University of Southern Denmark

Master Thesis

Classification of terrain based on proprioception sensing for multi-legged walking robot

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A thesis submitted in fulfillment of the requirements for the degree of Master of Science

in the

Embodied AI & Neurorobotics Lab
Faculty of Engineering

April 26, 2016

Declaration of Authorship

I, Bc. Martin BULÍN, declare that this thesis titled, "Classification of terrain based on proprioception sensing for multi-legged walking robot" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
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- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

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"*Favorite quotation.*"

Quotation Author

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Abstract

Faculty of Engineering

Embodied AI & Neurorobotics Lab

Master of Science

Classification of terrain based on proprioception sensing for multi-legged walking robot

by Bc. Martin BULÍN

The abstract is a concise and accurate summary of the research described in the document. It states the problem, the methods of investigation, and the general conclusions, and should not contain tables, graphs, complex equations, or illustrations. There is a single abstract for the entire work, and it must not exceed 350 words in length.. . .

Acknowledgements

Students may include a brief statement acknowledging the contribution to their research and studies from various sources, including (but not limited to)

Their research supervisor and committee, Funding agencies, Fellow students, and Family.

The acknowledgments and the people to thank go here, don't forget to include your project advisor…

Contents

List of Figures

List of Tables

List of Algorithms and Code Parts

Chapter 1

Introduction

The thesis must clearly state its theme, hypotheses and/or goals (sometimes called “the research question(s)”), and provide sufficient background information to enable a non-specialist researcher to understand them. It must contain a thorough review of relevant literature, perhaps in a separate chapter.

1-2 pages intro

1.1 Problem Formulation

1 page Motivation and Research Questions

1.2 Motivation for Chosen Methods

motivation for using proprioception sensing motivation for using a neural net as a classifier

1/2 page

1.3 Hypotheses

1/2 page

1.4 Thesis Outline

1/2 page

Chapter 2

State of the Art

chapter intro

2.1 Machine Learning and Classification

Machine Learning and Classification in general, different classifiers (SVM, k-NN, RandomForest, Bayes...)

2-3 pages

2.2 Introduction to Neural Networks

neural networks from the beginning, network types, principles its usage for classification

4-5 pages

2.2.1 Pruning Algorithms

based on the paper Pruning Algorithms - A Survey: a summary of what has been already done, principles 1-2 pages

2.3 Terrain Classification for Legged Robots

based on the literature : a summary of what has been already done in terrain classification, summary of different methods (visual, laser, haptic, proprioception, ...)

5-8 pages

Chapter 3

Master Thesis Objectives

objectives (goals) 1/2 page

Chapter 4

Neural Network Implementation

The account of the research should be presented in a manner suitable for the field. It should be complete, systematic, and sufficiently detailed to enable a reader to understand how the data were gathered and how to apply similar methods in another study. Notation and formatting must be consistent throughout the thesis, including units of measure, abbreviations, and the numbering scheme for tables, figures, footnotes, and citations. One or more chapters may consist of material published (or submitted for publication) elsewhere. See "Including Published Material in a Thesis or Dissertation" for details.

chapter intro

overall kitt_nn framework diagram

1 page

4.1 Structural Elements

kitt_net.py, kitt_neuron.py, kitt_synapse.py

structure diagram

1-2 pages

4.2 Learning Algorithm

Backpropagation implementation in python

algorithm

1-2 pages

4.3 Graphical User Interface

GUI description and its usage

printscreen

1 page

4.4 Pruning Algorithm

This is the novelty of the work, detailed description

algorithm

2 pages

4.4.1 General Validation

Information on the statistics and form of evaluation

XOR Dataset

evaluation on XOR dataset

MNIST Dataset

evaluation on MNIST dataset

further MNIST analysis

figures, tables

4-5 pages

Chapter 5

Terrain Classification for AMOS II

Classification, one of the most widely used areas of machine learning, has a broad array of applications (see chapter 1). To fit a classifier to a problem, one needs to define a problem data structure. Data consists of samples and discrete targets, often called classes. The samples are sooner or later converted into so called feature vectors of a specified length. The lenght of feature vectors usually determines an input of chosen classifier and number of classes sets an output.

