Design and simulation of disaster mitigation robot using machine vision

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Abstract. The goal is to provide a robust mobile robot to assist rescures in their operation by providing real time surveillance, remote operation as well autonomous operation. The mobile robot is capable of mapping using a LIDAR, this provides a map of the disaster zone which is then used to assess and provide a path planning for the most efficient rescue for the Mobile robot as well as the Rescuers. The built-in gas sensor reads the concentration of gases in the area, providing data on the environment in the disaster zone. The use of high definition cameras combined with Artificial Intelligence based image classification provides an edge in autonomous traversing and search and rescue. Disaster mitigation is an extremely dangerous task for the rescuers, a mobile robot such as LV-01 can be the difference between life and death.

Keywords. Disaster management, Mobile Robot, ROS, Machine Vision, convolutional neural networking, HaarCascade, Raspberry Pi, Arduino.

1. Introduction

Search and Rescue operation is an agonizing process for the first responders and the people entrapped, the use of robots to assist first responders in not an entirely new concept to begin with, the paper focuses on some unique design features and algorithms and how they can be of assist in search and rescue operations for the responders and the humans trapped. Robots that are used for assist can be of Aerial robots or Mobile Robots, LV-01 is a Mobile Robot. A variety of payloads can be attached to do various tasks such as mapping, remove obstacles, use of machine vision algorithms to identify specific targets, use of thermal cameras to identify people stuck in a dust covered environment, monitor operations, autonomous navigation, evacuating casualties and the use of collaborative robots for large scale operations. There are multiple kinds of disasters ranging on different levels destruction and loss of lives. For this research paper we have chosen Industrial disasters, specifically Gas Leak in Industries. An example of which is the gas leak that occurred on the night of second of December 1984 at the Union Carbide India Limited (UCIL) in Bhopal, Madhya Pradesh, India, which is
considered one of the worst industrial disasters in the world. Now the focus of the research begs to ask the question, How the use of robots can be used to prevent such disasters or assist in managing these disasters in the future. LV-01 can be attached with different payloads, Sensors, Actuators, Manipulators, Computing Modules, Algorithms all specifically customized to that mission. This research paper focuses on the primary payloads on the LV-01 to assist the first responders, Cameras and MQ135 gas sensor. The cameras combined with Machine vision algorithm can identify trapped in disasters. The Deep Learning algorithm focused on this research paper shows how a Convolutional Neural Network is trained and how it is used in the identification of trapped humans. The disaster zone is mapped, and the trapped humans are identified and the data from the Gas Sensor is used to identify the gas pockets to help the first responders come up with strategies to rescue the people trapped without being surprised by harmful gases. A RP-Lidar is used to map the environment. The detection of humans is done by Haarcasding and YOLO V3 (You Look Only Once Version 3). These two machine vision algorithms have been efficient when it comes to the training and detection. Both algorithms use OpenCV to use the video from the camera to be processed. Two cameras were used in combination, Raspberry Pi camera and an USB web camera, USB camera attached to a 70° Tilt and Pan gimbal to give a wide range of view. The HCSR04 ultrasonic range sensor under LV01 helps use to identify elevated areas and adjust the speed and path accordingly.

2. Literature Review

Robots have been used in disasters for quite a while and are commercially available, example RXR-M80BD firefighting mobile robot, worm robots that help in disasters such as earthquakes to navigate through the rubble to identify trapped humans, Unmanned Ariel Systems (UAS) used in Floods, Forest Fires and Pandemics in Reconnaissance and Delivery of medical supplies and food, the examples go beyond the and the uses, deeper. Mobile robots such as LV-01 serve as a universally adaptable system to make it a dynamic system that can be used for different types of uses, not limited only to Search and Rescue. The different sensors and algorithms embodied in the corresponding papers were the TF-miniLIDAR and RP-LIDAR which was used to create grid maps [23] [24]. The grid maps were further organized using occupancy-grid SLAM where the SLAM algorithms were governed by random-finite-sets (RFS) [13] and Rao-Blackwellized Particle Filter (RBPF) which improved the localization and was simulated on various platforms like MATLAB and ROS [21][26]. In another paper, a robotic arm is attached to the wheelchair making it more reliable with low cost and low power solutions [22]. Microsoft Kinect was also used in one case where the path-planning and navigation is projected through the information appropriated from the Kinect as laser data and mapped an area of 16 square meters [15]. Some papers only focus on the mathematical modelling rather than implementation of mapping and navigation where the experiments assure that these concepts function efficiently in complex indoor environments [25] [26]. Some of the challenges faced during the research of this topic include analyzing the gaps that need to be worked upon namely the navigation and obstacle avoidance. The challenge of generating a map in what would be described as a cloudy environment, where the presence of suspended particles such as dust, water vapor and other such debris found in industrial environments has distorted the laser readings often coming up with gaps and short comings. In other cases, the usage of hardware is defined in the paper, but the main functionalities were slipped and not implemented. Some papers the modeling is done without realizing the navigation, and the mapping is done only through algorithms requiring no hardware and as a result no mapping and navigation is simulated. But the future works in each research promises to fulfill these drawbacks with more benefits than shortcomings. For example, navigation without any prior mapping or hardware for localization.

