A Study on Detection of MEP Provision using Autonomous Mobile Robot

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Abstract

One of the key processes carried out by quality control experts to achieve the plaster clearance of the wall is the identification of mechanical, electrical, plumping (MEP) provisions. The inspection is done with the help of an approved engineering drawing. Checking provisions in a multistory build- ing is a tedious operation and is time consuming. Since detecting provisions is a repetitive activity, inspection engineer may lose interest or make mistake leading to incorrect inspection. The use of an autonomous mobile robot is demonstrated in this paper which is capable of detecting MEP provisions directly from the wall with the help of adequate algorithm. The simulation result shows the autonomous navigation and obstacle avoidance feature of mobile robot using required sensors along with navigation nodes in the customised world. Binary classification of provision is done by training Resnet-50 computational neural network model with custom made dataset.

Keywords: *Provisions, Unmanned Ground Vehicle(UGV), Husky Robot, Quality Control(QC), Gazebo, Autonomous Mobile Robot(AMR), Algorithm.*

I. Introduction

During construction for large buildings, processes such as inspection, MEP works, plaster clearance, painting and many more are tendered to specific process related companies. The final result will be the collaboration of all such mentioned processes. The contractor designates quality inspection engi- neers to conduct visual inspections of the facility to ensure efficient work flow and for ensuring everything is going as per the building plan. One such important inspection is the MEP provision inspection. The inspection engineers visually inspect the walls of the buildings to make sure the provisions have been laid at the required positions. The inspection process should be done with extreme caution because any faulty inspection can lead to a great deal of time and financial loss. In small buildings the process is quite easy but checking of provisions at each required place in a large multi-storey building or apartment is a tiresome task. Since it is a repetitive huge task, the probability of causing error or loosing interest from the side of inspection engineer is considerably high. In order to prevent such mistakes and aid the quality inspection engineer, an Autonomous

Mobile Robot (AMR) capable of detecting provisions directly from the wall is implemented.

The AMR chosen for this research work is Clearpath Husky A200 Unmanned Ground Vehicle. Husky robot is the best fit for construction sector because of its rugged nature and support for multi-terrain activity [1]. Husky robot customised with sensors and algorithms helps in navigation and detection. Resnet-50 is the preferred CNN model for binary classification as it has better performance to speed ratio as compared to other traditional models [2]. For avoiding obstacles in real time, the Adaptive Monte Carlo Localization (AMCL) technique is utilised . An external movebase python node incorporated with required position coordinates is used for navigating the robot to the desired locations where provisions are present. Section II presents the literature survey. Section III explains the methodology and implementation of the experiment. Section IV and V discusses the result, conclusion and future Work respectively.