Out of a wide range of classification methods, a feedforward neural network approach (see chapter 4) is chosen. The classification problem is connected to AMOS II, an open-source multi sensori-motor robotic platform. The task is to classify various terrain types, while the only input comes from proprioceptive sensors. The overall process is based on simulation data.

5.1 Overall process summary

The very first step is to make the AMOS II simulation run (section 5.2.2). Then a simple tripod gait controller is implemented. To generate various terrain types, the number of variable terrain quailities and their ranges are determined (section 5.3). Based on these qualities (parameters), a number of virtual terrains is defined (section 5.3) and an optimality of these parameters is briefly analysed (section 5.3).

Next, AMOS II (its simulation alternative) is forced to walk on every defined terrain type for a sufficiently long period of time and data from all proprioceptive sensors is saved. This data is then verified and failing experiments are removed. The data acquisition step is parameterized by a standard deviation of additive (Guassian) terrain noise and is run for several values.

Having a clean simulation data from all sensors, a feature vector structure is determined. Then a Gaussian signal noise is added. Finally, a dataset is created by splitting all the data into training, validation and testing sets. It is indicated on fig. 5.1, that several datesets and several classifiers are generated during the process. These packages may differ in following parameters.

Dataset parameters:

- terrain types included

- sensors on input
- samples length (number of simulation timesteps)
- terrain noise
- signal noise
- number of samples

Trained net parameters:

- neural network structure
- accuracy on training/validation/testing sets

An optimal neural network classifier is found. The optimal network is then pruned by the algorithm developed in section X. Classification performance of developed tools are compared to a *Scikit-learn* network classification library sknn [].

