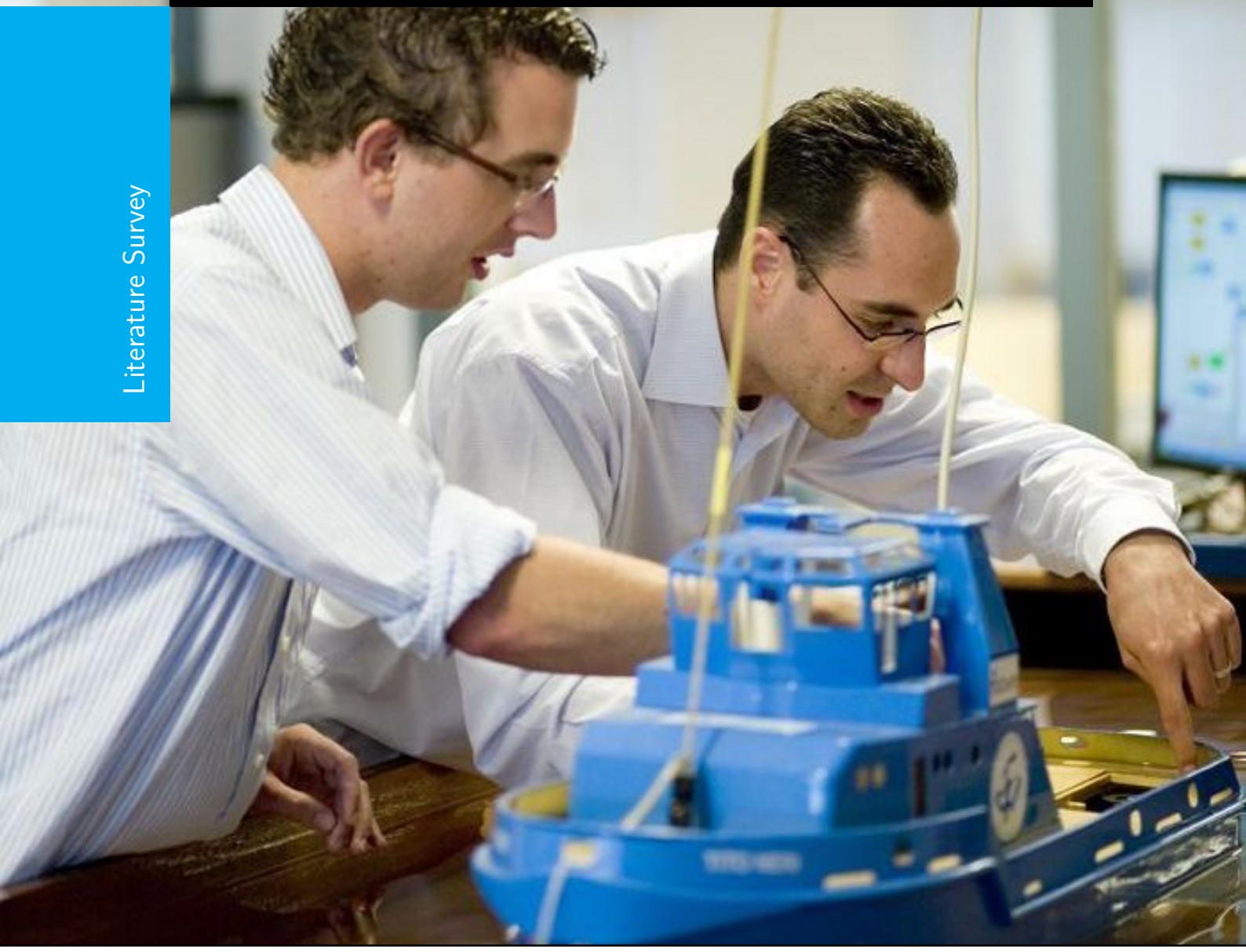
# Reinforcement Learning for Tracking Control in Robotics

Yudha Prawira Pane

Literature Survey



TU Delft Delft University of Technology

Delft Center for Systems and Control

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Literature Survey

Yudha Prawira Pane

January 9, 2015

Faculty of Mechanical, Maritime and Materials Engineering (3mE) · Delft University of Technology

The implementation work in this thesis was done at DCSC's robotics lab.

# Abstract

This is an abstract.

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# Preface

# Acknowledgements

I would like to thank my supervisor  for his assistance during the writing of this thesis...

By the way, it might make sense to combine the Preface and the Acknowledgements. This is just a matter of taste, of course.

Delft, University of Technology
January 9, 2015

Yudha Prawira Pane

"It can scarcely be denied that the supreme goal of all theory is to make the irreducible basic elements as simple and as few as possible without having to surrender the adequate representation of a single datum of experience"

— *Albert Einstein*

# Chapter 1

# Introduction

Reference or trajectory tracking is one of the building blocks to perform a complex task in robotics. Given a desired path/trajectory, the robot must be able to follow it as quickly as possible with minimum error. Capability to perform this precise tracking is crucial for robots that are to be deployed at manufacturing industries such as semiconductor, automotive, and recently, the emerging application of 3D printing.