3. LV-01 DESIGN AND DESCRIPTION

The design of LV-01 has been prioritized on modularity. The robot had to serve multiple missions within a short period of prep time. This was achieved by using dedicated packages for modules.
The idea being that the operator would bolt on the module and connect the dedicated wires to its respective ports and then launch the package associated with that package. This would greatly improve the robot’s versatility and help LV-01 to assist first responders in more grueling missions. The versatility can be further expanded by the operators designing and building their own modules, while the requirements being:
- The Module mounts to be compatible with the Rails.
- The Module compatibility with ARM.
This greatly reduces the requirements and makes it easier to design and implement custom modules on LV-01.

**Features:**
Mapping, AI Based detection of trapped humans, Modular system, Beyond line-of-sight control, PID tuned to tackle rough environment, Easy swap of modules, More than one module can be used, example: For this research MQ135 gas sensor, Lidar and Tilt and Pan camera were used as a proof of concept.

**Table of Components:**

| Component                                      |
|------------------------------------------------|
| Raspberry Pi 3b                                 |
| Arduino Mega                                    |
| Four 12v DC Geared Motor, 350 RPM                |
| Four OE-775 Hall – Effect Two channel Magnetic Encoder |
| Two LN298 Motor Driver                          |
| Servo Motors for the gimbal Actuation           |
| Modular Payload – MQ135 gas detection sensor     |
| HCSR04 Ultrasonic Sensor                        |
| Raspberry Pi Camera 5MP                          |
| Web Camera                                      |
| MPU6050 6 DOF IMU Sensor                        |
| RP- Lidar or TF – Mini Lidar                    |
| LED Lights                                      |

**Figure 1.** Proposed Design of LV-01.
4. Working Architecture

The working architecture provides a sense of how LV-01 works and how its prepared for the mission, providing an insight of how LV-01 assists with Search and Rescue Operation.

**Roslaunch LV-01 in Gazebo custom World and Rviz:** The first step is to launch the launch file either for the robot by itself or the dedicated launch package for different sensors. This brings up the URDF (Universal Robot Description File) in Rviz and Gazebo, to visualize the robot and the Laser scans.

**Roslaunch Yolo V3 Camera node for LV-01 RGB Camera:** LV-01 by default comes with two cameras. Raspberry Pi Camera and USB Camera. The USB camera provides a 70° tilt and pan as its attached to a gimbal which can be controlled by the operator. The raspberry pi camera is a stationary camera. The launch of the YOLO V3 node starts both the camera, and the video feed is published on the topic “/robot_camera_usb” and “/robot_camera_rasp”, the video feed is also shown as windows upon the launch of the node. The human detection algorithm is implemented on the USB camera, the tilt pan camera is used for Detection and navigation and the Raspberry pi camera is used for navigation only.

**Roslaunch LV-01 Teleop:** The LV-01 Teleop node is a modification of the twist_teleop_keyboard node, has dedicated key controls for the Tilt and Pan of the Camera gimbals in addition to two empty...
keys which can be uncommented in the code to enable them, these can be used for modules that require key commands.

**SSH Raspberry Pi and Laptop:** The robot uses a Raspberry Pi as its CPU, the raspberry pi on board LV-01 becomes a slave and the operator’s system as the master. The raspberry pi runs Ubuntu Lite 16.04. The configuration can be done via SSH or by configuring the Slave PC’s master IP address as the Master PC’s IP address. Subscription and publication of data from master pc to salve pc and vice versa will be possible. By SSH nodes on slave PC can launched from the Master PC.

**Rosserial communication between Arduino and Raspberry Pi:** The sensors are connected to the Arduino and by launching the rosserial node, communication between the raspberry pi and Arduino begins and transmitting and receiving data is now possible.

**Roslaunch Gmapping Node:** Launching the gmapping node, mapping is begun, and the laser data and the generated map is visualized in Rviz. [9][10][16].