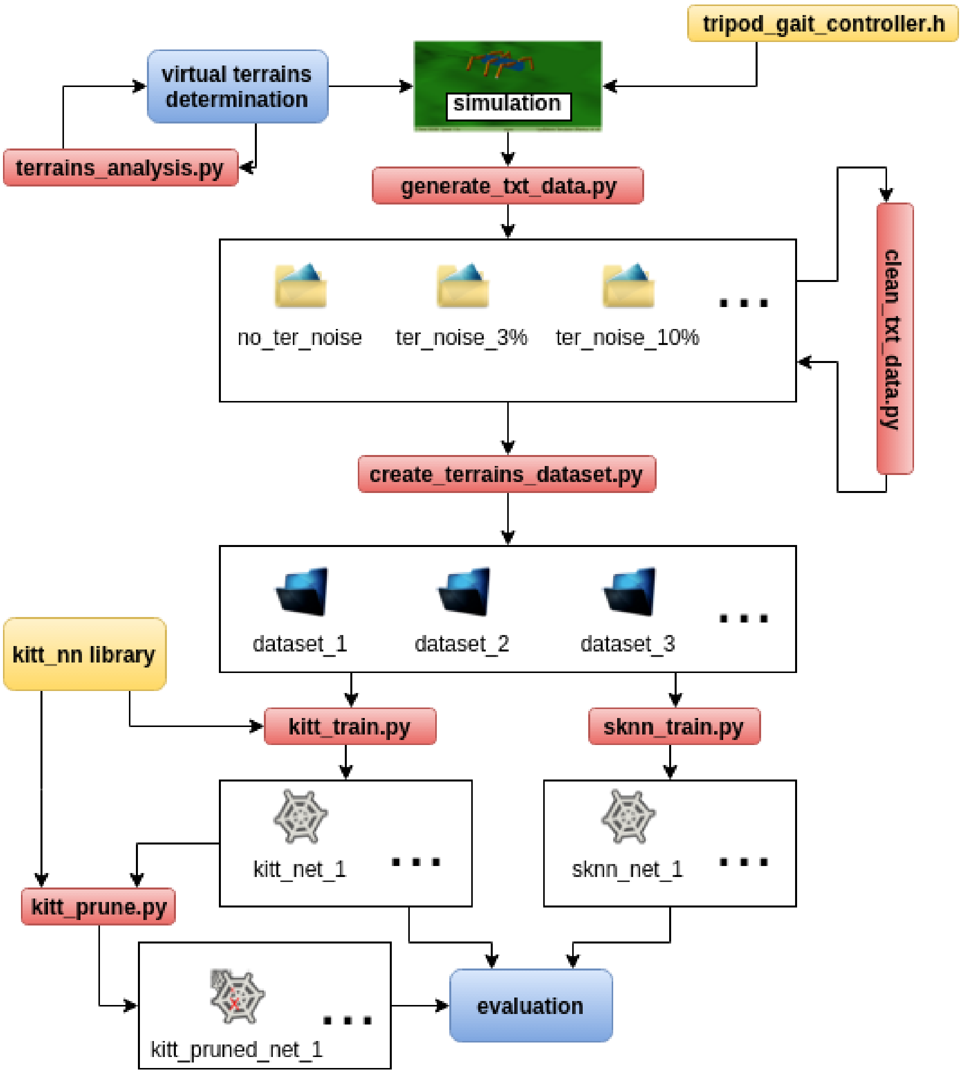

FIGURE 5.1: Terrain classification process - overall diagram.

5.2 Experimental Environment Specification

target machine description

3-5 pages

5.2.1 Hexapod Robot AMOS II

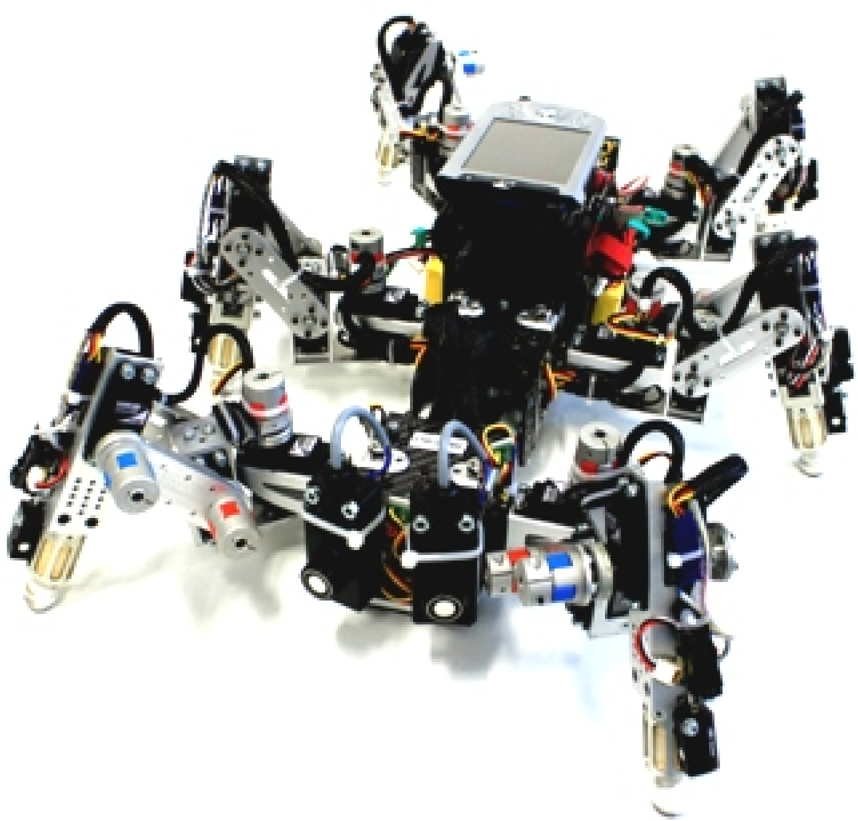

FIGURE 5.2: AMOS II.

