MOTION PLANNING IN PARTIALLY OBSERVABLE ENVIRONMENTS USING DEEP LEARNING

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INTRODUCTION

Autonomous robots are often tasked to navigate environments with incomplete information.

Additional information can be gained through the use of local sensors, whose data can be collected to construct a more informed environment map to assist in navigation and planning.

This project explores the use of deep learning as a means to construct an environment map for use in robot motion planning.

PROBLEM

- Magneto (Fig 1) is a quadrapod that can walk on ferromagnetic surfaces using electromagnetic feet
- Motion plans are compromised in the event of unsuccessful foot adhesion resulting from environments with unknown magnetic properties

Figure 1: Magneto hanging from the ceiling.

OBJECTIVES

The objectives of this project were to:

- Build a virtual simulation environment to perform the motion planning for Magneto
- Use foot placements to construct a map of the underlying magnetic environment using deep learning
- Navigate the underlying magnetic environment faster and with less invalid adhesions than uninformed random sampling

BACKGROUND

Fully Convolutional Network (FCN)

- Particular type of Convolutional Neural Network (CNN) composed entirely of convolutional layers
- Excel at image segmentation problems

Probabilistic Roadmap (PRM)

- Motion planning method which samples random configurations from the configuration space
- Planner connects samples until a path from start to goal has formed

VIRTUAL ENVIRONMENT

Simulator Mode (Fig 2)

- Visualises real-time motion planning and execution, foot placements and environment predictions in virtual GUI

Trainer Mode

- Performs headless simulation on all available CPU cores
- Generates training sample images

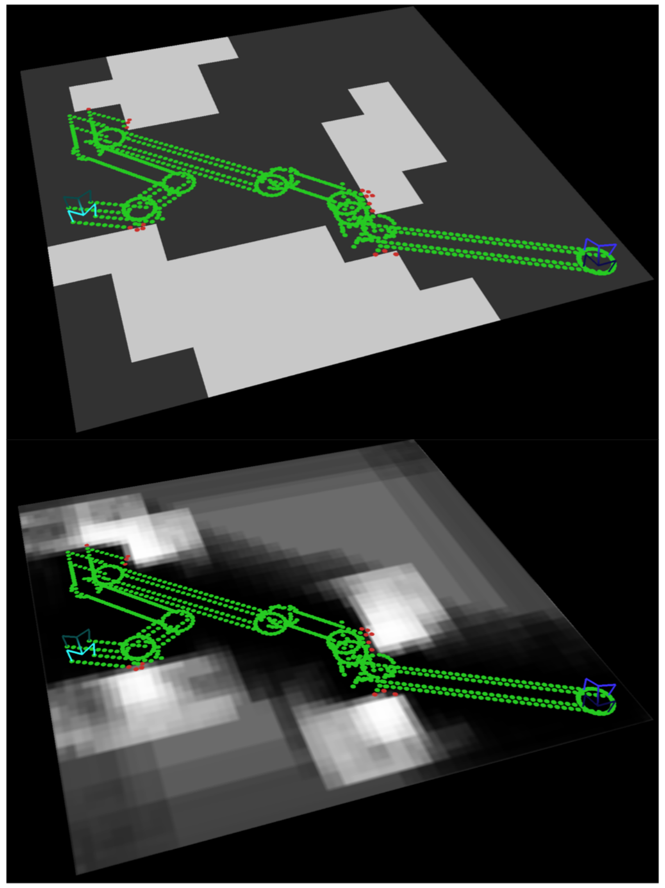

Figure 2: Simulator mode showing the actual magnetic environment map (top) and the model-generated map (bottom)

NEURAL NETWORK

- 9 layer FCN built with efficiency in mind
- 2.7k learnable parameters
- 52kB uncompressed
- <1ms inference time (laptop)
- Effectively learns underlying magnetic environment from foot placements (Fig 3)

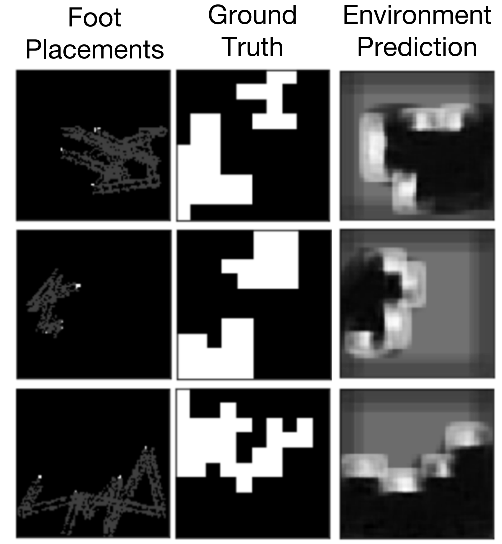

Figure 3: Three foot placement samples with their associated ground truth and predictions

RESULTS

- Solved maps 3-5x faster
- Made 50% less invalid adhesions
- Solved previously “unsolvable” maps

FUTURE WORK

- Compare FCN map construction method to existing methods (e.g. SLAM, occupancy grid mapping)

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