ARTIFICIAL NEURAL NETWORK-BASED ROBOTICS

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Master of Science in Electrical Engineering

by

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ABSTRACT

Artificial Neural Network-Based Robotics

Justin Ng

Artificial neural networks (ANNs) are highly-capable alternatives to traditional problem solving schemes due to their ability to solve non-linear systems with a non-algorithmic approach. The applications of ANNs range from process control to pattern recognition and, with increasing importance, robotics. This paper demonstrates continuous control of a robot using an actor-critic algorithm based on deep deterministic policy gradients (DDPG) originally conceived by Google DeepMind. The robot performs tasks such as locomotion within an enclosed area and object transportation. The paper also details the robot design process and explores the challenges of implementation in a real-time system.

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TABLE OF CONTENTS

LIST OF TABLES

Table Page

LIST OF FIGURES

Chapter 1

INTRODUCTION

Note: All project files can be found at `https://www.github.com/okayjustin/roborodentia2017`

1.1 Definitions and Assumptions

The robot is designed to only travel within a rectangular closed area of eight feet in the x direction and five feet in the y direction. The coordinate system is chosen as Cartesian with the origin placed at the bottom-left corner of the field. The position of the robot is always in the xy-plane since it cannot move vertically (z = 0). Therefore, x refers to the robot position along the x-axis and ranges from 0 to 8 feet, and y refers to position along the y-axis and ranges from 0 to 5 feet. Additionally, the robot can only rotate around the z-axis so θ refers to the angle of the robot in the xy-plane. Maintaining standard Cartesian coordinates, $\theta = 0^\circ$ is along the positive x direction while $\theta = 90^\circ$ is along the positive y direction.

1.2 Cal Poly Roborodentia

The robot is designed to compete in the 2018 Cal Poly Roborodentia, the university's annual intramural robotics competition, and thus conforms to its particular specifications and requirements. Briefly, autonomous robots collect and fire Nerf Rival Balls into nets to win points. A drawing of the field is shown below in Figure 1.1.

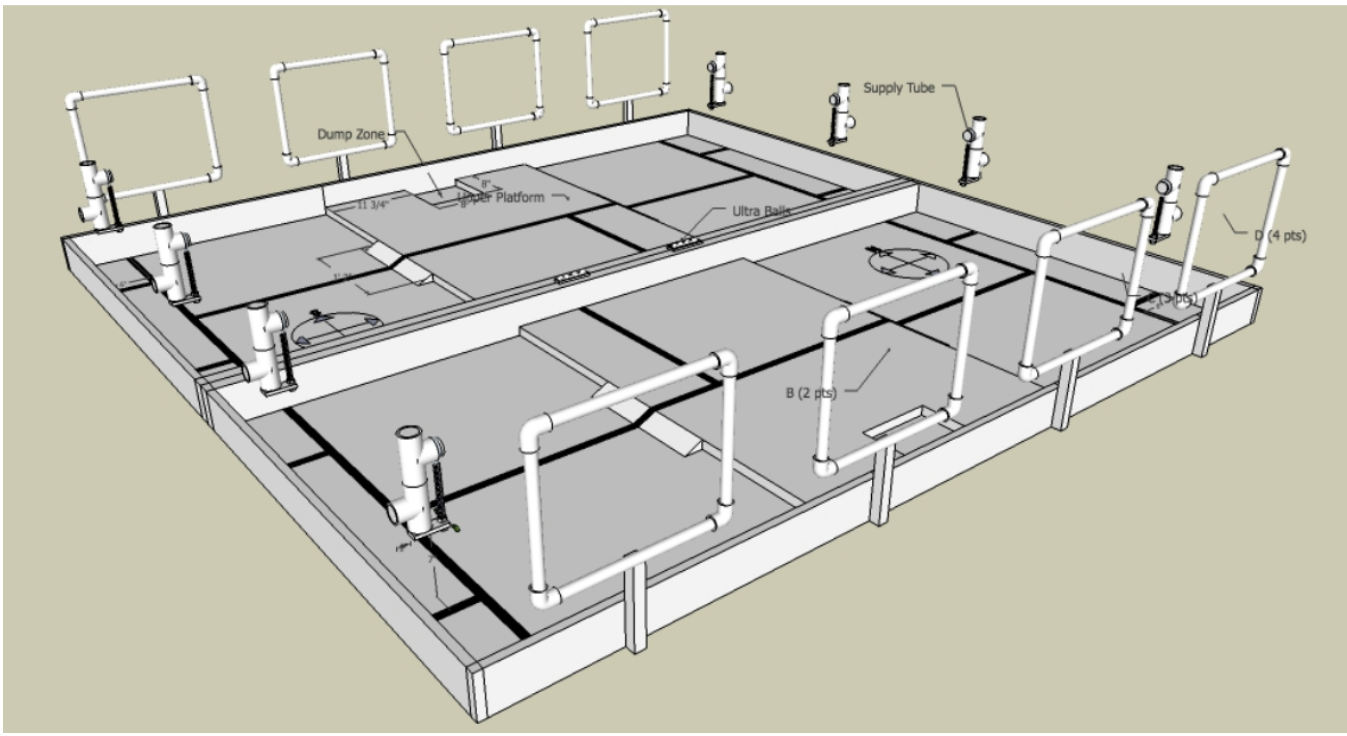

Figure 1.1: Roborodentia Field

Chapter 2

MECHANICAL DESIGN

Chapter 3

ELECTRICAL DESIGN

Chapter 4

FIRMWARE DESIGN

Chapter 5

SOFTWARE

5.1 Kalman Filters

The system relies on several different sensors to determine where it is within the environment, a problem commonly referred to as robot localization. The *Kalman Filter* (KF), an optimal state estimator, performs noise filtering and sensor fusion, the process of combining measurements from multiple sensors. The filter operates on the principles of Bayesian inference and uses statistically noisy measurements over time and knowledge of the system to produce a more accurate estimate of an unknown variable than with measurement alone.

