Simulators and Platforms: Robotic Soccer and FC Portugal

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Intelligent Robotics

- **Robotics**
  - Science and technology for projecting, building, **programming** and using Robots
  - Study of **Robotic Agents (with body)**
  - Increased Complexity:
    - **Environments:** Dynamic, Inaccessible, Continuous and Non Deterministic!
    - Perception: Vision, **Sensor Fusion**
    - Action: Robot Control (humanoids, increasing DOFs)
    - Robot Architecture (Physical / Control)
    - Navigation in unknown environments
    - **Learning** of complex task
    - **Interaction** with other robots/humans
    - **Coordination** and Multi-Robot Systems

Current State of Robotics

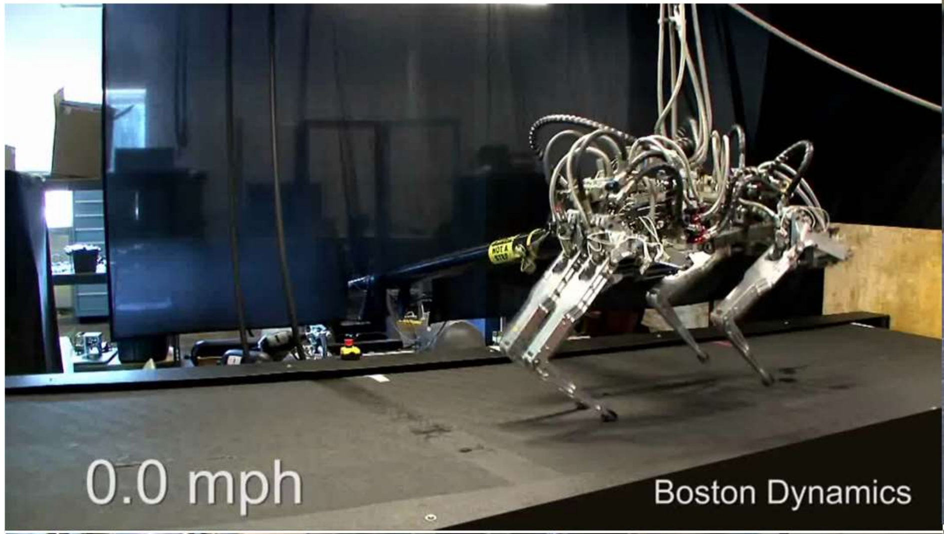
- **Used to Perform:**
  - **Dangerous** or difficult **tasks** to be performed directly by humans
  - **Repetitive tasks** that may be performed more efficiently (or cheap) than when performed by humans
- **Robots have moved from manufacturing, industrial applications to:**
  - **Domestic** robots (Pets – AIBO, vacuum cleaners)
  - **Entertainment** robots (social robots)
  - Medical and **personal service** robots
  - **Military** and surveillance robots
  - **Educational** robots
  - Intelligent buildings
  - **Intelligent vehicles** (cars, submarines, airplanes)
  - New industrial applications (mining, fishing, agriculture)
  - Hazardous applications (space exploration, military apps, toxic cleanup, construction, underwater apps)
  - **Multi-Robot Applications and Human-Robot Teams!**



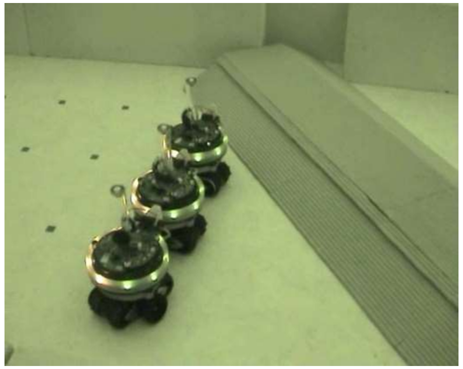



Current State of Humanoid Robotics

Current State of Sports' Robotics



Coordination in Multi-Robot Systems



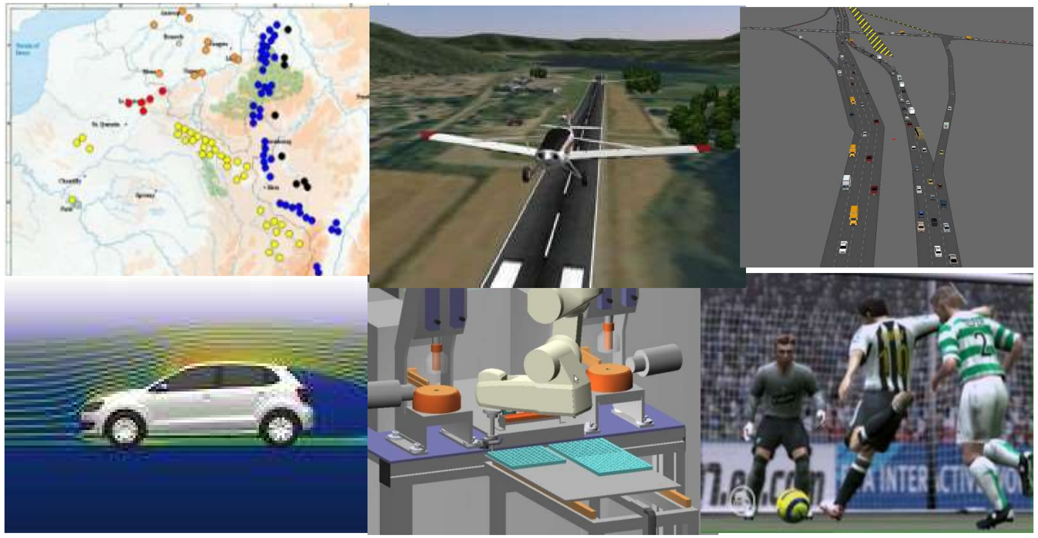
- Agents/Robots don’t live alone and have to work in a group…
- **Human-Robot Interaction**
- **Multi-Robot Coordination**

Coordination : “to work in harmony in a group”

- **Dependencies** in agent actions
- Global constraints
- **No agent**, individually **has enough resources**, information or capacity to execute the task or solve the problem
- **Efficiency:** Information exchange or tasks division
- **Prevent anarchy and chaos**: Partial vision, lack of authority, conflicts, agent’s interactions

Agent-Based Simulation

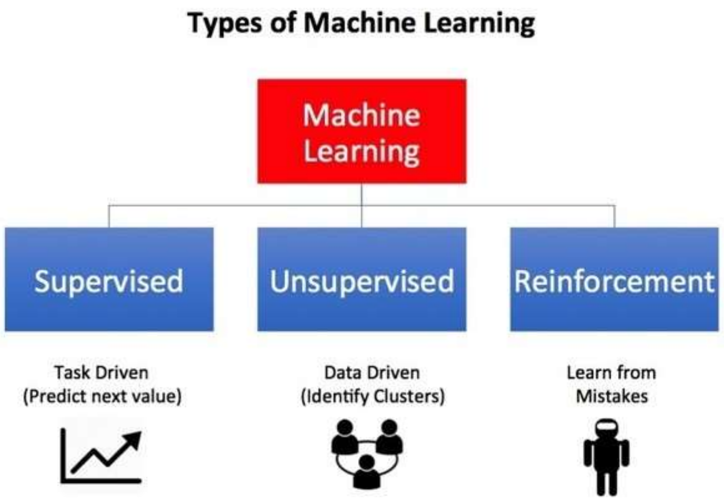
- **Simulation: Imitation of some real thing, state of affairs, or process, over time,** representing certain **key characteristics** or behaviours of the physical or abstract system
- Applications:
  – Understand system **functioning**
  – **Performance optimization**
  – Testing and validation
  – **Decision making**
  – Training and education
  – **Test future/expensive systems**

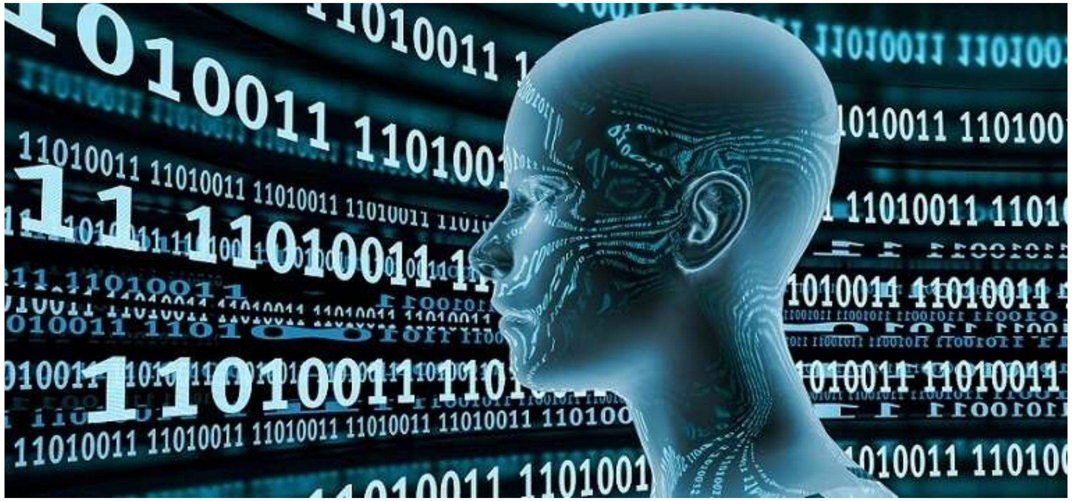


- For complex systems impossible to solve mathematically
- **Agent Based Modeling and Simulation**

Machine Learning

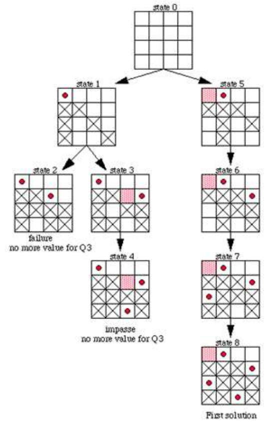
Machine learning is a field of artificial intelligence that gives **computer systems** the **ability to "learn"** (e.g., progressively **improve performance** on a specific task) **from data/results of their actions**, without being explicitly programmed

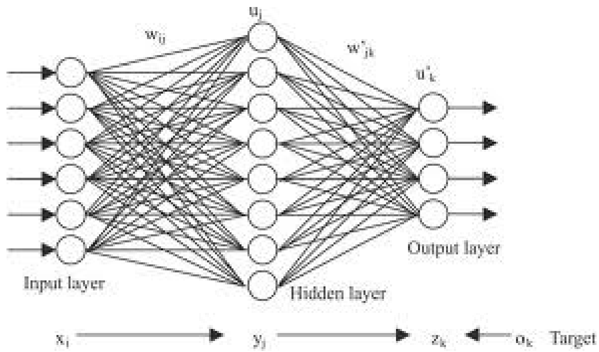




Learning and Optimization in MAS

- **Learning**
  - **Use of past experience to improve future performance**
- **Optimization**
  - **Choosing the best solution for a given problem**
- **Interesting topics:**
  - Modelling complex problems as Optimization Problems
  - Simulation Calibration/Validation
  - **Multi-Agent Learning**
  - Multi-Criteria Optimization
  - Stochastic optimization
  - Meta-heuristics (HC, SA, TS, GA, PSO, AC, …)
  - **Non-Parametric Contextual Stochastic Search**
  - Reinforcement Learning
  - Deep Reinforcement Learning: PPO, SAC, PPO2, …





