

# Reinforcement Learning of Action Sequences in Table Football

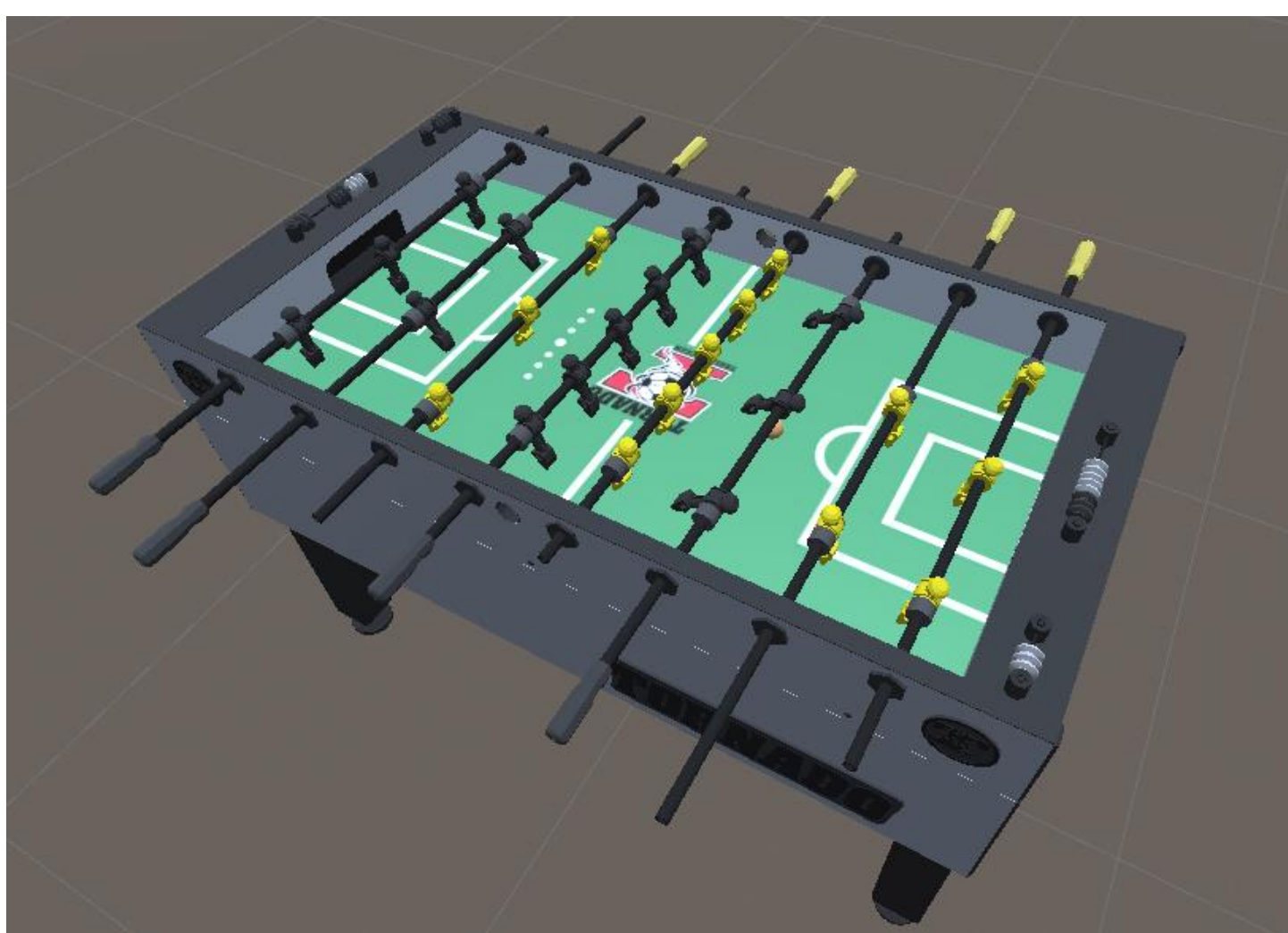
KU LEUVEN



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## Introduction:

- Define Action Sequences in Table Football.
- Passing between controllable players.
- Exploration of hybrid<sup>[1]</sup> Action space and its effect on the performance of the Agent.