**Serial Communication between the Master PC and Slave PC:** The nodes launched on the slave PC is visible on the master PC by using the rostopic list command on the terminal, and the data can be read by using the rostopic echo command.

**Sensor Data:** Sensor data from various sensors and the modules can be visualized on gazebo and Rviz. The sensors included by default are.

- a. MPU 6050 IMU.
- b. Motor Encoders.
- c. MQ135 Gas sensor.
- d. HCSR04 Ultrasonic Sensor.
- e. Lidar.
- f. Camera.
- g. Battery voltage monitor.

**Motor Controls:** A short test of the motor controls, gimbal actuation is tested, the modules are tested for output, default sensors are checked and the IMU is checked for calibration and then LV-01 is deployed for the mission. [1] [2]

5. **Features and Applications**

5.1 **Modular System:**

A Key feature of LV-01 is its modular design platform. The platform is built out of aluminum T-Slots, this means each module, such as Sensors, Computing Modules, Manipulators and Actuators can be easily mounted on the T-Slots slots using fabricated mounts example 3D-printed mounts. These Modules can be used in combination with one another, this means the robot can house quiet several combinations suited to different applications, not limiting the LV-01 to just Search and rescue.

5.2 **Applications:**

- o Search and Rescue
- o Security Patrolling
- o Agriculture
- o Defense
6. Convolution Neural Networking

Convolutional Neural Networking is used to analyze, process, and identify the trapped humans. Due to its high accuracy and ease of training, Deep learning algorithms were used. Two types of Deep learning methods were employed.

- YOLO V3.
- HAAR Cascade Classifier.

6.1 YOLO V3:

YOLO (You Only Look Once) is one of the most effective real time object detection algorithms available. It is an extremely simple and effective approach to real time object detection. The data required to create a custom model was taken using the robots camera, the robot was made to map the environment where human models were placed in positions that would mimic a fallen/ unconscious/ hurt position, a simple OpenCV script captured a picture every 1 second and saved into a file, these image were then annotated using an annotation tool called LabelImg, which created a .txt file for each image with the X-Y coordinates of the bounding rectangles and the label associated with that bounding box.[14]

![Figure 4. Working principle of Convolutional Neural Networking.](image)

![Figure 5. Recognition of human in an unconscious pose in real life.](image)

The images and the labels were then used to train YOLO model which generated a python file, which is then implemented in the OpenCV script to draw bounding boxes around the detected objects. A pre-
built Darknet model [6], custom weights and modified .config files were added is used in this research. The weights are customized to detect humans in unconscious positions. The team tested the human recognition algorithm upon us to test the accuracy. [3][5][14]

6.2 HAAR Cascade Classifier:

The HAAR Cascade is a machine learning algorithm that is widely used for feature detection that uses HAAR features for classification and detection. The HAAR features detected are based on several positive and negative images used to train the classifier with a certain suitable false alarm rate. Based on the features from the positive and negative image sets, the HAAR features are detected. The calculation of the features happens by creating integral images instead of computing every pixel of the image for obtaining features. Then Adaboost trains the classifiers based on combining several weak features to form a strong feature which would be used by the classifier. Later the implementation of the cascade classifier takes place where each stage is a weak learner, and the capability of each stage is used by the next stage iteratively thus improving the low false negative rate during the final stage. Using several positive images of the people lying on ground with the background being the negative images. Upon training the model for 3 stages with a false alarm rate of 0.05, the results were obtained. [3][8]

Figure 6. Recognition of unconscious human in simulated Environment.

Figure 7. Recognition of human in upright position in simulated environment.
7. Simulation

Gas asphyxiation occurring in factory environments immediately affects the worker’s lung and the severity depends upon the type of gas that has leaked. To mimic the same scenario, a factory environment has been set up in Gazebo where the robot can be deployed to detect the gas concentration in the surroundings while simultaneously mapping the environment autonomously. The simulation environment consists of mannequins that lay on the ground which mimic the unconscious worker. Upon detection, the coordinates of the worker’s position are sent to the rescue team along with the map so that the rescue operation can take place with ease. [4][10][11][13]

![Simulation Image](image_url)

Figure 8. Red balls represented as Gas and the Humans are depicted in fallen positions.