II. RELATED WORK

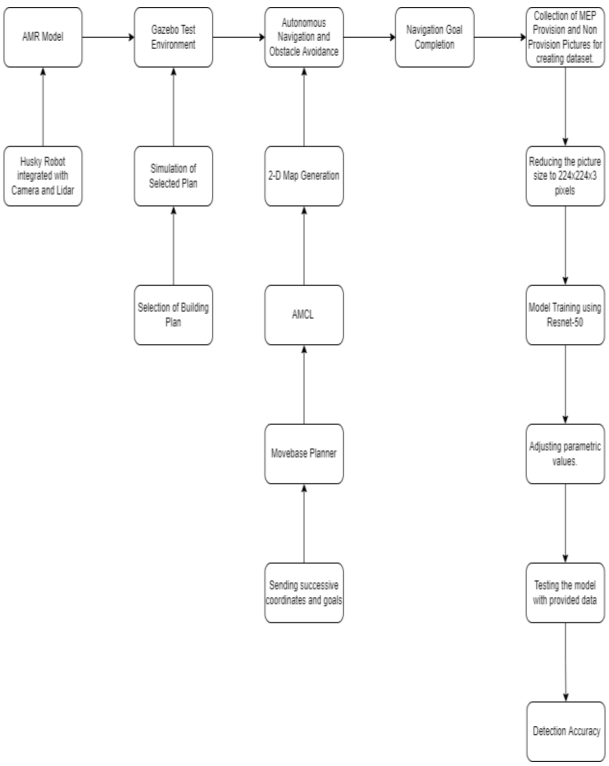
Quality inspection robots are nowadays becoming so pop- ular in the market. But in construction industry, the role of inspection robots are very less [3]. The research works related to robotics in the construction sector and papers related to convolutional neural networks (CNN) are discussed. In this paper the authors conducted research with deep learning solu- tion to distinguish covid-19 patients from pneumonia patients [4]. Recent study depicts that patients with COVID19 exhibit certain radiographic abnormalities on their chest X-rays. The method is tuning a pre-trained ResNet-50 architectures to increase model performance and reduce training time. The goal is reached by gradually resizing input images to 224x224x3 pixels.The particular approach helped the authors to achieve accuracy of 96.23 percent. In this paper the authors proposed a quality inspection robot which is capable of detecting MEP provisions with the help of arucomarkers [5]. Arucomarkers are placed in place of provisions and the robot scans and identifies the provisions.This paper put forwards a solution consisting of deep learning technique that identifies MEP components such as sockets, switches and radiators in BIM. Systems such as scan-to-BIM transform picture and point cloud data into comparable 3D models. [6]. This paper proposes 50 convolutional layer deep ResNet-50 for fault diagnosis [2]. ResNet-50 is trained on ImageNet using transfer learning as a feature extractor for fault diagnosis. The proposed CNN has been tested on three datasets. The results achieved are high as 98.95 percent, 99.99 percent and 99.20 percent, which proves that ResNet-50 performs better than other DL models and conventional techniques. In this paper the authors proposed a robot called Quicabot which is particularly aimed at bringing out building defects [7]. They were successful in implementing an automated mobile robot, a laser scanner, a colour camera, a thermal camera, and an inclinometer which make up a robotic system. The quicabot checks for hollowness, fracture, evenness, alignment, and inclination.

With the advancements in technology , the robotics and au- tomation field have already made the mark in many dominant sectors. Many areas are still left for robots to assist and bring in innovations. One such area is the construction sector. Many research papers are available in detection of MEP modules and components but onsite detection of MEP provisions is limited. In this Project work, we are aiming to implement a mobile robot that can navigate autonomously and has the capability of detecting MEP provisions directly from the wall.

III. METHODOLOGY AND IMPLEMENTATION

Fig. 1 shows the schematic representation of the entire process which is carried out in this particular experiment.

Fig. 1. Flow Chart of entire process



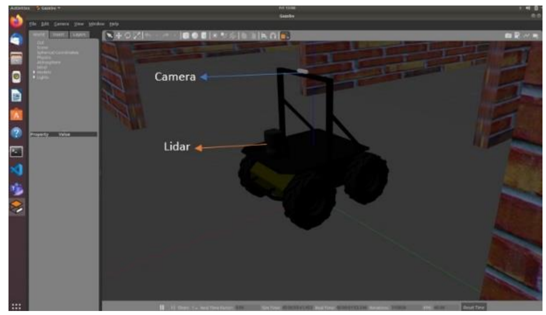
A. Robot Operating System

An open-source operating system for robots is called ROS (Robot Operating System). Hardware abstraction, low-level device control, the implementation of frequently used functionality, message-passing between processes, and package management are just a few of the capabilities and services offered by ROS. Additionally, it includes libraries and tools for creating, developing, and executing programmes across a variety of computers [8]. For our Work we have installed the Melodic Version of ROS in Ubuntu 18.04 OS. The robotics part of this project work is done in Gazebo which is a ROS based simulation Platform.

B. Robot Model and Sensors

The Autonomous Mobile Robot selected for this project is Husky A200 Rover. Husky is a multi-terrain robot and is best suited for construction environment because of the rugged body structure.