Statistics by International Federation of Robotics (IFR) [1] shows that the global sales of industrial robots continues to increase steadily. In 2014, it is expected that the total number of industrial robots installed reaches 205,000 units, a rise of approximately 15 % from previous year. The survey points out that the mature markets such as automotive, electronics, and metal are responsible for such growth.

Meanwhile, there is also a growing interests in applying robots to relatively new applications such as 3D printing, architecture, and art. For instance, research done by Gramazio et. al [2] [3] aims to push the capability of industrial robots to make direct fabrication based on CAD model a reality. The advantage of using robots over conventional CNC machines lies on their flexibility, easy-to-adapt feature, and high degrees of freedom (DoF) – enabling execution of difficult configuration in 3-dimension (3D) space. These aforementioned applications demand high precision since a minuscule of error could lead to a defect product or even worse, a disaster. Therefore a precise, accurate reference tracking capability is inevitable.

In order to achieve this, a reference tracking control is needed. However, a robot brings along non-linearities, noises, and external disturbances that are difficult to model, let alone compensate. This unknown properties often hinders the controller to perform optimally. A class of controllers which solely depends on the system's model will surely suffer a poor tracking accuracy. The natural answer to this problem is to introduce a controller capable of adjusting its parameter overtime by comparing the reference to the actual trajectory. By doing so, the controller will have an extra degree of freedom to compensate for the unknown properties hence improving the tracking quality. The controller of such characteristic belongs to the class of adaptive controller.

In this thesis, a method to improve the performance of nominal controller by using Reinforcement Learning (RL) is proposed. Despite decades of extensive research on RL, its application to

optimize tracking problem in robotics is still a relatively unexplored topic. Based on the literature, there are three potential approaches to address the tracking problem. The first one comes from the work of Lewis et. al. on RL for optimal control. Lewis and his group have been developing a comprehensive research on RL for solving the solution to adaptive optimal control. Their research has been extended for discrete [4] and continuous time [5], for linear [6] and non-linear system [7]. Furthermore, their technique could also be applied in Q-learning [4] and actor-critic structure [7]. The second approach is proposed by Bayiz et. al. in [8]. The paper discusses a slightly different approach by using RL to learn disturbance compensation for nonlinear system. This disturbance compensation acts as an additive input signal to the control signal. Finally, the third approach uses the notion of adaptive gain scheduling. Buchli et.al present an algorithm called Policy Improvement with Path Integral ($PI^2$) to vary the gain of a Proportional Derivative (PD) controller in order to achieve a desired terminal state [9] [10]. Having explained the motivation of this thesis, now we are ready to define the research problem.

## 1-1 Problem Definition

The fundamental problem in this literature study concerns the non-optimal performance of nominal controller with respect to reference tracking task. Hence the research question can be raised as follows.

*"Is it possible to integrate Reinforcement Learning technique to a nominal controller in a certain structure such that reference tracking performance of the controlled system significantly improves?"*

While conducting a research, it is often wise to restrict oneself to a simple context, but still captures the essential elements of the original problem [11]. Therefore, in answering this question, some simplifying assumptions are made.

1. The system to be controlled is fully actuated
2. The system to be controlled is observable. This assumption is necessary in order to satisfy Markov property [12].
3. Nominal, stabilizing controller is available
4. Identification reveals some information about the system, but alone is not adequate to design an accurate reference tracking controller.

## 1-2 Goal of the Thesis

The goal of this thesis are as follows:

1. To provide a general framework of improving tracking control using RL
2. To apply and compare existing method of RL for tracking application to the 3D printing robot setup
3. To come up with modification or improvement of previous methods

## 1-3 Literature Study Approach

In order to build a strong theoretical foundation for later implementation, the following literature approach is used. The order does not necessarily represent a sequential process.

1. To gather as many relevant papers as possible from reputable academic search engines. Relevant means papers which deal with RL and control system. Additional pointer to tracking problem is heavily considered. Examples of sources being used are Web of Science, IEEE Xplore and Google Scholar.
2. To discuss the detail of future experimental setup (UR5 3D printing robot) with Marco de Gier, who was working on the setup at the time this literature is written.
3. From the papers, extract existing methods which have the potential for application to the future experiments. So far, there are 3 different methods that are considered. These methods will be explained in detail in Chapter 3.
4. Create simple simulation programs showing how each method works

## 1-4 Outline

The structure of this literature review is arranged as follows. In the next chapter, an introductory materials of RL is presented. This covers the framework widely used in RL (Markov Decision Process), the principle of value and policy iteration, the formulation of RL for continuous space, and the actor-critic structure which suits the framework of control system. Chapter 3 provides the result of literature study being conducted. This includes the detailed explanation of methods found and their comparison. Furthermore, a new controller is proposed.