Robotic Games and Competitions

Robotic Competitions - RoboGames

Robotic Competitions - RoboGames

Robotic Games and Competitions

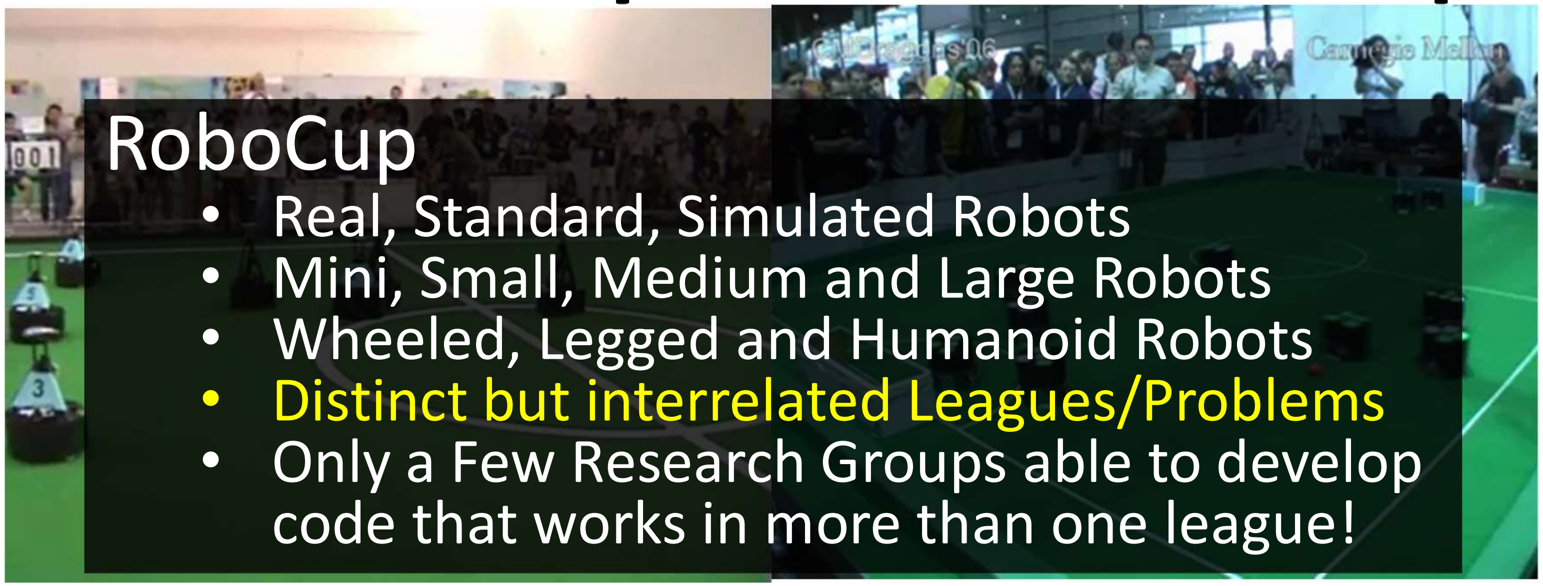
Benefits

- Research inspiration
- Hard deadline for creating fully functional system
- Common platform/problem
- Exchange of research ideas/solutions
- Continually improving solutions
- Excitement for students/researchers at all levels
- Large number of teams/solutions created
- Encouragement for flexible software/hardware

Dangers

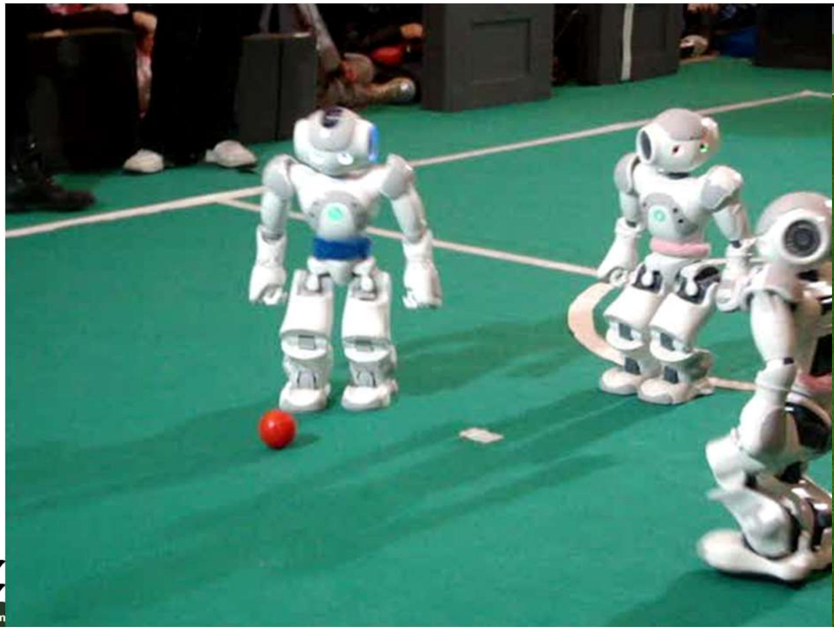
- Obsession with winning
- Domain dependent/ hacked solutions
- Cost escalation
- Difficulty in entering at competitive level
- Restrictive rules
- Invalid evaluation conclusions

Robotic Competitions - RoboCup

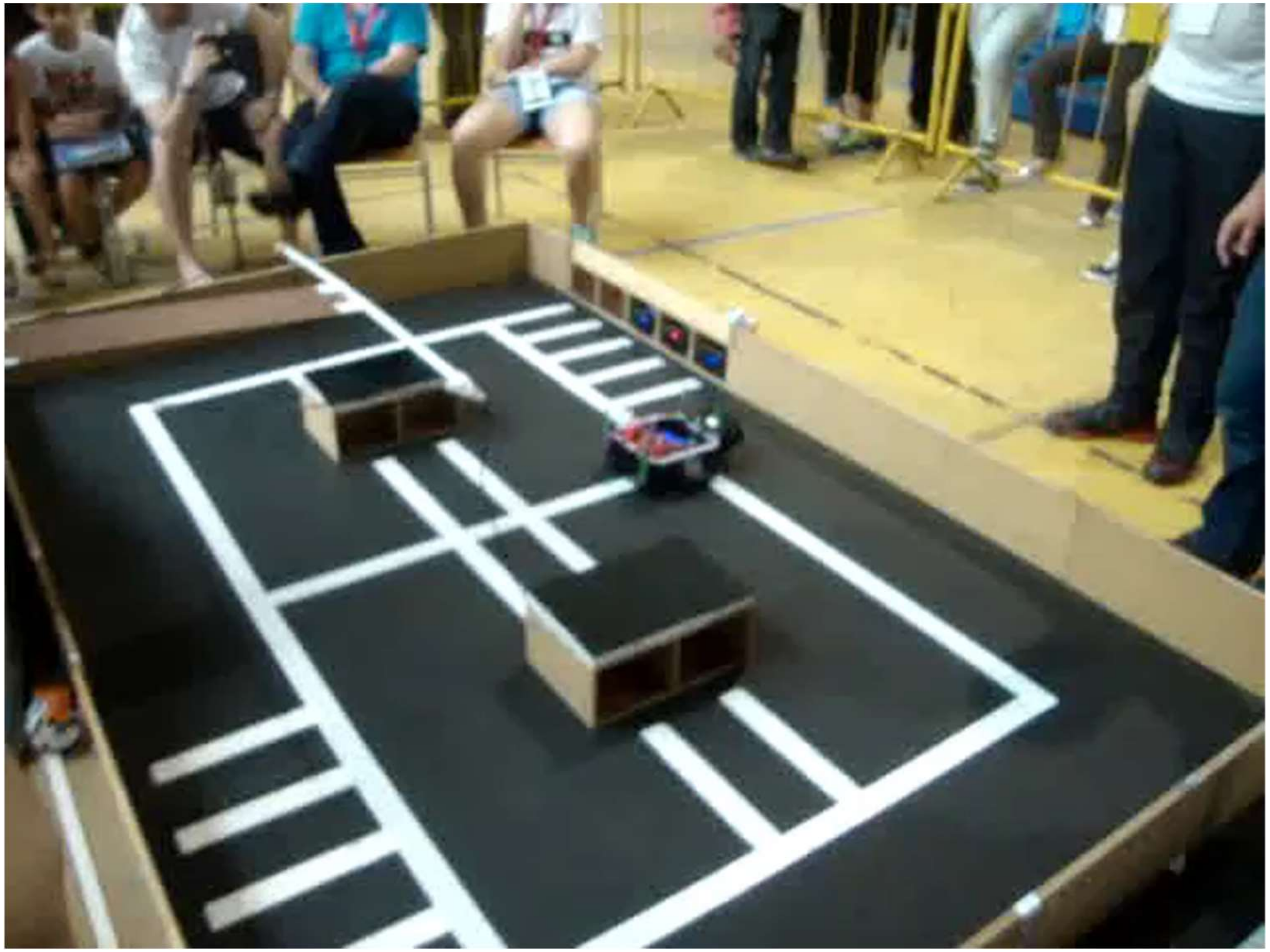


RoboCup

- Real, Standard, Simulated Robots
- Mini, Small, Medium and Large Robots
- Wheeled, Legged and Humanoid Robots
- Distinct but interrelated Leagues/Problems
- Only a Few Research Groups able to develop code that works in more than one league!



Festival Nacional de Robótica - Robot@Factory



Main Research Questions

How to **Coordinate** heterogeneous **Multi-Robot Teams** executing **flexible tasks** in dynamic, adversarial environments?

How to define **Flexible Human-Robot Interaction** methods enabling Human-Robot Cooperation in dynamic environments?

How to **Learn Complex and Flexible (multi)Robot Skills** in dynamic environments?

How to **Formalize Sports' Concepts** to be able to develop **Intelligent Robots** that **Play or Analyze Sports?**

Key Issues in Human-Robot Teams

- Sensor Fusion and Multi-Sensor Intelligent Perception
- **Multi-Robot Coordination**/Flexible Strategy
- Adaptive Strategy
- **Flexible Multimodal Interaction**
- **Human Robot Cooperation**
- Adaptive Interaction
- **Realistic Simulation**
- Bridging the Gap between Simulation and Robotics

Key Issues in Sports Analysis and Simulation

- **Player and Ball Detection and Tracking**
- Player/Individual Action Recognition
- Team/Collective **Action Recognition**
- **Formalizing Sports Concepts**
- Creating **Player Models**
- Creating **Team Models**
- Realistic Player Simulation
- Realistic Team **Simulation**

RoboCup: Objectives

- Joint International Project:
  - **(Distributed) Artificial Intelligence**
  - **Intelligent Robotics**
- **Soccer** – Central Research Topic:
  - **Very complex collective game**
  - **Huge amount of technologies** involved:
    - Autonomous Agents, Multi-Agent**/Multi-Robot Systems**, **Cooperation**, **Communication**, **Strategic Reasoning**, Robotics, Sensor Fusion, Real-Time Reasoning, Machine Learning, etc

Main Goal:

"By 2050, develop a team of fully autonomous humanoid robots that may win against the human world champion team in soccer!"