5.2.2 LPZ Robots Simulation

It is a part of a simulation software called *LpzRobots* provided by the University of Leipzig (*Research Network for Self-Organization of Robot Behavior*) under GPL license.

5.3 Virtual Terrain types

Since the verification is based on the simulation only, the goal is to design an authentical virtual environment. For this purpose various terrain types need to be virtually imitated.

Luckily, the **LpzRobots** AMOS II simulator supports some terrain settings. In the main simulation file (*main.cpp* - see A), a *'rough terrain'* substance is being initialized and passed through a handle to a *TerrainGround* constructor.

PART OF CODE 5.1: Setting a terrain ground in main.cpp

```
Substance roughterrainSubstance(terrain_roughness, terrain_slip,
                     terrain_hardness, terrain_elasticity);
oodeHandle.substance = roughterrainSubstance;
TerrainGround* terrainground = new TerrainGround(oodeHandle,
                     osgHandle.changeColor(terrain_color),
                     "rough1.ppm", "", 20, 25, terrain_height);
```

As part of code 5.1 shows, the terrain substance is defined by four parameters: **roughness**, **slipperiness**, **hardness** and **elasticity**.

Besides the substance handle, the *TerrainGround* constructor takes six more arguments.

terrain_color : simulation ground color

"rough1.ppm" : an image in the .ppm format, a lowest common denominator color image file format (*PPM Format Specification*), a bitmap height file

"" : texture image (not used)

20 : walking area x-size

25 : walking area y-size

terrain_height : maximum terrain height

Terrain qualities

Out of the listed ground parameters, some of them are picked up and being called *terrain qualities*, as they define a specific terrain type.

It has been decided not to change the *.ppm* image for various terrains and so *rough1.ppm* is fixed. Also the walking area is set to (big enough) final size of *20x25*. The color is variable, however, besides the simulation graphics it does not have any effect on results.

Therefore, a virtual terrain type is defined by five qualitites. Each of them is a float number from an empirically stated range [1]. (table 5.1).

TABLE 5.1: Terrain qualities and their ranges

	min value	max value
roughness	0.0	10.0
slipperiness	0.0	100.0
hardness	0.0	100.0
elasticity	0.0	2.0
height	0.0	0.1

[1] The upper range limits have been set up based on significant changes in robot behaviour for various parameter values.

Terrains parameters determination

To determine a terrain type, one has to come up with the five parameters from table 5.1.

First, number of identifiable virtual terrain types needs to be determined. For purposes of this thesis, it has been decided to create **14 terrain types**. Their parameters (showed in table 5.2) have been set up intuitively, based on the AMOS II simulated behaviour. With respect to the qualities ranges from table 5.1, the values have been normed to (0, 1).

TABLE 5.2: Virtual terrain types parameters.

#	*terrain title*	*roughness*	*slipperiness*	*hardness*	*elasticity*	*height*
1	**carpet**	0.3	0.0	0.4	0.15	0.2
2	**concrete**	1.0	0.0	1.0	0.0	0.0
3	**foam**	0.5	0.0	0.0	1.0	0.7
4	**grass**	0.5	0.0	0.3	0.3	0.5
5	**gravel**	0.7	0.001	1.0	0.0	0.3
6	**ice**	0.0	1.0	1.0	0.0	0.0
7	**mud**	0.05	0.05	0.005	0.25	0.2
8	**plastic**	0.1	0.02	0.6	0.5	0.0
9	**rock**	1.0	0.0	1.0	0.0	1.0
10	**rubber**	0.8	0.0	0.8	1.0	0.0
11	**sand**	0.1	0.001	0.3	0.0	0.2
12	**snow**	0.0	0.8	0.2	0.0	0.2
13	**swamp**	0.0	0.05	0.0	0.0	1.0
14	**wood**	0.6	0.0	0.8	0.1	0.2

Colors linked to the terrains in table 5.2 are used in the simulation as well as in the figures in Results section.

