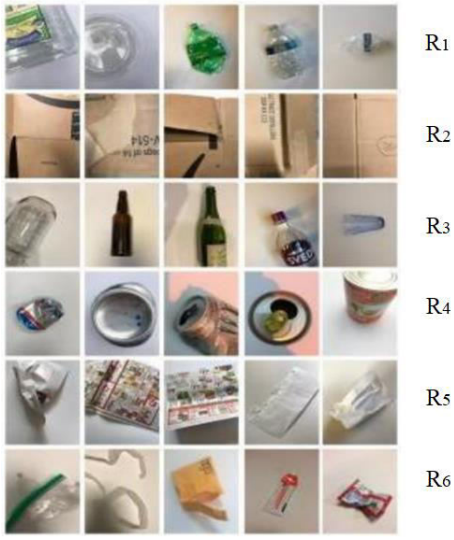


Figure 4.6: Path Formation from source to destination

In fig 4.6, the path grid is represented in green and red colored lines within which the system will proceed moving to reach the marked destination.

B. Object Classification Module



R1: Plastic; R2: Cardboard; R3: Glass; R4: Metal; R5: Paper; R6: Object

Figure 4.7: Database

The fig 4.7 is the created database for recognition and classification of the object. The database is

trained with 343 cardboard, 293 glass, 310 metal, 524 paper, 384 plastic, 87 Object images.

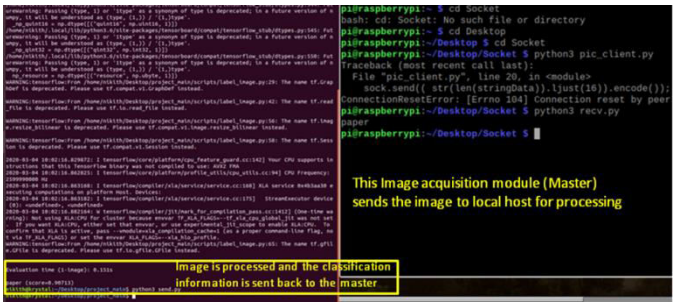


Figure 4.8: Object Classification Master and slave communication

The fig 4.8 is the object classification unit, the robotic system captures the image and sends it to a local processor through wifi band and then the image processing is performed. The end results of the process is sent back to the master system and this keeps track of the objects in the data base.

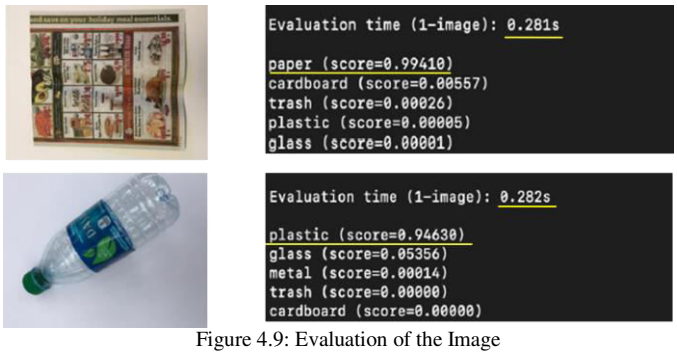


Figure 4.9: Evaluation of the Image

The fig 4.9 is the testing image for which the evaluation time and accuracy is displayed.