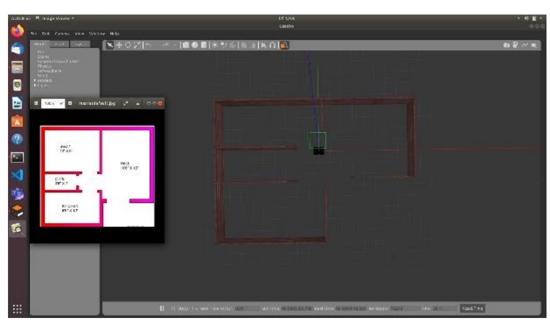
Fig. 2. Robot model with Camera and Lidar



As shown in Fig. 2, Sensors like Camera and Lidar are incorporated for successful implementation of autonomous navigation, obstacle avoidance and also for visual inspection of the provisions. Husky is equipped with a sensor arch in order to incorporate camera. The camera sensor helps the user to view the world from the robot's perspective. The Camera used is Intel's real sense camera. Intel's Realsense is the best fit as it can scan outdoors, even in full sunlight as well as in low light. It has good build quality and can withstand bumps and shocks with no major degradation of performance. In order to navigate autonomously by avoiding obstacles, sensor fusion is done by taking readings from camera and lidar.

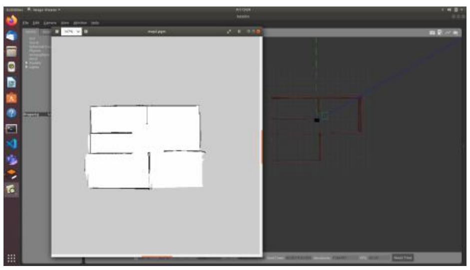
C. World Creation

Fig. 3. Building plan simulated in Gazebo



Entire work is done on simulation based ROS platform. The world setup considered for this experiment is the plan of 1 bedroom-hall-kitchen (BHK) building. The plan is simulated in the Gazebo Environment as shown in Fig. 3. A computer programme called Gazebo has the ability to simulate 3-D environments containing robots, obstacles, and a variety of other items. A physical engine is used by Gazebo to provide light, gravity, and inertia. The simulator enables the user to evaluate and test the robot in simulated environment without any harm to the real robot [9].

Fig. 4. 2-D Occupancy Grid Map

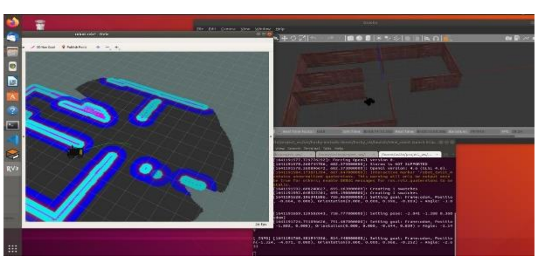


The Robot model incorporated with sensors is spawned in the simulated world and Gmapping is done as shown in Fig. 4.

D. Autonomous Navigation and Obstacle Avoidance

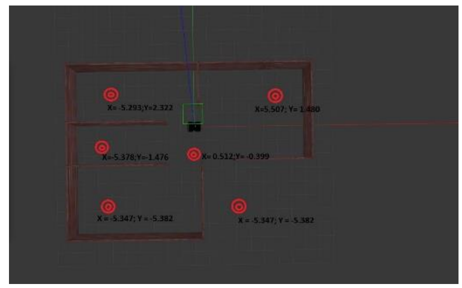
For enabling autonomous navigation, real time position coordinates obtained from Husky's Odometery readings are fed into an external movebase python node.

Fig. 5. Obstacle Detection



Blue line highlights shown in Fig. 5 is the process of robot detecting obstacles. Location coordinates in the simulated world where the robot is supposed to navigate is shown in Fig. 6. Adaptive Monte Carlo Localization (AMCL) algorithm is used in the background for avoiding obstacles in realtime. A two-dimensional probabilistic localization system for robots is called as AMCL. The algorithm tracks a robot's pose against a known map using a particle filter. As shown in Fig. 7, the robot autonomously navigates to the required coordinates one after the other.