Analysis of chosen parameters

In general, proper data preparation is an important part of classification tasks, hence a brief analysis is presented.

The goal is to imitate real terrains authentically as possible and at the same time to generate such terrains, that are clearly distinguishable from each other. The more two terrains differ the better classification results are expected.

Having five terrain qualities calls for a 5-D space, which is difficult to illustrate or even imagine. Therefore, formula 5.1 is used to compute a similarity factor of two terrain types (the five qualities are listed in table 5.1 and table 5.2).

$$SF_{t_1,t_2} = \sum_{i=1}^{5} |quality(i,t_1) - quality(i,t_2)| \tag{5.1}$$

Naturally, equation 5.1 ends up with $SF_{similar} = 0.0$ for two terrains with exactly same parameters and $SF_{different} = 5.0$ for two terrains differing most possibly.

The following figure (5.3) shows the variability (similarity factors) of generated terrains.

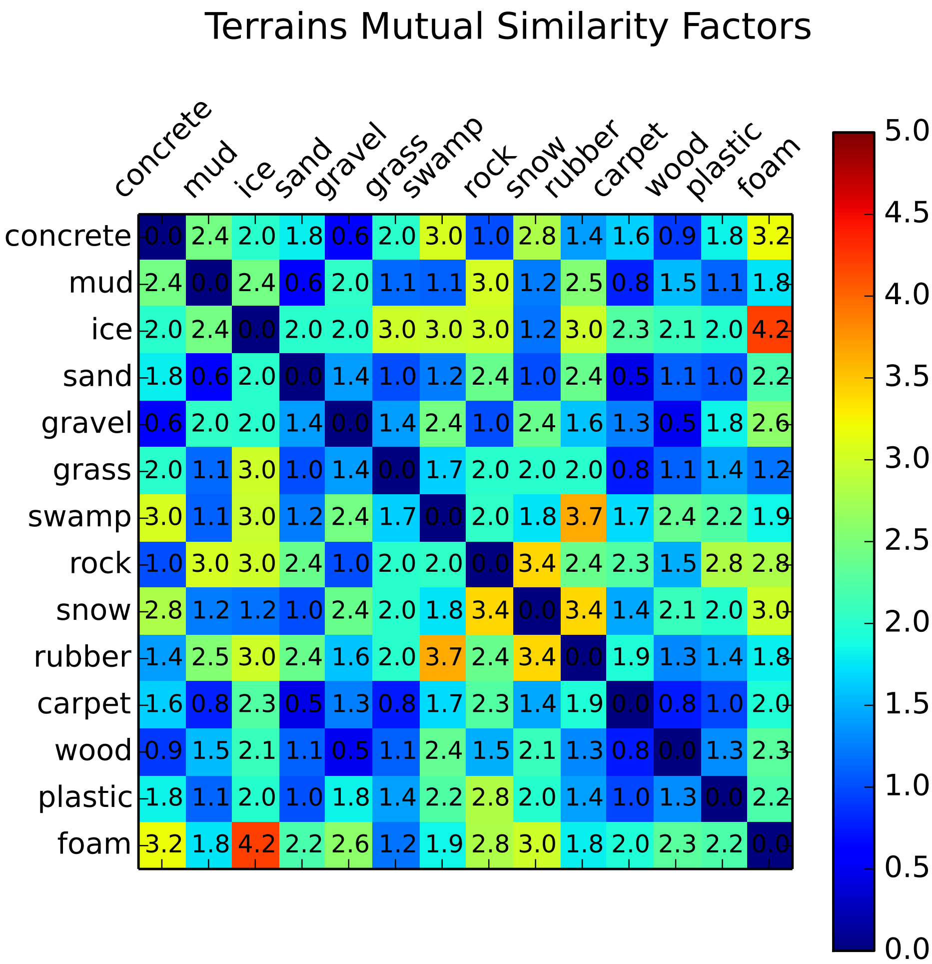

FIGURE 5.3: Variability of generated terrain types.