8. Simulation Results and Outcomes

To detect harmful gases MQ135 gas sensor is used as an add-on module rather than hardwiring the sensor directly in Raspberry pi, to provide a modular approach. The concentration of the gas present is measured in PPM (Parts per Million). Starting off with an already existing engine, it made for an excellent approach in terms of reliability and efficiency of detecting harmful toxic gases, the MQ135 is designed to detect.[13]

1. Ammonia Gas (NH3)
2. Sulfide Gas (H2S)
3. Benzene Gas (C6H6)
4. Carbon Monoxide (CO)
5. Alcohol Vapors

In the simulation the presence of gases was displayed in the form of Red Spheres, an OpenCV algorithm was used to identify the Red Spheres to mimic the presence of gas, when the Sphere is detected the value of the gas is displayed in all uppercase and in red to alert the presence of gas. A Launch file for the MQ135 was made in ROS, when launched the URDF of the Robot with this sensor
will be launched in Rviz and Gazebo to provide a visual of the robot and to give an idea of the dimensional constraints. LV-01 by default has a 5cm-All-Time system, which basically means always keep a 5cm distance from all surroundings, this can be turned off by the operator to squeeze LV-01 into tight spaces in trade of some damage to the robot. Modularity, Efficiency, Useability and Mission were the key priorities in this project. Some of the Red Spheres were placed very close to the simulated unconscious humans in the simulation, this is to mimic the time constraints and priorities the rescue approach accordingly. [7][21]

| Table 1. Hyper parameters in Training HaarCascade Classifier. |
|---------------------------------------------------------------|
| Number of Positive Images | 40 |
| Number of Negative Images | 276 |
| Number of Stages | 25 |
| Feature Type | HAAR |
| Sample Width | 25 |
| Sample Height | 24 |

| Table 2. Basic Parameters in Training Yolo v3 for image classification |
|---------------------------------------------------------------------|
| Max batches = 2000 * no. of classes | 2000 |
| Subdivision | 2 |
| Width | 720 |
| height | 1280 |
| Channels | 3 |
| Filters = (no. of classes +5) * 3 | 459 |
| Number of images used in training | 148 |

9. Discussion

Two algorithms were used to train the image classifier algorithms, both were trained on Intel i7 based PC with a dedicated Nvidia Graphics card clocked at 2.9 GHZ – 4.9 GHZ and using a Nvidia GeForce GTX 1650.

9.1 HaarCascade Training

HaarCascade training requires Positive and Negative images, where the positive images are compared against the negative images to differentiate and identify the image from the background.

9.2 Yolo V3 Training

Yolo v3 training requires the images to be annotated, Labeling GUI application [27] is used to annotate the images. This generates, A text document for each image containing the X, X1, Y and Y1 coordinates for the bounding box in the image, Text document named “Labels” which consists of the labels used to annotate the images, in our case “Person” was the label used.
9.3 Comparison between HaarCascade and Yolo v3

Table 3. Comparison between HaarCascade and Yolo v3

| Parameters                  | HaarCascade | Yolo v3 |
|-----------------------------|-------------|---------|
| Poses by humans             | Random      | Random  |
| Accuracy                    | 89%         | 93%     |
| Time consumed to train      | 54 minutes  | 59 seconds |
| No. of images used in training. | 148        | 148     |

10. Conclusion and Future Scope

The purpose of this research was to identify effective strategies for dealing with search and rescue operations in disastrous regions. The choice of these two CNN algorithms because they are the most efficient to run on ARM based applications. Based on the implementation, the ideas were brought up as HaarCascade and CNN in YOLO. The environment was demonstrated in gazebo which depicted a scenario inside a factory where the humans and the gas leakages were detected successfully. We also arrived at a conclusion that collaborative mobile robots could also be useful in current times for covid detection among crowds. The amount this could improve and save the lives of others is worth exploring with minimal human intervention and thorough planning to proceed with the rescue operation. Based on the comparison table mentioned above, Yolo V3 has a higher accuracy in detecting Unconscious humans at the cost more time required to train compared to HaarCascade classifier that trades Accuracy for shorter training periods, these numbers could be changed by adjusting the Hyper Parameters for both the algorithms and would be done as a future scope.

Future scope for LV-01 includes sensor payloads, actuator payloads and manipulators. The incorporation of multiple rovers with different payloads and the collaborative operations including the use of aerial robots. Collaboratively would work with multiple rescuers in different parts of the disaster zone, based on an interlinked communication system between LV-01 (Mobile Robot), Drone (Aerial Robot), Control Station and Rescuers (Handheld Computer Tablets or Smart devices). An integrated system of multiple robots sharing data in real-time which can be accessed by all rescuers present there to aid in the most efficient rescue mission.

Addition of various sensors such as Thermal Imaging cameras and the addition of Beyond visual range communication system.

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