## 1-5 Nomenclature

# Chapter 2

# Reinforcement Learning Preliminaries

This chapter is dedicated to present a concise theory of reinforcement learning. The first section will show how a certain goal can be formalized as a reward maximization – one of the ideas which serves as a basic foundation of Reinforcement Learning (RL). Section 2-2 explains the basics of Markov Decision Process (MDP), a general framework used in RL problem. Subsequently, an intuition of value and policy iteration will be developed in section 2-3. The fourth section will present the extension of RL for continuous space. Finally, section 2-5 will discuss the actor-critic structure which is a natural representation for control system problem.

## 2-1 Goal as Cost Minimization

The nature of RL is inspired by the way living organisms learn to reach their desired goals. Animals for instance, learn by first acting on the environment, observe the changes that occur, and improve their action iteratively. One example is a circus lion that is tasked to perform acrobatic show while its trainer observing the progress. If the lion successfully executes the task, it will be rewarded with foods. Conversely, punishment will be inflicted whenever it fails. The lion initially has no idea of how to perform the task. However through trial and error, it will follow its instinct to increase the frequency of receiving rewards while trying its best to avoid punishments. In a certain duration of training, the circus lion will be finally able to perform the task flawlessly.

Now we will formalize above illustration for robotics application. A robot can be described by its states $x_k$ with subscript $k$ denoting time instance. Applying an action $u_k$ will bring the robot to state $x_{k+1}$ with immediate reward $r_{k+1}$. Subsequently, at $k+1$ the robot applies $u_{k+1}$ which yields state $x_{k+2}$ and $r_{k+2}$. This action-state-update iteration is run for infinite time instances. The goal is defined as maximization of cumulative reward the robot receives. In control engineering, reward is usually replaced with cost. In that case the goal is defined as minimization problem. Starting from now, we will define goal as minimization of future cost $J$.

From the sequence of cost obtained over time, we can define a formalization of goal, called expected return. Return $R_t$ is a function that maps the sequence of costs into real number. An example of return is the sum of the costs.

J =

## 2-2 Markov Decision Process

MDP is defined as a tuple $\langle X, U, f, \rho \rangle$ which satisfies Markov property [13]. The detailed explanation of Markov property can be found on [12] section 3.5 but the main idea is that to determine the probability of a state at certain time, it is sufficient to only know the state of previous time instance. The elements of the tuple are:

- $X$ is the state space
- $U$ is the action space
- $f : X \times U \to X$ is the state transition function (system dynamics)
- $\rho : X \times U \to \mathbb{R}$ is the reward function

In control engineering, $f$ represents the system dynamics which is a transition function mapping a current state and action to the one-step ahead state up to a probability distribution. This probability distribution is mathematically denoted in Equation (2-1).

$$\Pr\{x_{t+1} = x', r_{t+1} = r | x_t, u_t\} \tag{2-1}$$

where $x$ denotes state, $u$ denotes action, and $r$ denotes immediate reward obtained upon applying the input on the corresponding state.

## 2-3 Value and Policy Iteration

Value function describes how good a particular state or state-action pair in terms of expected return. T

## 2-4 Reinforcement Learning for Continuous Space

## 2-5 Actor-Critic Structure

# Chapter 3

# Reinforcement Learning for Tracking Problem: A Survey

This is real chapter for Delft Center for Systems and Control (DCSC), ok? We will use it as a demo for the different headings you can use to structure your text.

## 3-1 Dynamic Tuning via Reinforcement Learning

This is the first section .

This is the subsection of the first section.

## 3-2 Nonlinear Compensation for Tracking via Reinforcement Learning

This is second section.

## 3-3 Reinforcement Learning for Optimal Tracking Control

This is third section.

## 3-4 Self-Proposed Controller [tentative]

# Chapter 4

# Simulation & Verification

## 4-1 Simulated Setup

This chapter will cover figures and math.

## 4-2 Simulation Result and Analysis

## 4-3 Discussion

Chapter 5

# Future Work and Experiments Plan

Chapter 6

# Conclusion

# Appendix A

# Appendix

Appendices are found in the back.

## A-1 Simulation Program

### A-1-1 A MATLAB listing

```
%
% Comment
%
n=10;
for i=1:n
    disp('Ok');
end
```

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# Glossary

## List of Acronyms

| | |
|---|---|
| **DCSC** | Delft Center for Systems and Control |
| **RL** | Reinforcement Learning |
| **MDP** | Markov Decision Process |
| **DoF** | degrees of freedom |
| **PI$^2$** | Policy Improvement with Path Integral |
| **PD** | Proportional Derivative |
| **3D** | 3-dimension |