Robots for Disaster Management

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Abstract

The past years have seen many deadly natural disasters including hurricanes, earthquakes, flooding and landslides. Search and rescue efforts have saved numerous lives but numerous others were lost.

At the same time, robotic technology is becoming more widespread, and brings with it the potential to assist in these search and rescue scenarios.

Despite many impressive advances, robots still lack the ability to function as humans do in complex environments. Importantly, this includes being able to interpret and understand complexities of the world as humans do.

This short paper explains our first steps towards better robot cognition, for use in search and rescue scenarios. To this end, we focus particularly on the ability to understand the current surroundings of the robot. Our setup involves collecting data from a mobile robot moving between three different settings, and using this to train a neural network to identify the current setting. The robot will then be able to roam around in an environment and identify the three settings, marking them on the map it creates of the environment.

Themes— Disaster management.

1 Introduction

This past year witnessed devastating hurricanes: Harvey, Irma and Maria sowed destruction across the Texas coastline, the Caribbean islands and the Florida peninsula. An earthquake of magnitude 7.1 in Mexico killed hundreds of people. The monsoon flooding in Bangladesh killed over 1200 people and caused one of the worst regional humanitarian crises in years. The deadly mudslides in Colombia and the flooding and landslides in Sierra Leone killed hundreds more. Deadly natural disasters wreaked havoc around the globe during 2017.

Search and rescue efforts following these natural disasters saved the lives of numerous people, but how can we do more? One approach is to deploy robots for earlier response, quicker access to almost inaccessible or dangerous areas, delivery of survival items or preliminary surveying of the initial damage. In the case where alerts were issued before disaster struck, sleeper robots can be secured at key locations, to be deployed as soon as possible. Search and rescue robots are the ideal technology to assist during disaster management.

Search and rescue robots perceive the environment through multiple sensors providing a visual representation of their surroundings. However, to enable a search and rescue robot to comprehend what is observed in its surrounding is still challenging. Compared to human cognition, robot perception is still rudimentary.

Consider the possibility of a search and rescue robot autonomously exploring an area it is deployed in, and making its own inference about the best actions to take in that environment. This requires that the robot continuously update its understanding of an ever changing environment.

Inspired by the way in which humans are able to make sense of their environments, we seek to provide them with the capability to interpret spatial regions as being similar to regions they have encountered before. This would assist with everything from finding survivors to choosing how to navigate the area.

As stepping stone towards creating the mobile robot technology described above, we draw on machine learning techniques, and in particular convolutional neural networks (ConvNets) [1]. The recognition of the three settings is currently demonstrated in a simulated environment.

This forms part of an overall research agenda that aims to develop autonomous systems capable of interpreting their surroundings. In particular, we are investigating how concepts can be learned by comparing new experiences to existing knowledge.

2 Preliminary work

Autonomous mobile robots detect surroundings using sensors such as radar, LIDAR, GPS, odometry, and cameras. Algorithms stitch these together to construct models of the environment. Autonomous mobile robots often have some prior information regarding their surroundings. In the case that the robot encounters a discrepancy in the surroundings it should update these concepts to continuously expand its understanding of the environment.

The first step of this work is to give the robot enough information to create an understanding of its environment. To test the idea for repeatable experiments, we have set up three controlled rooms marked by simple wallpapers: one with walls covered in bubbles, one with gears and one with cubes, as seen in figure 1. This was done both physically and in simulation.

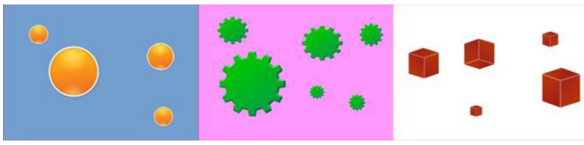

Figure 1: Examples of the bubble, gear and cube room walls

The Pioneer platform (figure 2), fitted with the ASUS RGBD camera, was used to roam around the rooms and capture data. The data was then used in a ConvNet using pre-trained weights of the VGG16 ConvNet [2] to allow the robot to identify a room as one of the three seen in figure 1. This was tested in simulation as seen in figure 3.

Figure 2: Pioneer platform and user interface

3 Results

The robot first gathered 300 images of each environment, and the ConvNet was trained on 100 of these images to be able to distinguish between them. We then presented the robot with 100 new images, and tasked it with identifying the correct room.

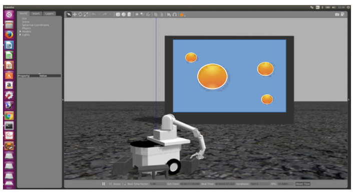

Figure 3: Screenshot of the CHAMP simulator identifying the bubble template

The ConvNet has an 84% accuracy. The confusion matrix for the training on the three different rooms can be seen in figure 4.

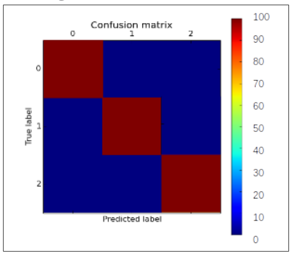

Figure 4: Confusion matrix of the ConvNet on the three different settings.

4 Discussion

In future work, we will have the robot roam around an area while identifying a list of objects it encounters. In this way, the identification of an environment provides insights into the objects expected therein, and vice versa. So, for example, this would help the robot infer likely locations to find survivors or tools in a disaster zone.

We also aim to ultimately incorporate these ideas into a multi-robot system, which would allow for distributed responses to disasters.

5 Conclusions

The difference between how machines interpret an environment and how humans interpret an environment is still significant. This has inspired the idea of building up towards creating a mobile robot that can make more intelligent inferences about its surroundings.

Acknowledgments

The authors gratefully thank Sicelukwanda Zwane for the setup of the CHAMP simulated environment in Gazebo.

References

[1] Niko Sunderhauf, Sareh Shirazi, Feras Dayoub, Ben Upcroft, and Michael Milford. On the Performance of ConvNet Features for Place Recognition.

[2] https://www.cs.toronto.edu/~frossard/post/vgg16/