## Problem Statement:

Action Type	Rotation	Translation	Rot. Speed	Tran. Speed	On/Off Move
Discrete all	D	D	constant	constant	-
DCCS	D	D	C	C	-
DCCM	C	C	-	-	D
Continuous all	C	C	-	-	-

D = Discrete, C = Continuous

### Types of passes:

- Ball control (tick-tacking)
- Forward Pass 5 to 3 player:
  - vs Static opponent: Non-factor, single position
  - vs Dynamic opponent: rhythmic, random static, random movement
  - vs Enemy agent
- Adding Noise
- Transfer: Mirror, Another rod.

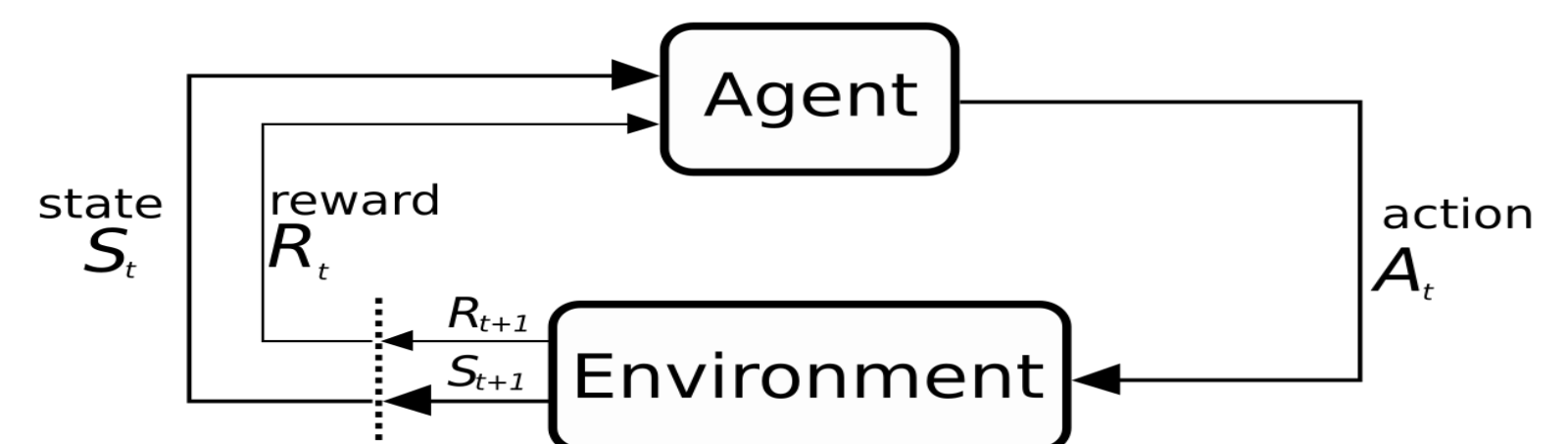
Metrics: speed of ball, time to completion, success rate (opponent type).

## Methodology:

MDP:  $\{S, A, T, R, p(s_0), \gamma\}$

Model free<sup>[2]</sup>, On-policy

Policy Gradient method: PPO<sup>[3]</sup>



## Reinforcement Learning Setup:

Observations (Normalized)