RoboCup: Official Competitions

1997 – Nagoya (Japan)
1998 – Paris (France)
1999 – Stockholm (Sweden)
2000 – Melbourne (Australia)
2001 – Seattle (USA)
2002 – Fukuoka (Japan)
2003 – Padua (Italy)
2004 – Lisbon (Portugal)
2005 – Osaka (Japan)
2006 – Bremen (Germany)
2007 – Atlanta (USA)
2008 – Suzuhu (China)
2009 – Graz (Austria)
2010 – Singapore (Singapore)
2011 – Istanbul (Turkey)
2012 – Mexico City (Mexico)
2013 – Eindhoven (Holland)
2014 – João Pessoa (Brazil)
2015 – Hefei (China)
2016 – Leipzig (Germany)
2017 – Nagoya (Japan)…

Local Championships:
German Open (European), Japanese Open, Australian Open, American Open, **Portuguese Open**, Dutch Open, Iranian Open, China Open, LARS/SBR…

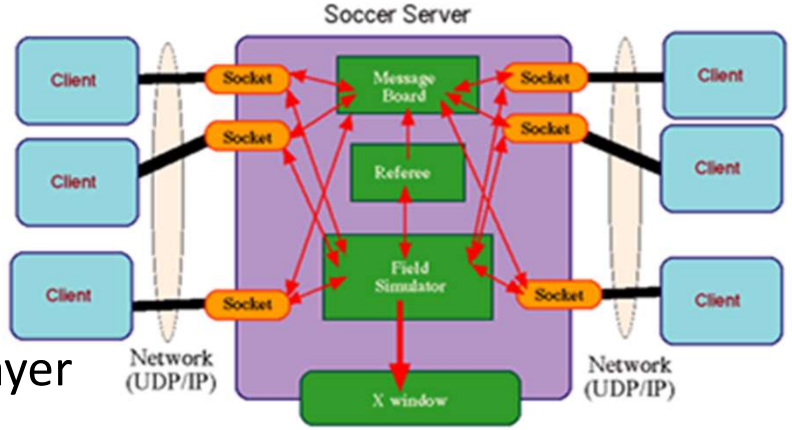
Participant/Awarded Countries:
Germany, USA, Japan, China, Iran, **Portugal,** Brazil, Australia, Holland, Singapore

Soccer Leagues
- **Simulation: Sim2D, Sim3D (Humanoids), Coach, MR**
- **Robots Small-Size**
- **Robots Middle-Size**
- **Standard Platform** (**Aibo**; **NAO**)
- Humanoid Robots (Kid, Adult)

RoboCup Rescue
- **Simulation**, Virtual, Robotic

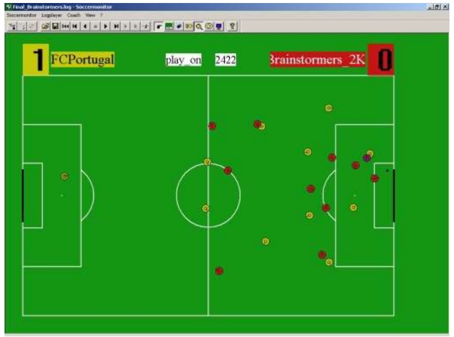
RoboCup Junior
RoboCup@Home
RoboCup@Work

RoboCup Leagues: Simulation 2D



Server Architecture

- **Virtual Robots** on a 105*68m Virtual Field
- Teams of 11 players plus a coach
- 2D Simulator+Monitor (Client-Server System)
- Robots controlled by different agents
- Agents (player's brains) control a single player
- **Simulator**/Server:
  - **Receives** agent **commands**
  - **Simulates** objects' **movement**
  - **Sends perceptions** to agents
- **Simulation Characteristics**
  - **Real-Time** - Human
  - Distributed – 24 Processes
  - **Inaccessible** (hidden), Continuous and Dynamic World
  - **Errors** in: Perception, Movement and Action
  - **Limited Resources** and Communication
  - **Multi-Objective**

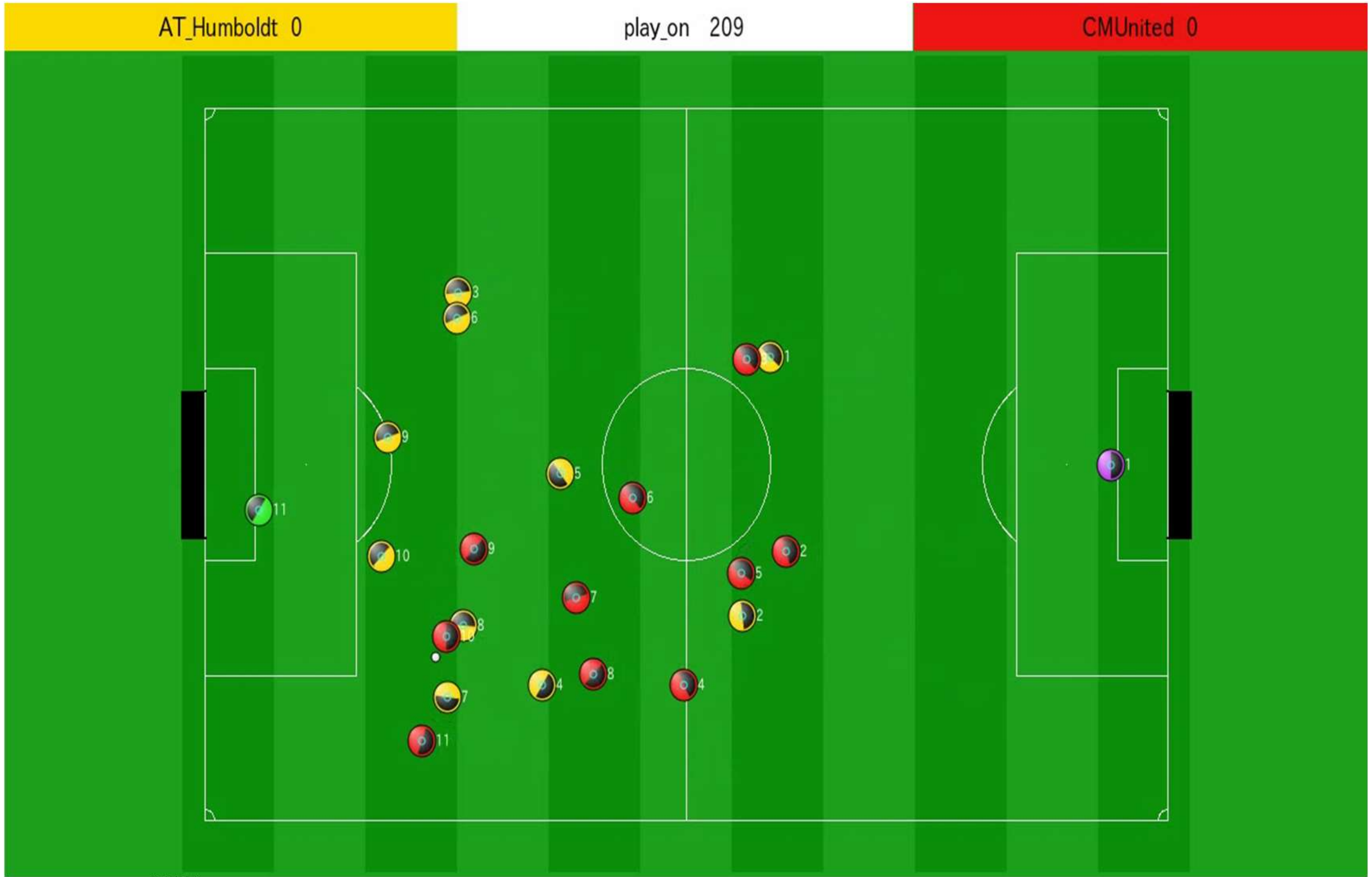


RoboCup Leagues: Simulation 2D

- 1997: League Start -> Simple Play

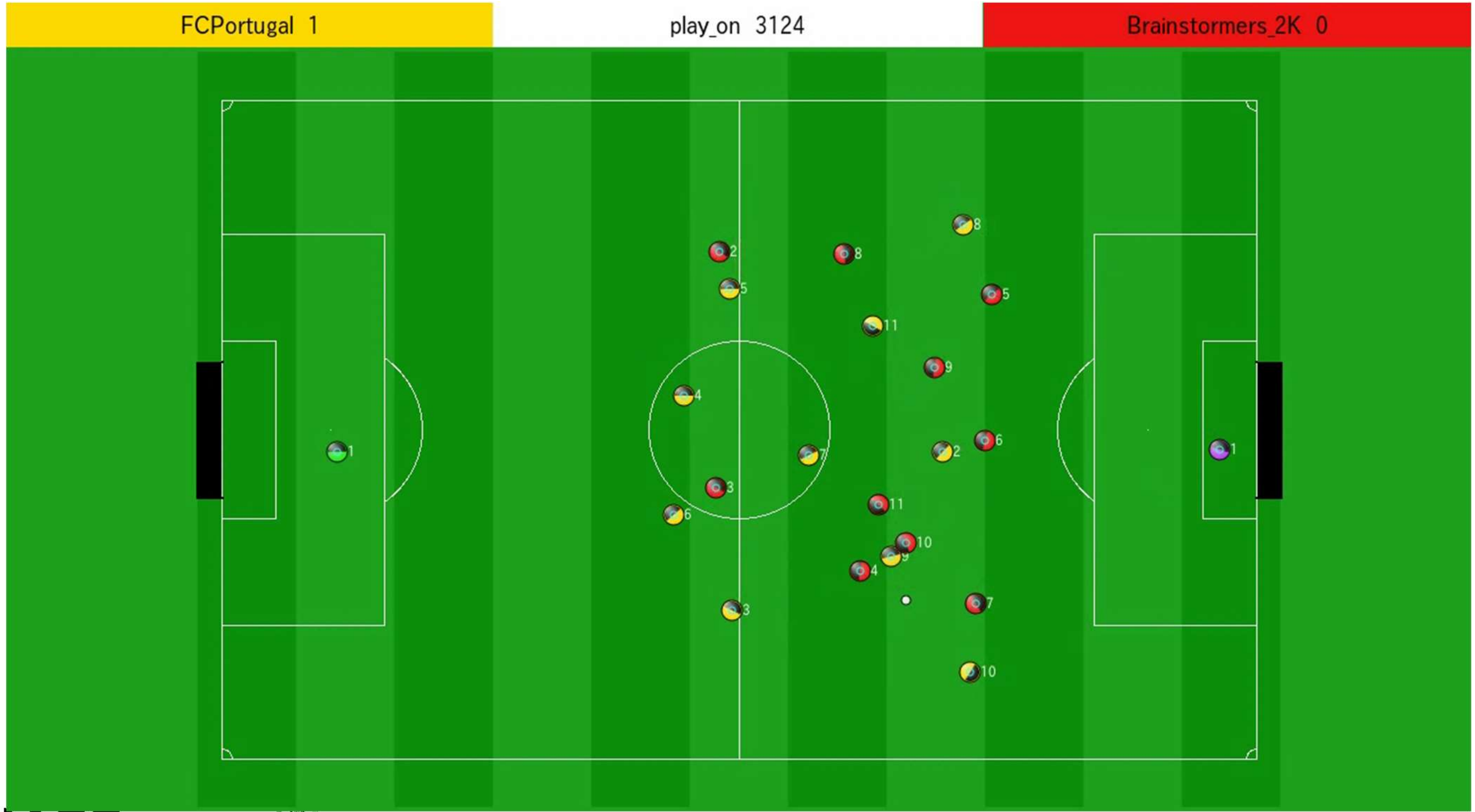
RoboCup Leagues: Simulation 2D

- **1998: Simple Passing and Good Individual skills**



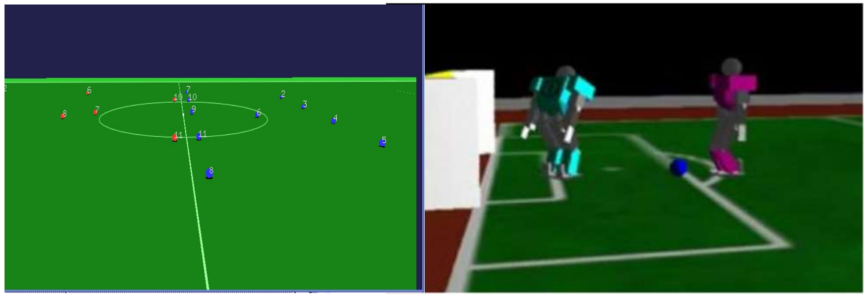
RoboCup Leagues: Simulation 2D

- 2000: Formations and Soccer like Playing



Simulation 3D League (Humanoids)