5.1.1 Algorithm

The Kalman Filter algorithm and equations are reproduced here from Roger Labbe's excellent interactive online book [2]. The algorithm consists of two stages (not including initialization): prediction and update. During the first stage, the filter uses the current state and a process model (typically a function of time) to estimate the state in the next time step along with its uncertainty. The second stage uses sensor measurements to update the estimation by taking a weighted average based on the ratio of uncertainty between the prediction and measurement.

Initialization

Before the first run of the filter, initialize the estimated state ($\mathbf{x}$, also called the posterior) and estimated state covariance matrix ($\mathbf{P}$).

Predict

During the predict phase, the process model is used to predict the future state (known as the prior) ($\bar{\mathbf{x}}$) after one time step by summing the posterior ($\mathbf{x}$) multiplied by the *state transition function* ($\mathbf{F}$) with the control input model ($\mathbf{B}$) multiplied by the control input ($\mathbf{u}$). The covariance of prior ($\bar{\mathbf{P}}$) is larger than the posterior covariance ($\mathbf{P}$) due to uncertainty in the process model ($\mathbf{Q}$).

$$\bar{\mathbf{x}} = \mathbf{F}\mathbf{x} + \mathbf{B}\mathbf{u}$$

$$\bar{\mathbf{P}} = \mathbf{F}\mathbf{P}\mathbf{F}^T + \mathbf{Q}$$

Update

Make measurements ($\mathbf{z}$, measurement mean) and determine their accuracy ($\mathbf{R}$, measurement noise covariance). Calculate the residual (or difference) ($\mathbf{y}$) between the measurement and the product of the measurement function ($\mathbf{H}$) and the prior from the previous phase. $\mathbf{H}$ converts the prior from the state space to the measurement space. Calculate the weighting factor ($\mathbf{K}$, Kalman gain), valued between 0 and 1, based on the whether the measurement or prior is more accurate. Set the new posterior, $\mathbf{x}$, to an average of the measurement and prior, weighted by $\mathbf{K}$. Finally, update the posterior's covariance, $\mathbf{P}$, based on the measurement certainty. The algorithm

then loops back to the predict phase using the newly-calculated posterior.

$$\mathbf{y} = \mathbf{z} - \mathbf{H}\bar{\mathbf{x}}$$

$$\mathbf{K} = \bar{\mathbf{P}}\mathbf{H}^T(\mathbf{H}\bar{\mathbf{P}}\mathbf{H}^T + \mathbf{R})^{-1}$$

$$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{K}\mathbf{y}$$

$$\mathbf{P} = (\mathbf{I} - \mathbf{K}\mathbf{H})\bar{\mathbf{P}}$$

5.1.2 Design

The desired state variable $\mathbf{x}$ is chosen as the linear position, velocity, and acceleration in the x and y directions as well as the angular position, velocity, and acceleration about the z-axis:

$$\mathbf{x} = [x \ y \ \theta]^T$$

$$\dot{\mathbf{x}} = [\dot{x} \ \dot{y} \ \dot{\theta}]^T$$

$$\ddot{\mathbf{x}} = [\ddot{x} \ \ddot{y} \ \ddot{\theta}]^T$$

The process model for position and velocity:

$$\begin{cases} \bar{x} = x + \dot{x}\Delta t + 0.5\ddot{x}(\Delta t)^2 \\ \bar{\dot{x}} = \dot{x} + \ddot{x}\Delta t \\ \bar{\ddot{x}} = \ddot{x} \end{cases}$$

Which can be written in the form:

$$\begin{bmatrix} \bar{x} \\ \bar{\dot{x}} \\ \bar{\ddot{x}} \end{bmatrix} = \begin{bmatrix} 1 & \Delta t & 0.5(\Delta t)^2 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \end{bmatrix}$$

$$\bar{\mathbf{x}} = \mathbf{F}\mathbf{x}$$

The measurement vector is chosen as:

$$\mathbf{z} = \begin{bmatrix} z_x & z_{\ddot{x}} & z_y & z_{\ddot{y}} & z_\theta & z_{\dot{\theta}} \end{bmatrix}^T$$

The measurement noise matrix is shown below. The off-diagonals are 0 because the noise between sensors is assumed to be uncorrelated.

$$\mathbf{R} = \begin{bmatrix} \sigma_x^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{\ddot{x}}^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_y^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{\ddot{y}}^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_\theta^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{\dot{\theta}}^2 \end{bmatrix}$$

Chapter 6

NEURAL NETWORK DESIGN

Chapter 7

CONCLUSION

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