Only Necessary Rods:  $(x, \theta)$

Ball:  $(x, y)$

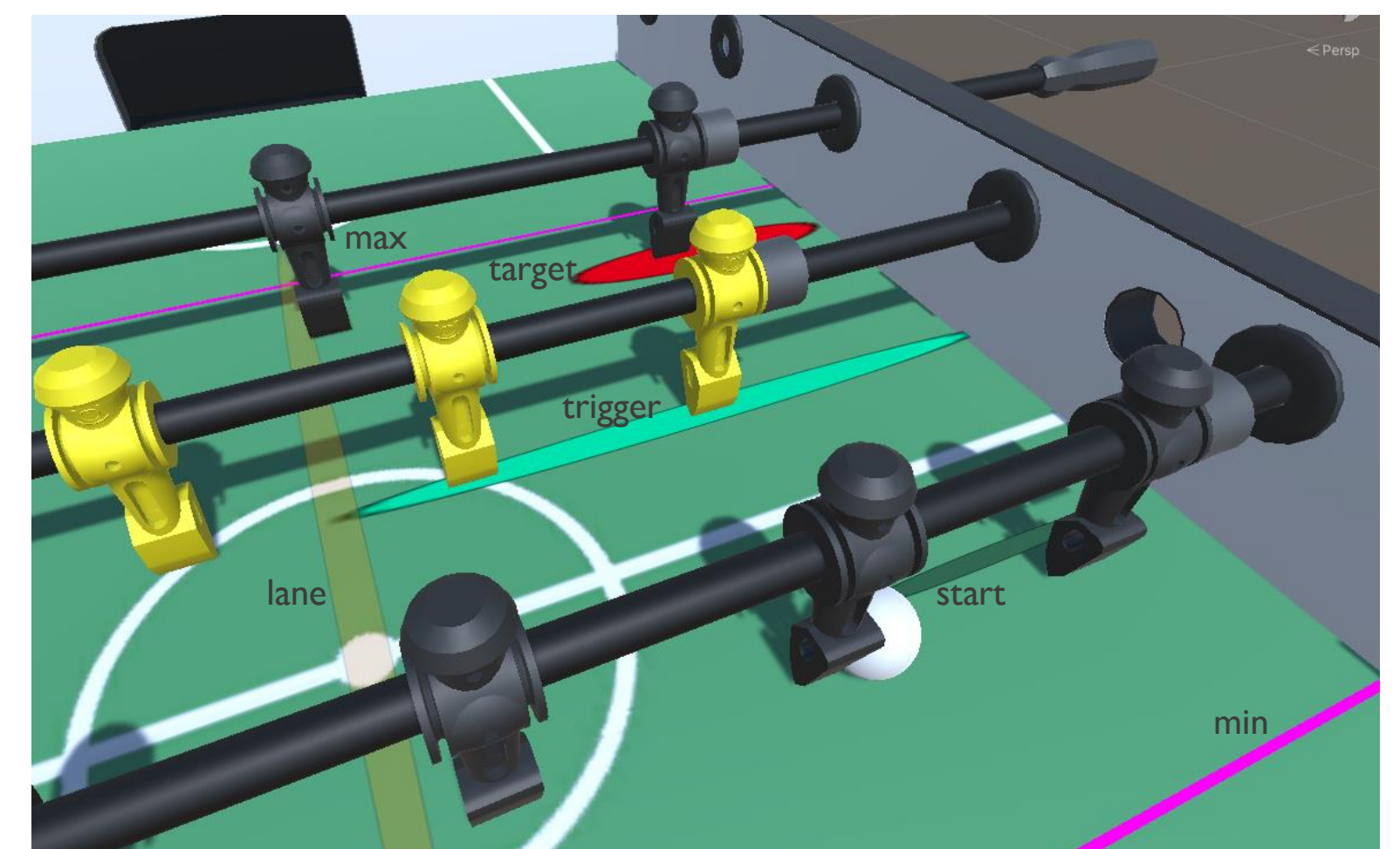
Actions

Translation: Action  $\times \Delta t \times \text{Speed}$ .

Rotation: Action  $\times \Delta t \times \text{Speed}$ .

Rewards:

Ball position or collisions.



## Results:



### Tick-Tacking:

- Discrete all: Easy to train, Jumpy moves not human-like.
- DCCS: Slower at start, Learns robust moves.
- DCCM: Discrete choice is not helpful for tick-tacking.
- Continuous all: Slower to train, Human-like moves.

[1] Z. Fan, R. Su, W. Zhang, and Y. Yu. Hybrid actor-critic reinforcement learning in parameterized action space, 2019.  
 [2] A. Morris and F. Cushman. Model-free rl or action sequences? Frontiers in Psychology, 10, 2019.  
 [3] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov. Proximal policy optimization algorithms, 2017.