- Third dimension and complexities from real robots
- **Realistic physics and Robot Model:**
  - Spheres in 2004
  - Humanoids in 2007
  - NAO Robot Model: 2008
  - Heterogeneous Robots: 2013
- **Strong relation with SPL**
- 2 vs 2 -> 6 vs 6 -> 9 vs 9 -> 11 vs 11
- Server/Simulator (**SimSpark**)
  - Updates world state
  - Forces the "**laws of physics**": collisions, drag, gravity, ...
  - Send sensor information (**perceptors**)
  - Executes actions (**effectors**)
  - Enforces soccer rules – referee
- **Very difficult to create competitive skills by hand!**

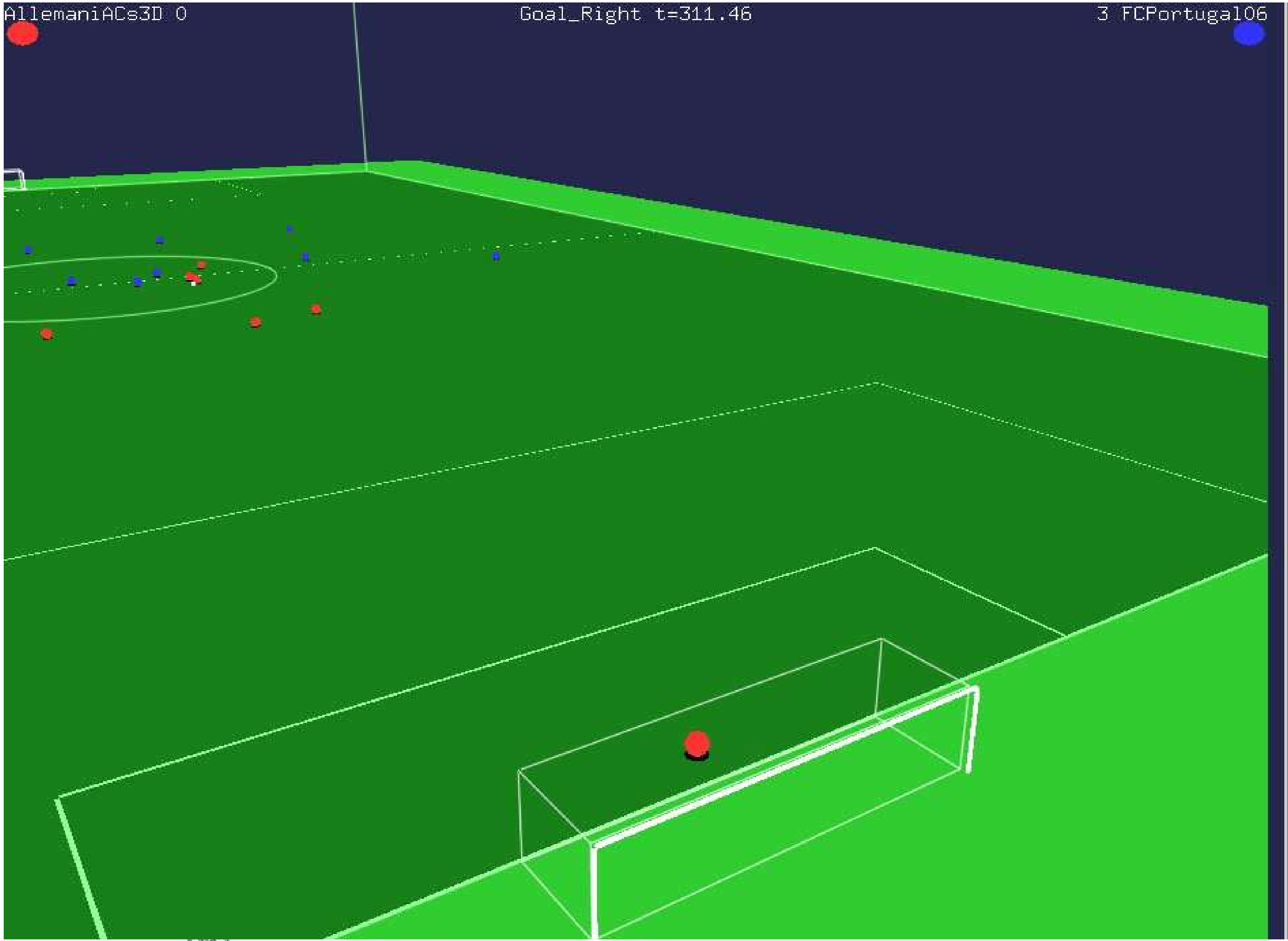


(a) real robot (b) virtual robot

Simulation 3D – Spheres model

- 2004-2005: Very Basic playing!
- 2006: Formations/High-level playing!

Simulation 3D – Spheres model



Simulation 3D – Humanoid model

- 2007-2010: Very Basic playing!
- 2011: Formations/High-level playing!

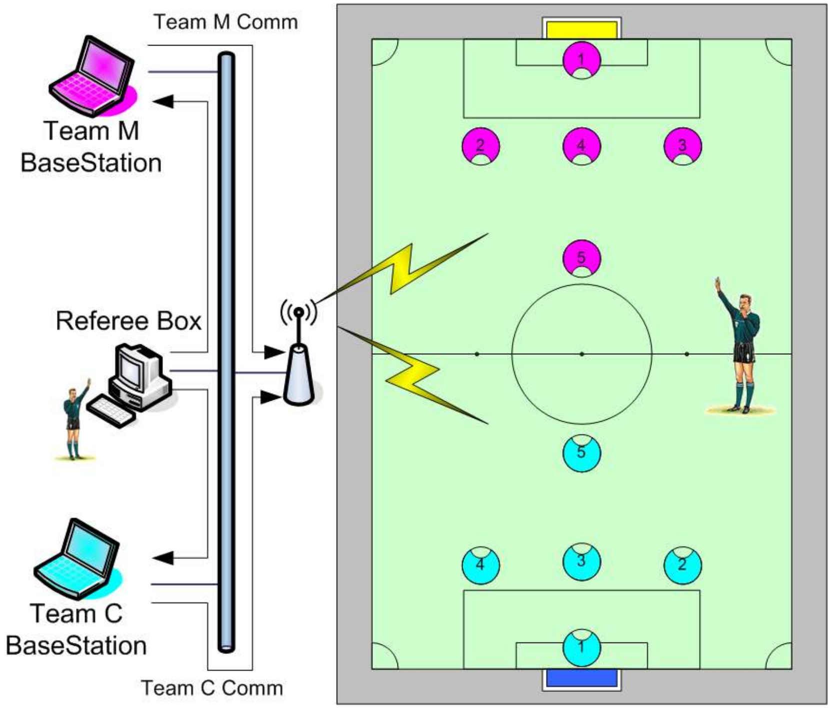
Simulation 3D – Nao model

- Same Robot but completely different skills: Walk, getup, kick

Simulation 3D – Nao model

Middle Size League

- Robots are completely autonomous
- 5 robots per team
- Robots around 50x50cm and 80cm height
- Field 18mx12m, green with white lines
- MSL rules based on official FIFA laws



Middle Size League

- 1998-2007: Very Basic playing! Individual Dribbling!
- 2008: Formations SBSP/High-level playing/Setplays!

Flexible Strategy for RoboCup

- **RoboCup Leagues: Simulation 2D, Simulation 3D, Small-Size, Middle-Size, SPL and Search and Rescue**
- **Applications in four distinct teams:**
  - **FC Portugal** *(University of Porto/Aveiro/Minho)*
    - Simulation 2D, Simulation 3D, Coach, MR, Rescue, SPL
  - **CAMBADA** *(University of Aveiro) – Prof. Nuno Lau*
    - Middle-Size League, RoboCup@Home
  - **5DPO** *(University of Porto) – Prof. A.P.Moreira*
    - Small-Size League, Middle-Size League
  - **Portuguese Team** *(University of Porto/Aveiro/Minho)*
    - SPL – Standard Platform League
- **More than 40 awards in International Competitions for these 4 Teams!**

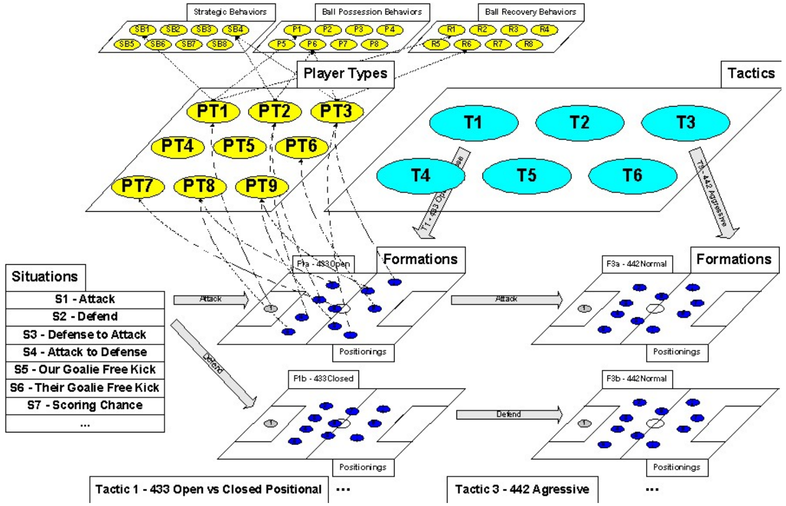
The Coordination Problem

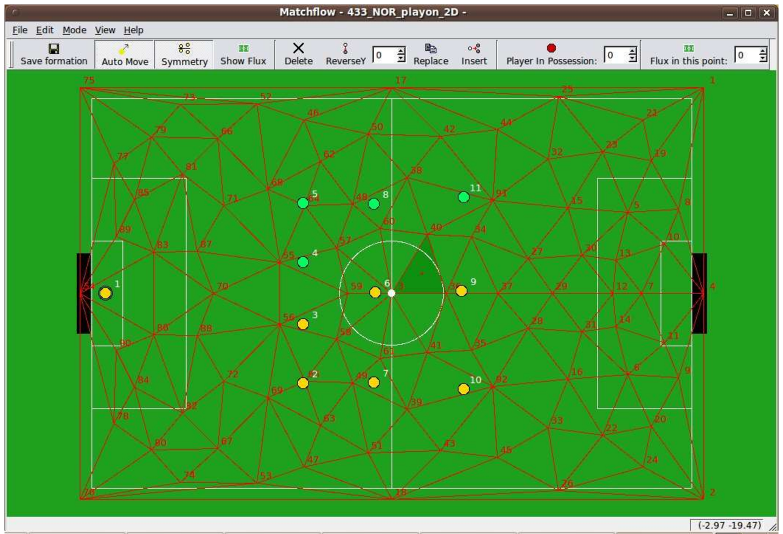
- Coordinate autonomous robots decisions to carry out team tasks as efficiently as possible
- Coordination challenges
  - Strategy
  - Coaching
  - Role assignment
  - Formation
  - Plan execution
  - Interaction
  - Learning
  - Communication