Fig. 6. Position Coordinates



E. Creation of Dataset and Model Training.

In order to make the Robot identify Provision directly from the wall, Machine Learning (ML) model has to be trained with MEP Provision and Non Provision dataset. Since the required dataset is not available on the internet, manual creation of dataset is done.

Fig. 7. Robot Navigation

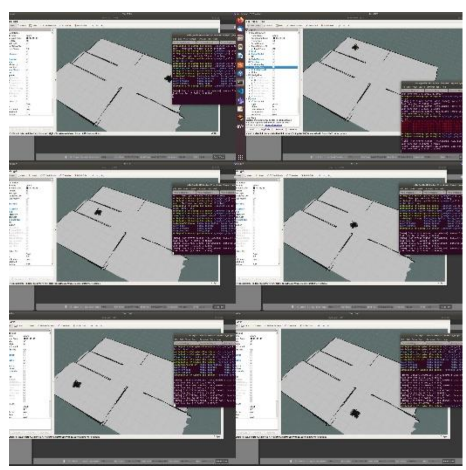


Fig. 8. Pictures of Provision

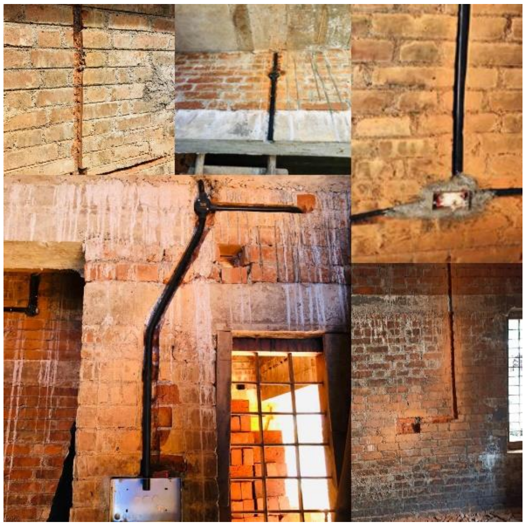


Fig. 8 shows the sample pictures of Provisions. A total of 1280 images were collected for creating dataset which contains both provision and non-provision pictures. Out of which, 70 percent of the image is used for training and 30 percent of the image is used for testing. Exact count corresponds to 897 images for training and 383 images for testing. The pictures are then converted to 224x224x3 pixel size using python code to make them fit for training on CNN model. The custom made dataset are re-trained on pre-trained resnet-50 CNN using transfer learning technique. Data augmentation is done on the dataset using image data generation function. In order to achieve maximum accuracy the parametric values in algorithm are adjusted accordingly. The batch size is set to 32, epochs to 10 and early stop patience to 5.

F. Detecting Provisions.

In real world,the robot navigates to required position coor- dinates where provisions are present and capture images for identification by applying ML algorithm. Since the proposed research work are done in simulation, robot navigates to each coordinates in gazebo environment assuming the provisions are present at mentioned coordinates. Robot navigates to each of the provided coordinates one after the other by completing each goal and finally returns back to the original position.