5.4 Net Input Fixation

Determination of sensors to be used and its transformation into a feature vector

2-3 pages

5.5 Data Acquisition

Description of how the data has been acquired from the simulation and saved as .txt, adding terrain noise

2 pages

5.5.1 Terrain Noise

5.6 Data Processing

Cleaning the data (deleting incomplete ones), adding signal noise, transformation into datasets, splitting into training-validation-testing sets

2-3 pages

5.6.1 Signal Noise

5.7 Training and Classification

Neural net training with several parameters and comparison with training with scikit-neuralnetwork library

2-3 pages

5.7.1 Scikit-neuralnetwork library

brief description of the library and its usage 1/2 pages

1 page

Chapter 6

Experimental Evaluation

The account of the research should be presented in a manner suitable for the field. It should be complete, systematic, and sufficiently detailed to enable a reader to understand how the data were gathered and how to apply similar methods in another study. Notation and formatting must be consistent throughout the thesis, including units of measure, abbreviations, and the numbering scheme for tables, figures, footnotes, and citations. One or more chapters may consist of material published (or submitted for publication) elsewhere. See "Including Published Material in a Thesis or Dissertation" for details.

evaluation (tables and figures) of classification:

- various terrain noise standard deviation values
- various signal noise standard deviation values
- various sensors on network input (only foot, only angle...)
- various timesteps used as one sample (-> time needed for detection)
- various number of detected terrains as outputs
- various network structures
- various training parameters (epochs, learning rate, batch size...)

evaluation of neural nets as a classifier:

- comparison to other classifiers on the same data, classifiers are ready provided by sknn library

evaluation of proprioception sensing against other methods (visual, haptic, laser...):

- comparison to the results from the literature

evaluation of the pruning algorithm:

- various starting structures, ends up with the same minimal-optimal structure?
- various noise types, same minimal structure?
- speed comparisons of the fully-connected vs. pruned structure
- further analysis:
    - which sensors are redundant/crucial

- which sensors are important for which terrain
- comments on the minimal structure and benefits of having it

10-15 pages (many figures, tables)

6.1 Discussion

2-3 pages, maybe together with the figures and tables

Chapter 7

Conclussion

In this section the student must demonstrate his/her mastery of the field and describe the work's overall contribution to the broader discipline in context. A strong conclusion includes the following:

Conclusions regarding the goals or hypotheses presented in the Introduction, Reflective analysis of the research and its conclusions in light of current knowledge in the field, Comments on the significance and contribution of the research reported, Comments on strengths and limitations of the research, Discussion of any potential applications of the research findings, and A description of possible future research directions, drawing on the work reported. A submission's success in addressing the expectations above is appropriately judged by an expert in the relevant discipline. Students should rely on their research supervisors and committee members for guidance. Doctoral students should also take into account the expectations articulated in the University's "Instructions for Preparing the External Examiner's Report".

2-3 pages

7.1 Future Work

All references:

(Zenker et al., 2013) and (Kesper et al., 2012) and (Xiong, Worgotter, and Manoonpong, 2014) and (Mou and Kleiner, 2010) and (Coyle, 2010) and (Hoepflinger et al., 2010) and (Ahmed, 2015) and (Ordonez et al., 2013) and (Bermudez et al., 2012) and (Reed, 1993) and (Spenneberg and Kirchner, 2007) and (Belter, 2011)

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[Misb] *Research Network for Self-Organization of Robot Behavior.* http://robot.informatik.uni-leipzig.de/software/. last modified: 06. July 2015.

Appendix A

Code Documentation

Write your Appendix content here.

Appendices must be limited to supporting material genuinely subsidiary to the main argument of the work. They must only include material that is referred to in the document.

Material suitable for inclusion in appendices includes the following:

Additional details of methodology and/or data Diagrams of specialized equipment developed Copies of questionnaires or surveys used in the research Do not include copies of the Ethics Certificates in the Appendices.