Formalizing Sports' Concepts

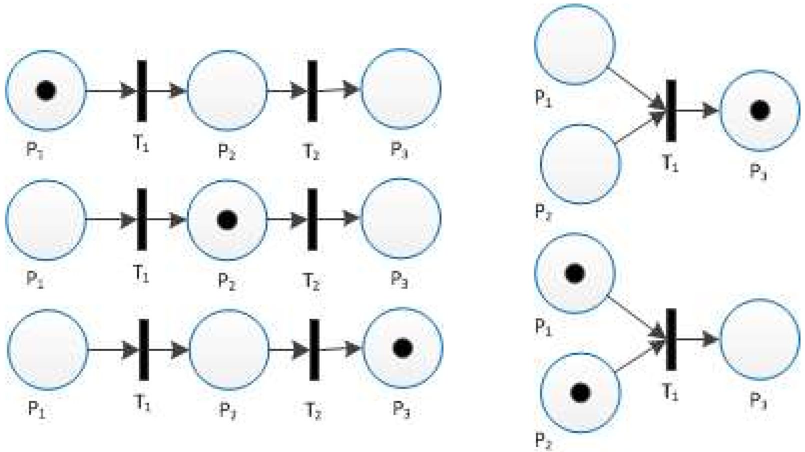
- Team/Collective Behaviour
  - Strategy
  - Tactics
  - Formations
  - Setplays
  - …
- Player/Individual Behavior
  - Action
  - Pass/Shot
  - Tackle/Interception
  - …

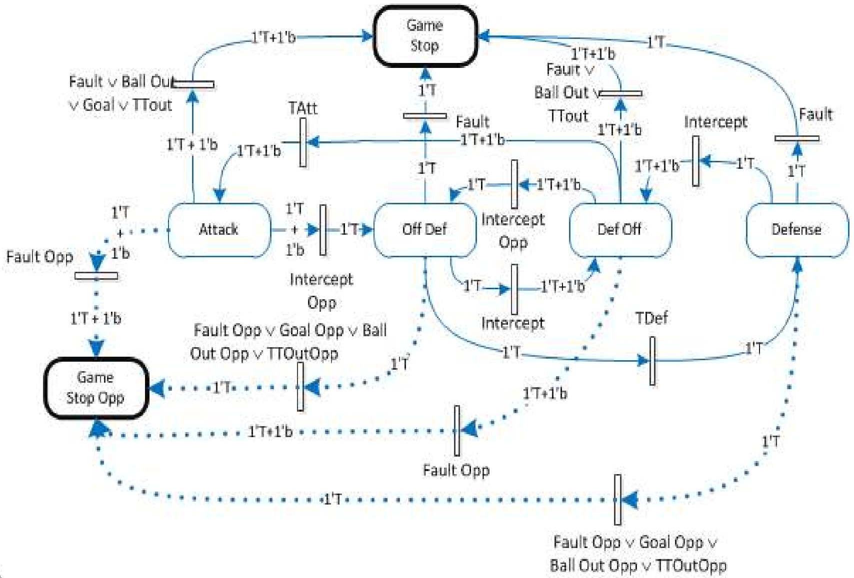
- Petri Nets
- BNF – Bakus Naur Forms
- SExpressions
- Ontologies
- Logic and Fuzzy Logic
- Data Mining