Fig. 9. Link to ML execution

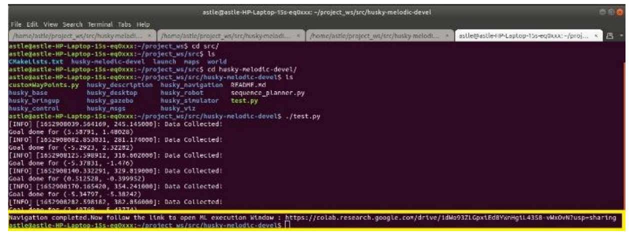


Fig. 10. Train Confusion Matrix

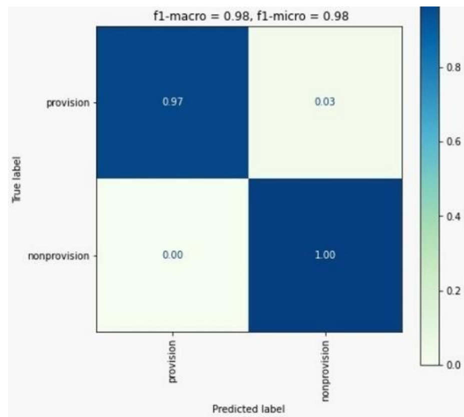
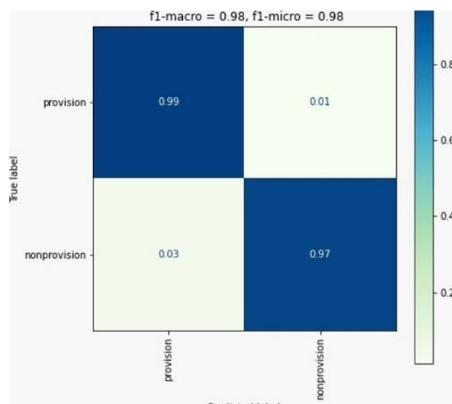


Fig. 11. Validation Confusion Matrix



After completing navigation,a message with the link gets displayed in the terminal as shown in Fig. 9 which in turn navigates the user to the ML execution window. Since in simulation it is not possible to take live pictures of provisions, therefore provision pictures that needs to be tested are manu- ally provided. By clicking the run button after opening the link, the user will get the accuracy in the form of matrix and graphs. If the accuracy is above minimum threshold then the particular data has been identified as provision. Fig. 10 and Fig. 11 shows the train and validation confusion matrix obtained as a result of successful completion of ML training and testing. Since this research focuses on binary identification, matrix consist of provision and non provision as the two labels. The matrixes defines that an accuracy of about 97 percent is achieved from the respective model.

IV. RESULT

Husky Robot which is capable of autonomously navigating in an orderly manner is successfully implemented in the sim- ulation Gazebo Environment. The Robot Model is equipped with necessary sensors such as Lidar and Camera in order to facilitate obstacle avoidance and navigation. Manual creation of the MEP Provision and Non Provision dataset are done in order to train the Machine Learning model. The custom made datasets are then trained on Resnet-50 CNN. Fig. 12 and Fig. 13 shows the model accuracy and model loss. By extracting information from the graphs it can be noted there is no further improvement after the 5th epoch. Therefore the iteration stops at 5th epoch and accuracy is calculated. An accuracy of about 97 percent is obtained from the model during testing phase. Thus it can be concluded from the research that binary detection of MEP provision is successful.

Fig. 12. Model Accuracy

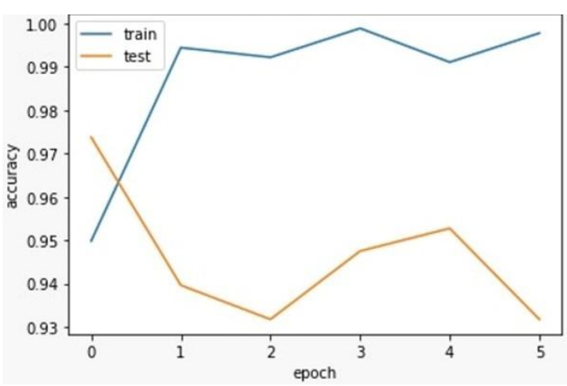
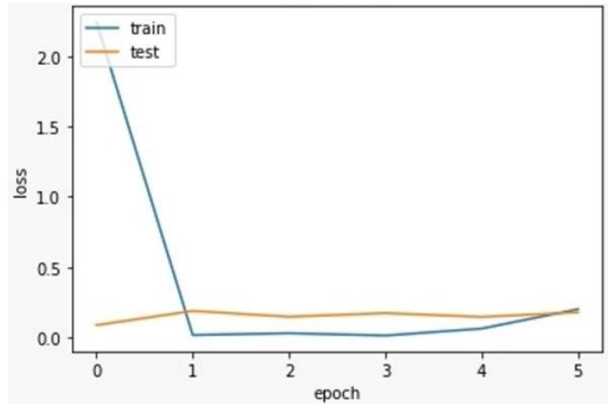


