EDUARDO ROSSO BARBOSA

TRAINING MOTOR SKILLS FOR A SIMULATED ROBOCUP 3D HUMANOID ROBOT USING REINFORCEMENT LEARNING

(*pre-defense version, compiled at August 9, 2024*)

Trabalho apresentado como requisito parcial à conclusão do Curso de Bacharelado em Ciência da Computação, Setor de Ciências Exatas, da Universidade Federal do Paraná.

Área de concentração: *Computação*.

Orientador: Eduardo Todt.

CURITIBA PR

2024

RESUMO

Palavras-chave: Palavra-chave 1. Palavra-chave 2. Palavra-chave 3.

ABSTRACT

Keywords: Keyword 1. Keyword 2. Keyword 3.

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

3DSSL	3D Soccer Simulation League
RL	Reinforcement Learning
ML	Machine Learning
DINF	Departamento de Informática
UFPR	Universidade Federal do Paraná

LIST OF SYMBOLS

CONTENTS

1 INTRODUCTION

Robocup is an international initiative that promotes scientific advances on robotic intelligence through competition, the initiative is divided into several different leagues, each one with it's own set of problems and focus, the subject of our work is the 3D Soccer Simulation League (3DSSL) who provides a simulated enviroment, physics and humanoid robots.

Within 3DSSL rich environment and tools, the challenge focused in this work is motor control of the humanoid robot in several tasks utilizing Reinforcement Learning (RL) as the training method. RL is a machine learning technique inspired by the natural idea of learning by trial-and-error, selecting actions that maximizes the reward.

Since RL is heavily dependent on sample size, the simulated environment is a cheap and efficient way of generating a great quantity of data when compared to real life, as it can lean on paralelism, can run faster than real-time, does not depend on an external agent to restart the task if the robot falls and the only hardware needed is the computer to run the simulation.

The 3DSSL current league champion is the *FC Portugal* team, as it was shown in (Abreu et al., 2023) they were able to successfully train the agent in a skill-sets such as *sprint-kick* and *locomotion* that allowed the agents to perform in the competition. All the skills are represented by one or two neural network policies trained by RL.

The codebase for the *FC Portugal* provides a strong foundation to develop new skills and behaviors, so it was utilized and modified to train the agent to achieve our goals.

1.1 OBJECTIVE

This study aims to showcase how RL performs in training a policy to perform a long-jump skill.

1.2 STUDY OUTLINE

2 BACKGROUND

This chapter reviews the literature

2.1 3D SIMULATION LEAGUE

2.2 REINFORCEMENT LEARNING

2.3 PROXIMAL POLICY OPTIMIZATION

3 RELATED WORK

This chapter shows related work

3.1 EXAMPLE

4 PROPOSAL

This chapter shows the specific configurations utilized to train the proposed new skills

4.1 SKILLS

All of the following skills have their

4.1.1 Jump

State space: - Observasion size of 70 Float numbers (32 bits) - Composed of all joint positions + torso height - Stage of the underlying Step behavior

Action Space: - Size 11 - Composed of all

Reward: - MAX (Displacement in the y-axis, 0) ”’

4.1.2 Long Jump

The Long Jump skill is inspired by the homonym sport, where the athlete must gain velocity in a short run and leap forward as far as possible from a takeoff point, called indicator board.

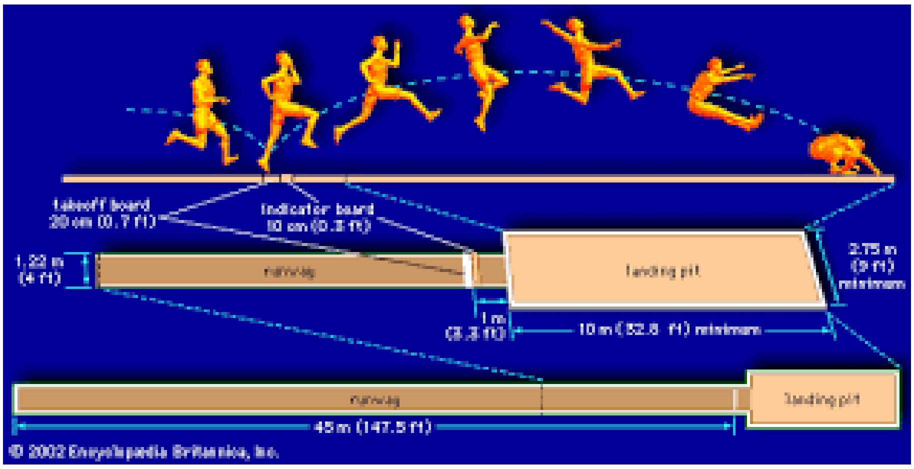

Figure 4.1: Long Jump schematics

To train the agent within 3DSSL it is set an invisible line in a distance of 1/30th of the field length from the agent as the takeoff line. The line can be vizualied as one grass strip lenght, as showed in the image below.

the reward is different before and after the

State space: - Composed of all joint positions + torso height - Stage of the underlying Step behavior

Reward: - Positive displacement in the y-axis, or 0 ”’

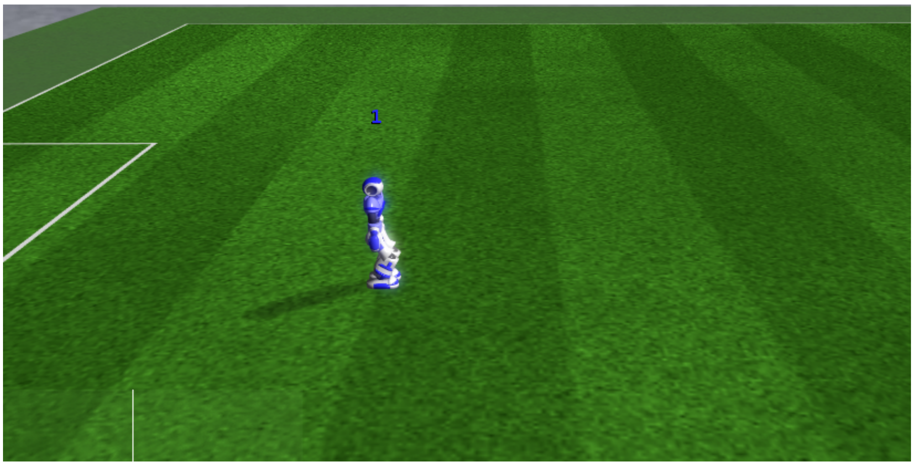

Figure 4.2: Agent on the starting point of a long jump

5 RESULTS AND DISCUSSION

This chapter shows results

5.1 EXAMPLE

6 CONCLUSION

This chapter shows Conclusion

6.1 EXAMPLE

REFERENCES

Abreu, M., Reis, L. P., and Lau, N. (2023). Designing a skilled soccer team for robocup: Exploring skill-set-primitives through reinforcement learning. *arXiv preprint arXiv:2312.14360*.