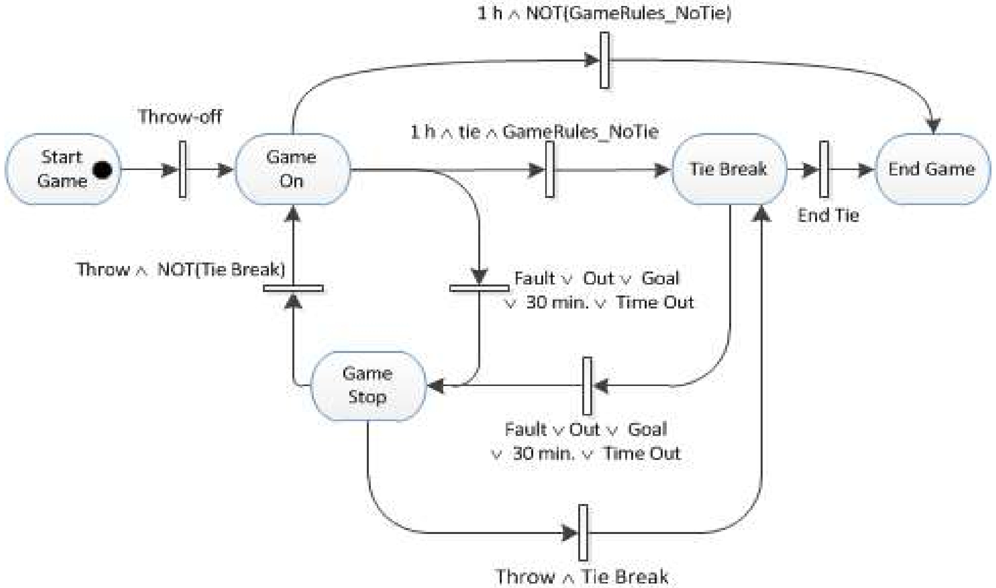




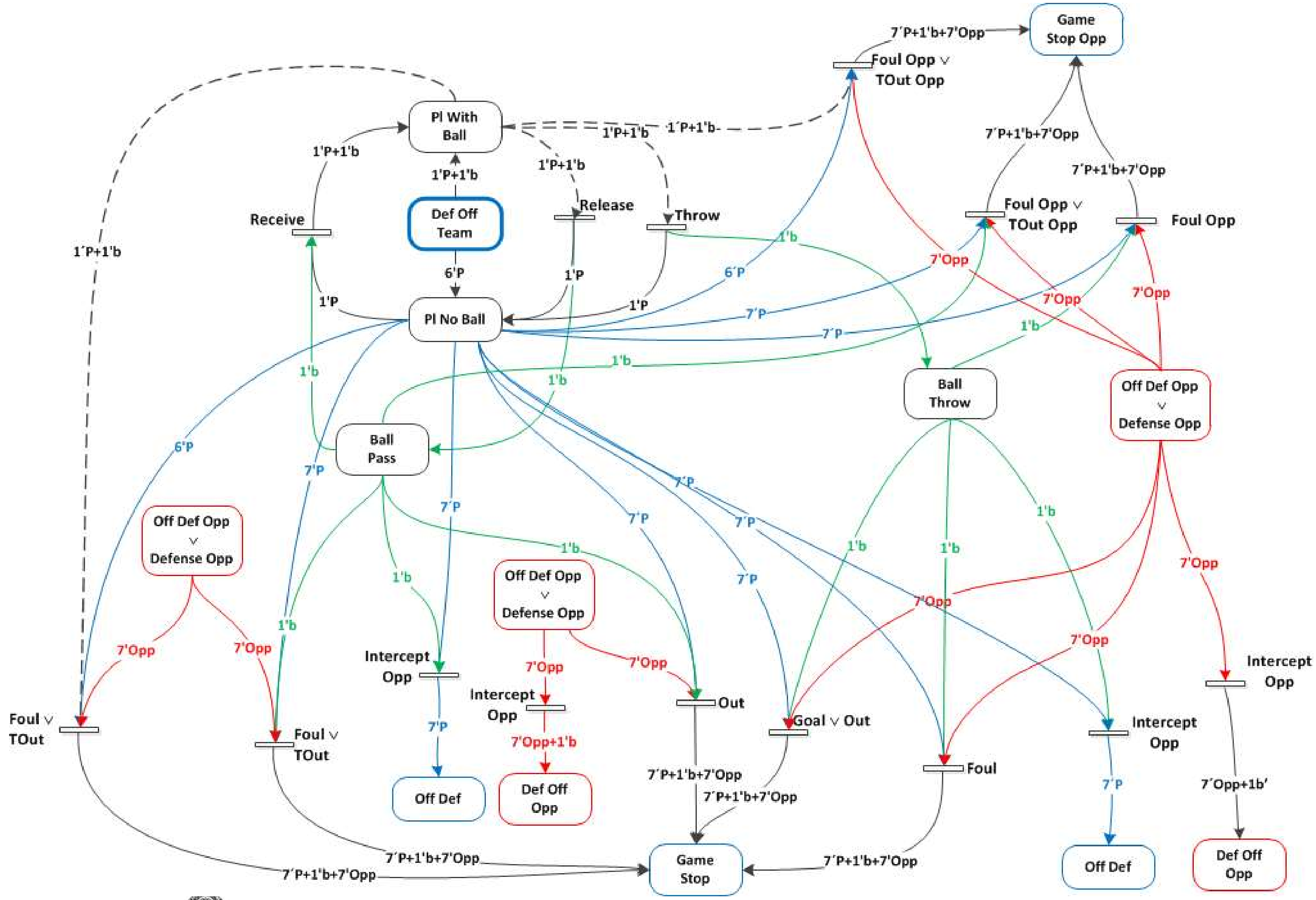
Game Analysis with Petri Nets



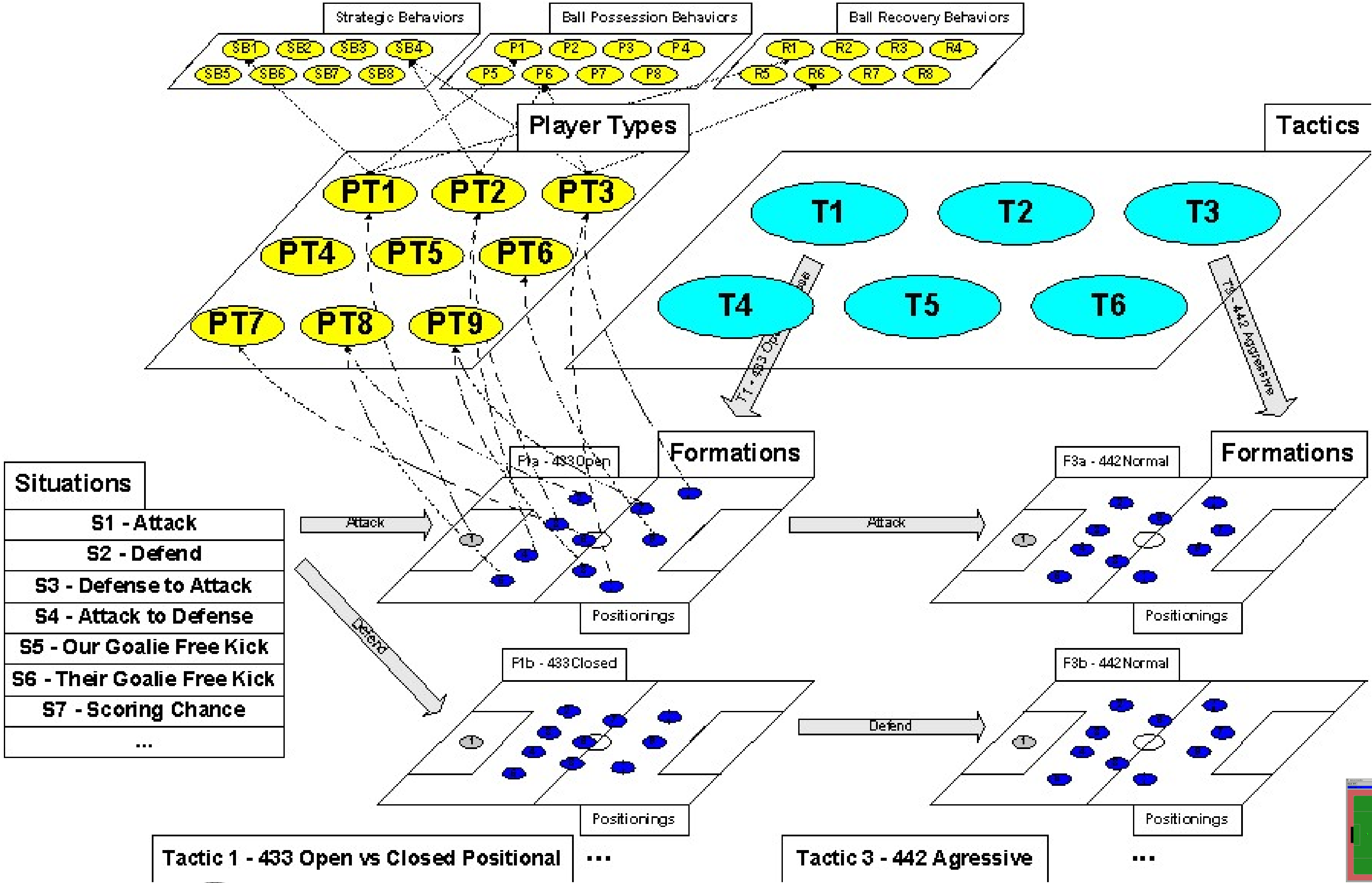


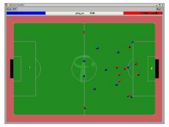


Game Analysis with Petri Nets

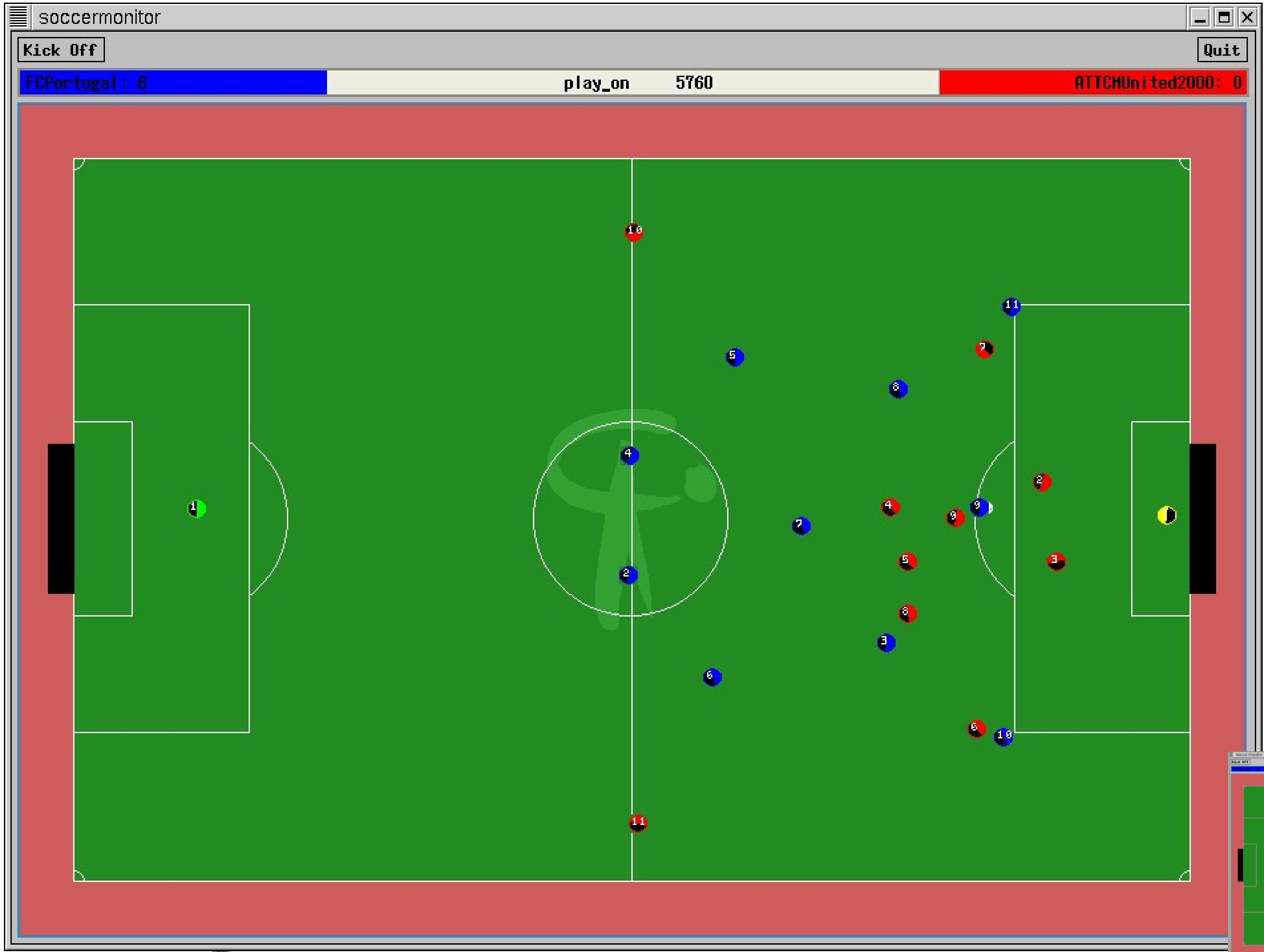


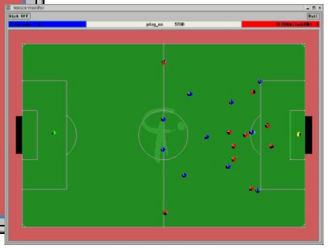
Simulation of a Team Strategy



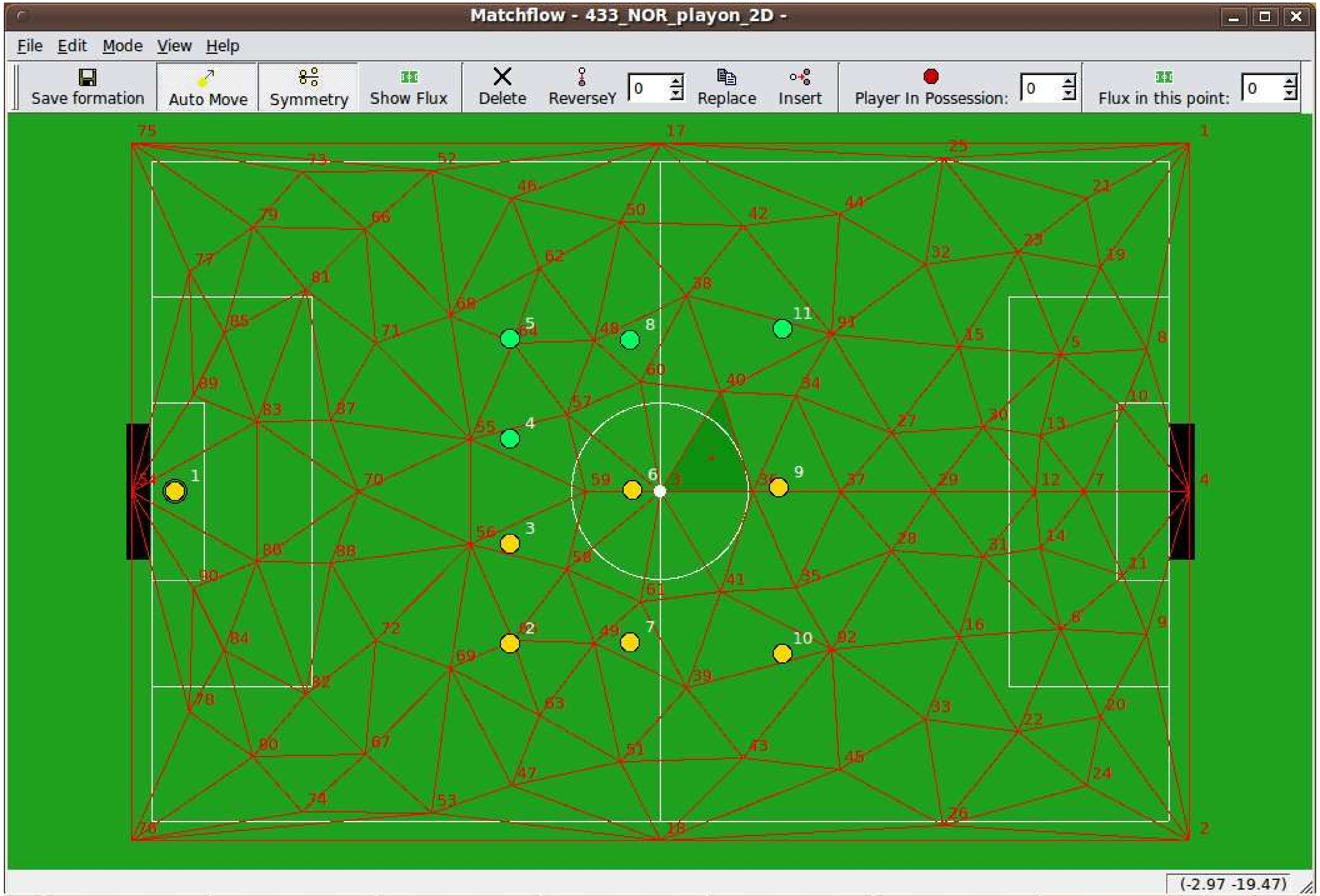