Fig. 13. Model Loss



V. CONCLUSION AND FUTURE WORK

After successful implementation of the entire work in simu- lation, one can carry out the exact process to hardware imple- mentation. By making the Robot capable of visual Inspection, time consumption and basic errors can be reduced to a great extend and therefore workers can concentrate more on other important aspects. This particular work primarily focuses on binary identification of provisions. After completion of this work, many new foundations can be laid on it. One such futuristic work is by providing the robot with the required unique dataset so the robot will be able to identify and classify the type of provisions to which it belong to whether it is Mechanical, Electrical or Plumping provisions. Despite the fact this research have only created an introductory part into the foremost remedy of MEP installation, extra work linked to second and final fixes could be produced on top of the simulated result. Construction inspection is one sector where automation has yet to make a substantial impact and this research could be the start of something groundbreaking.

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References

[Sai Charan Dekkata. Model Predictive Control for Unmanned Ground Vehicles Using Robot Operating System. PhD thesis, North Carolina Agricultural and Technical State University, 2021.

Long Wen, Xinyu Li, and Liang Gao. A transfer convolutional neural network for fault diagnosis based on resnet-50. Neural Computing and Applications, 32(10):6111–6124, 2020.

Juan Manuel Davila Delgado, Lukumon Oyedele, Anuoluwapo Ajayi, Lukman Akanbi, Olugbenga Akinade, Muhammad Bilal, and Hakeem Owolabi. Robotics and automated systems in construction: Understanding industry-specific challenges for adoption. Journal of Building Engineering, 26:100868, 2019.

Muhammad Farooq and Abdul Hafeez. Covid-resnet: A deep learning framework for screening of covid19 from radiographs. arXiv preprint arXiv:2003.14395, 2020.

R Jawad, R Anikesh, and G Gayathri. Autonomous mobile robot for visual inspection of mep provisions. In Journal of Physics: Conference Series, volume 2070, page 012199. IOP Publishing, 2021.

John Kufuor, Dibya D Mohanty, Enrique Valero, and Fre´de´ric Bosche´. Automatic mep component detection with deep learning. In Interna- tional Conference on Pattern Recognition, pages 373–388. Springer, 2021.

Rui-Jun Yan, Erdal Kayacan, I-Ming Chen, Lee Kong Tiong, and Jing Wu. Quicabot: Quality inspection and assessment robot. IEEE Transactions on Automation Science and Engineering, 16(2):506–517, 2018.

Morgan Quigley, Ken Conley, Brian Gerkey, Josh Faust, Tully Foote, Jeremy Leibs, Rob Wheeler, Andrew Y Ng, et al. Ros: an open-source robot operating system. In ICRA workshop on open source software, volume 3, page 5. Kobe, Japan, 2009.

Nathan Koenig and Andrew Howard. Design and use paradigms for gazebo, an open-source multi-robot simulator. In 2004 IEEE/RSJ In- ternational Conference on Intelligent Robots and Systems (IROS)(IEEE Cat. No. 04CH37566), volume 3, pages 2149–2154. IEEE, 2004.

Jingjing Guo, Qian Wang, and Jae-Hyuk Park. Geometric quality inspec- tion of prefabricated mep modules with 3d laser scanning. Automation in Construction, 111:103053, 2020.

SB Nickerson, P Jasiobedzki, D Wilkes, M Jenkin, E Milios, J Tsotsos, A Jepson, and ON Bains. An autonomous mobile robot for known industrial environments. Autonomous Robot for a Known environment, pages 1–28, 1997.

Rajesh Kannan Megalingam, Akhil Raj, Sakthiprasad Kuttankulangara Manoharan, and Vijay Egumadiri. App based teleoperated uv disin- fectant robot for covid cause. In 2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC), pages 277–281. IEEE, 2021.

Rajesh Kannan Megalingam, Anandu Rajendraprasad, and Sak- thiprasad Kuttankulangara Manoharan. Comparison of planned path and travelled path using ros navigation stack. In 2020 International Conference for Emerging Technology (INCET), pages 1–6. IEEE, 2020.