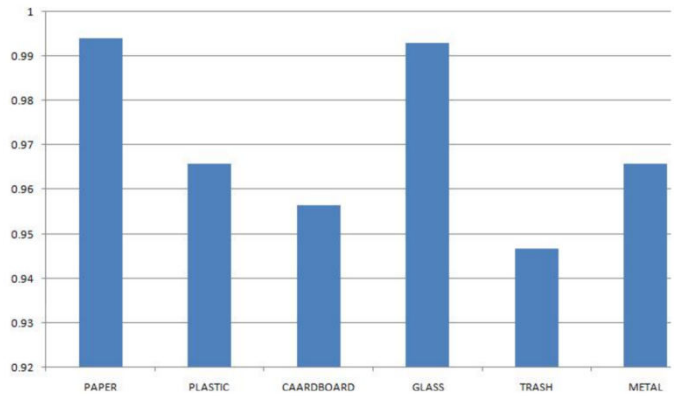


Figure 4.10: Accuracy Performance

The fig 4.10 is the accuracy graph. This graph illustrates the system's accuracy performance on identifying and classifying the object. The system is 99.3% accurate on identifying paper and glass, 96.6% on identifying metal and plastic, 95.7% on identifying cardboards, and 94.8% on identifying trash

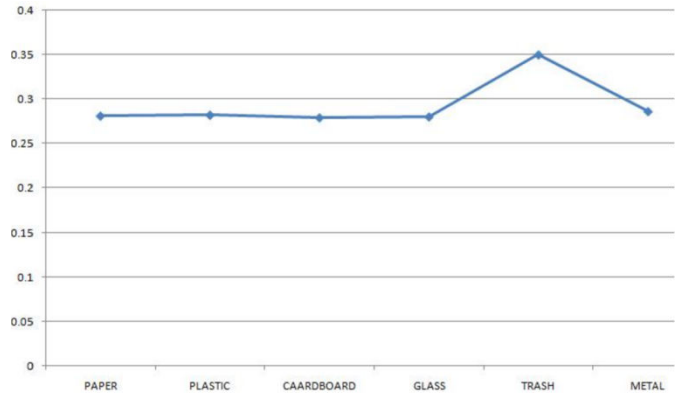


Figure 4.11: Time analysis

The Fig 4.11 displays the accuracy and the speed of the object classification. More images added in the data base would further increase the accuracy of the system in identifying the objects, however overall all the type of objects are classified is up to the accuracy above 94% and the time taken to identify the objects is about 0.27 seconds.

C. SLAM based Autonomous Navigating Object Identifier

The Slam based autonomous navigating object identifier has three layers they are top, middle and bottom layers.

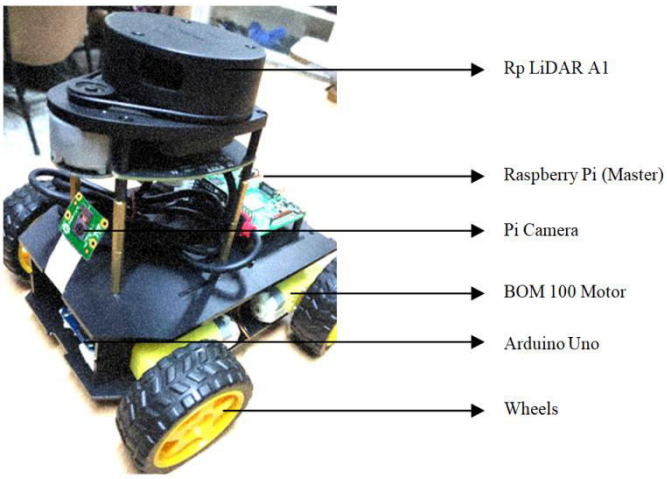


Figure 4.12: SLAM based Autonomous Navigating Object Identifier

The fig 4.12 is SLAM based Autonomous Navigating Object Identifier it uses pi camera to capture images and LiDAR to scan the environment. The top layer consists of LiDAR. The Middle Layer consist of Raspberry pi and the bottom layer consist of another raspberry pi to which the pi camera is connected, Arduino Uno, power source, Bluetooth module and the Motor driver L293D are present.

V. CONCLUSION AND FUTURE WORK

The Autonomous navigating object identifier can be used as a commercial product in day today application such as (i) a cleaning robot with proper payloads attached (ii) an environment monitoring robot (iii) factory robot for delivery purpose (iv) a defense and security purpose robot which could be used for automatic surveillance. With increased training and efficient path planning algorithms this robot will be a revolutionary automatic navigating environment leaning capable robot.

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