Formations: SBSP vs SPAR and DPRE



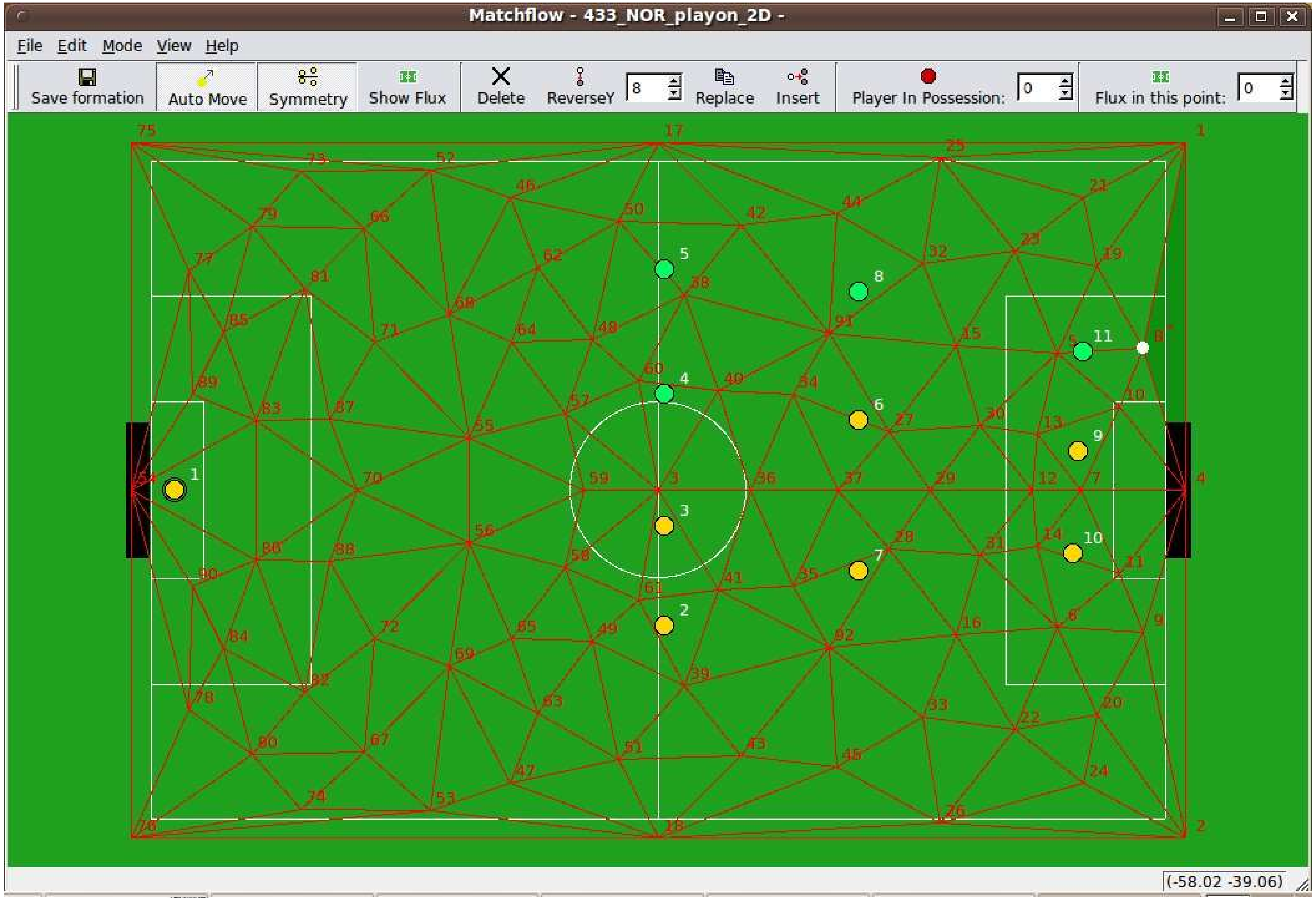


SBSP with Delaunay Triangulation



Based on Akiyama, 2007

SBSP with Delaunay Triangulation



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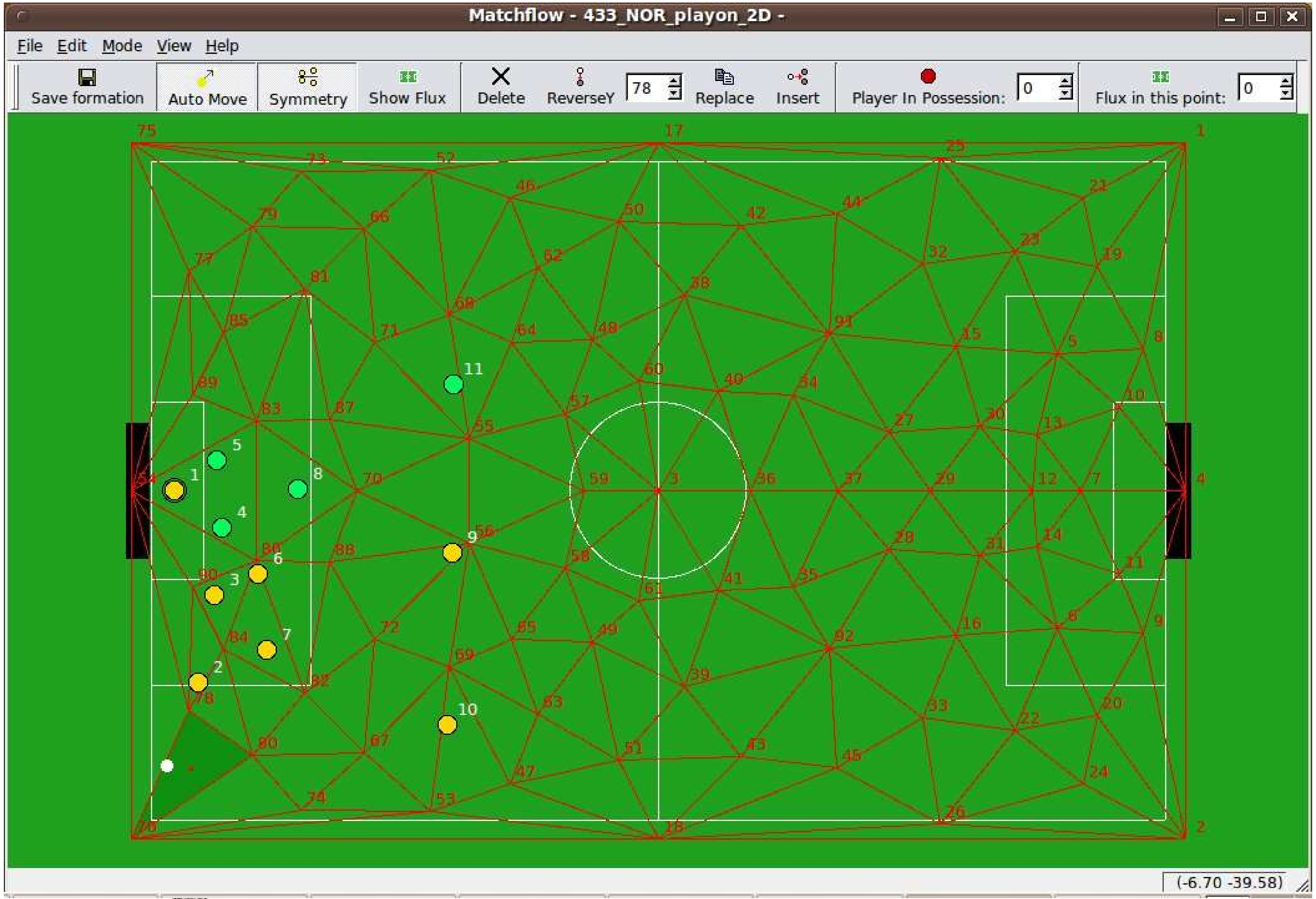

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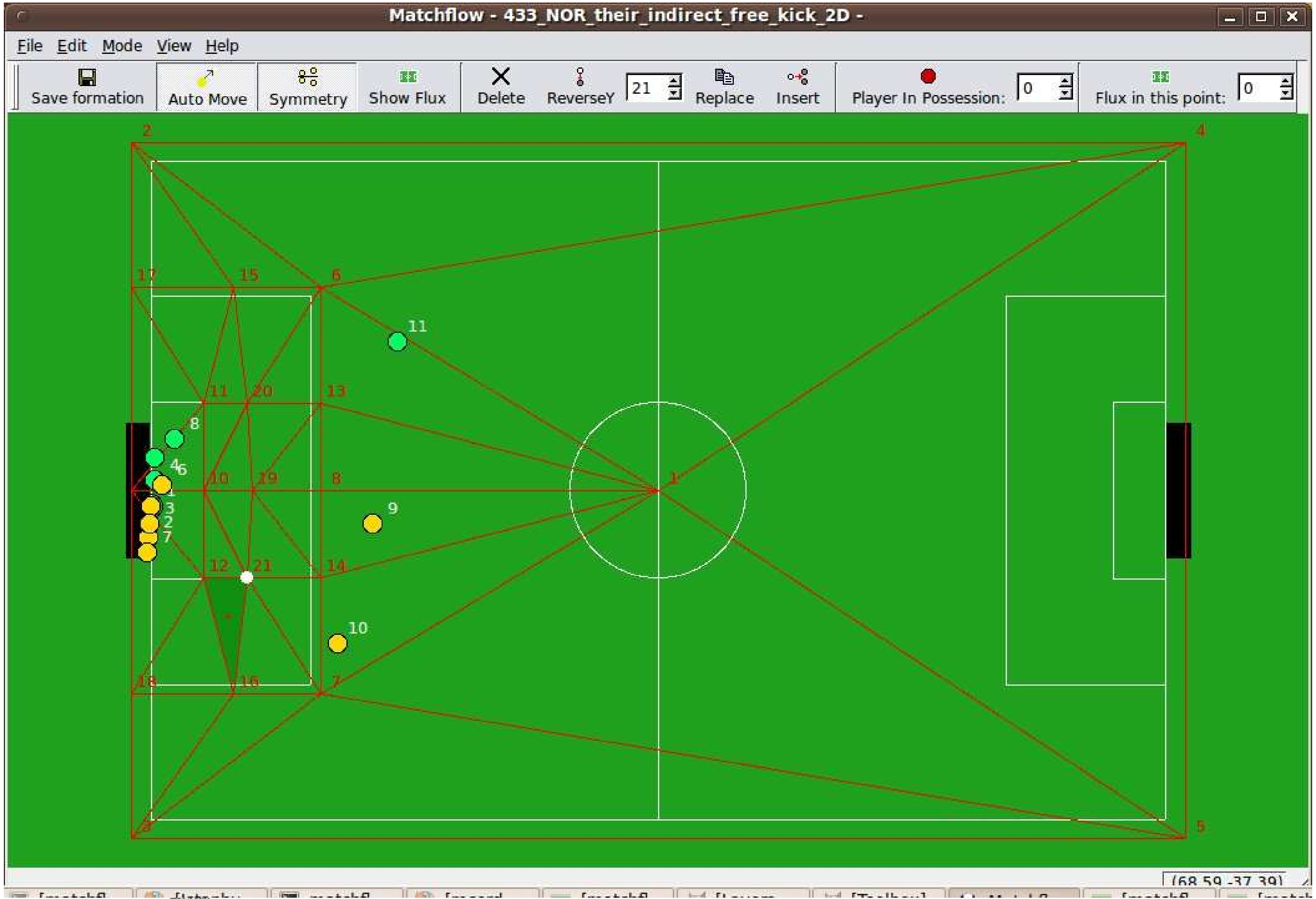

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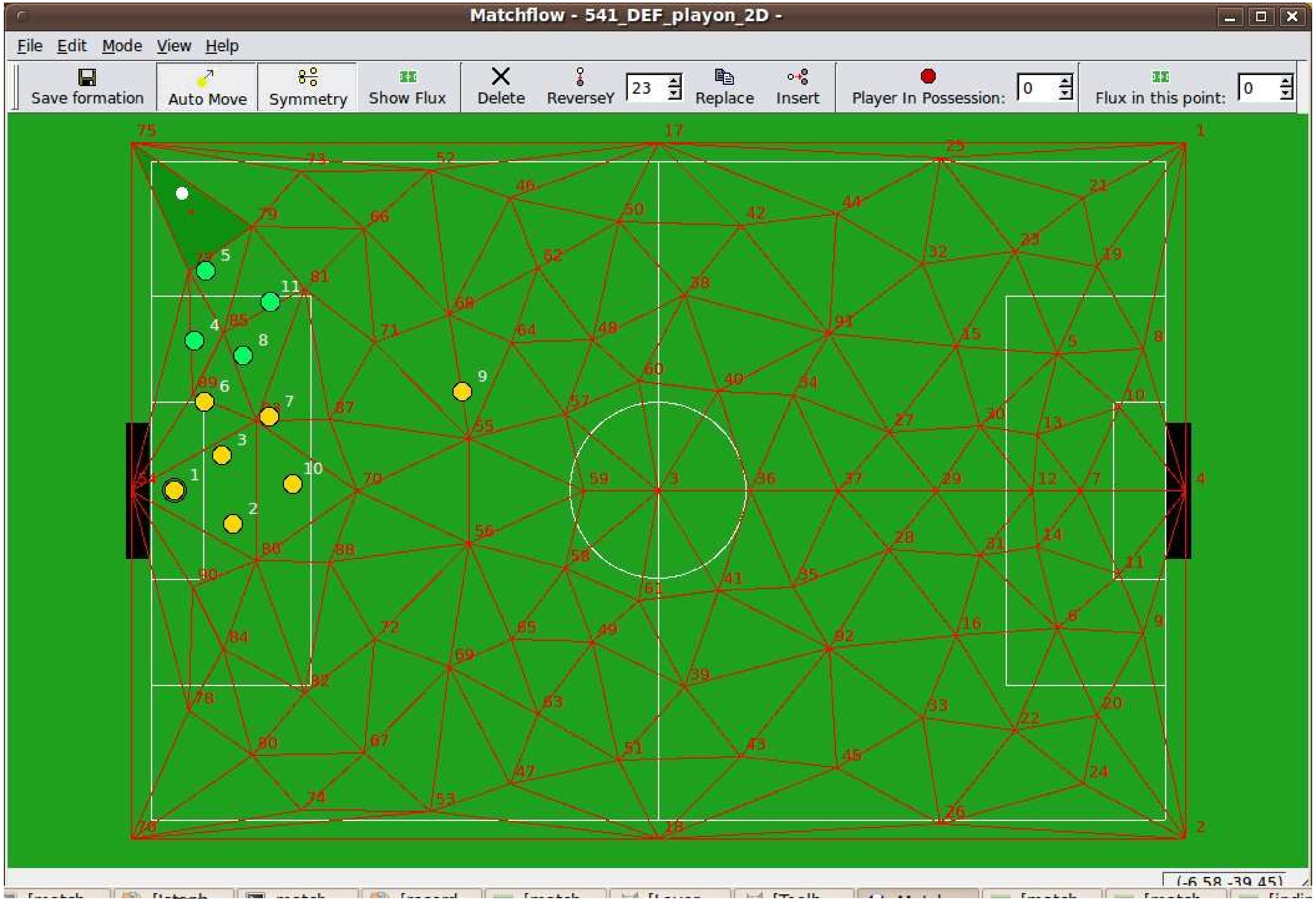

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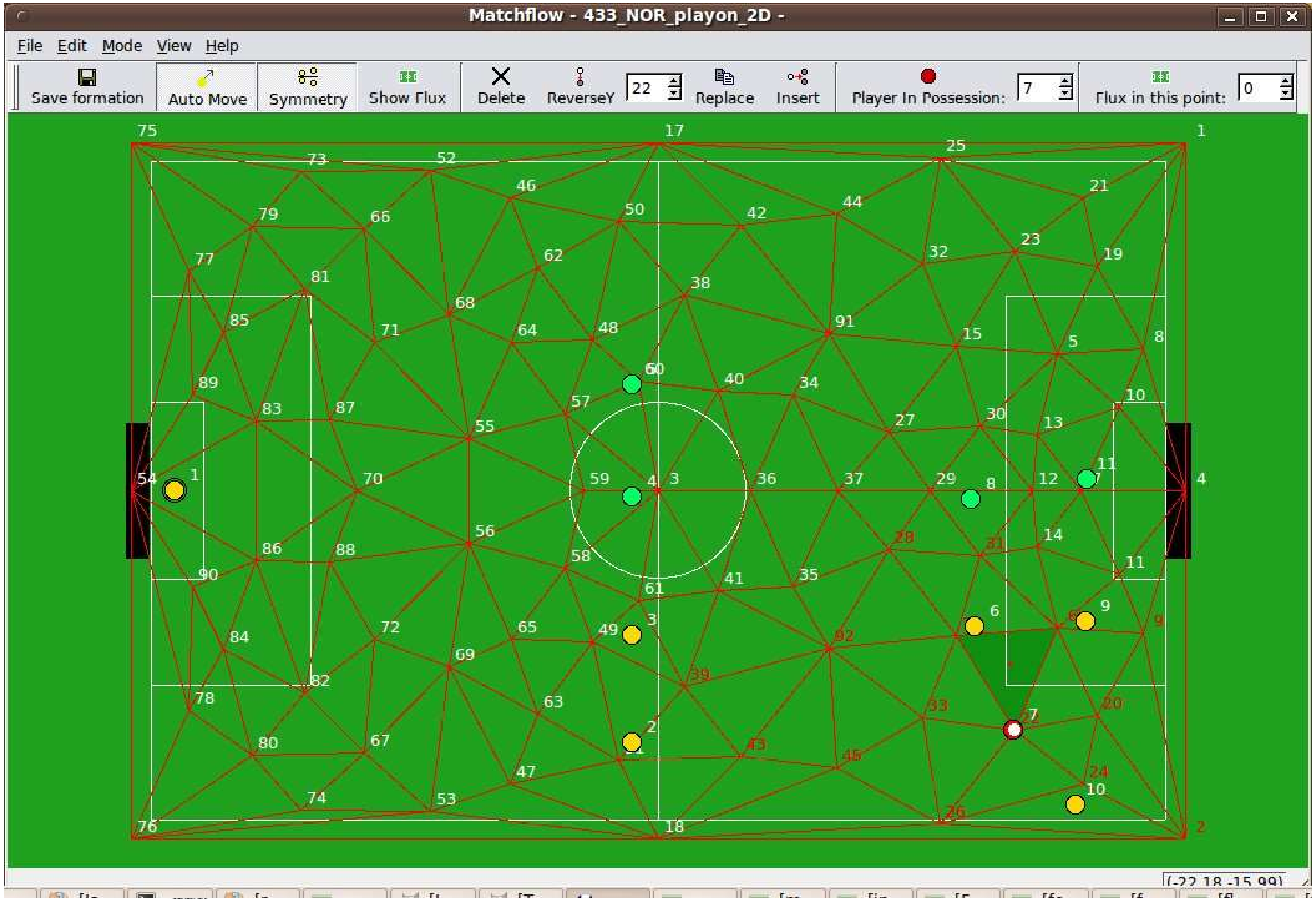

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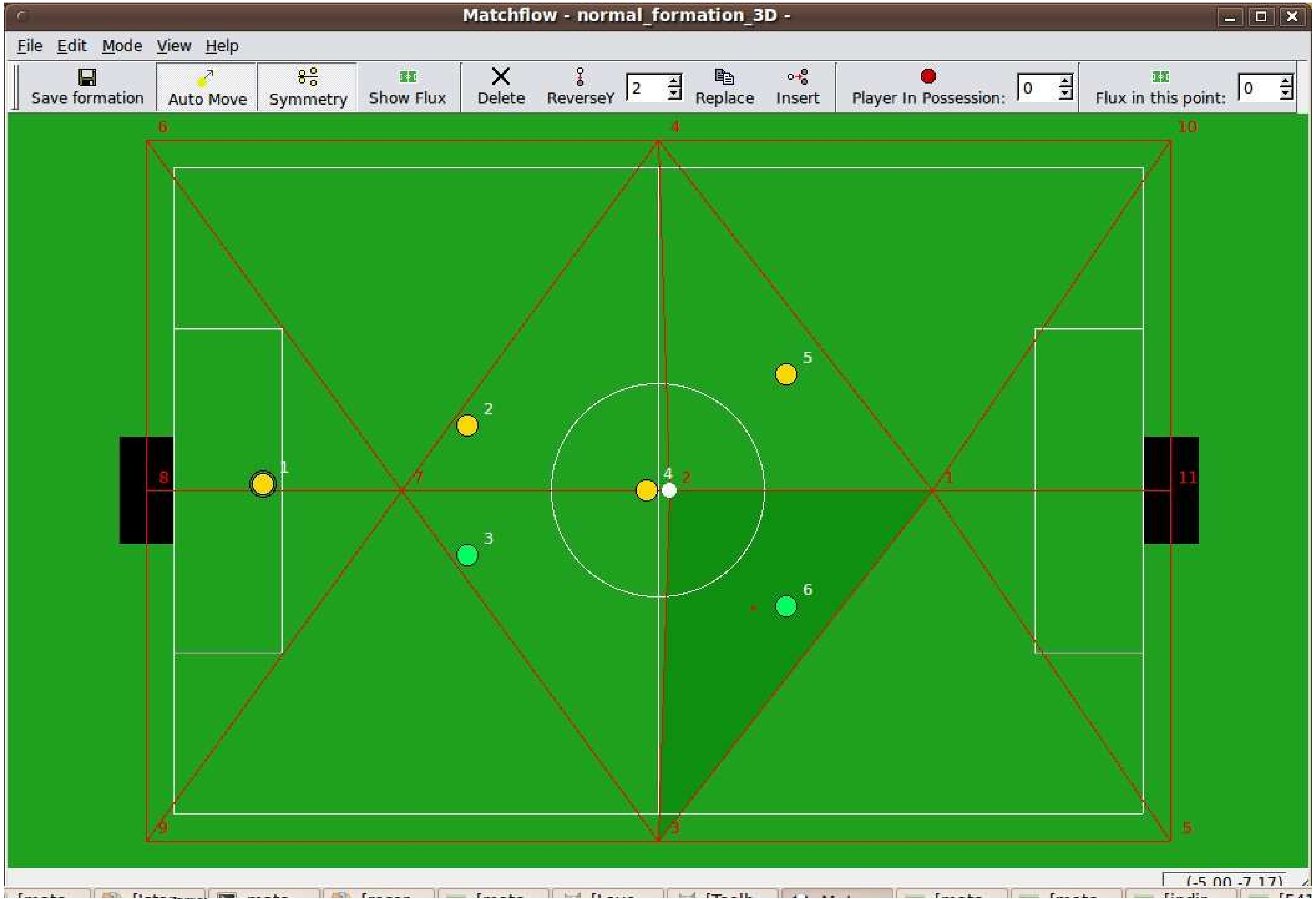

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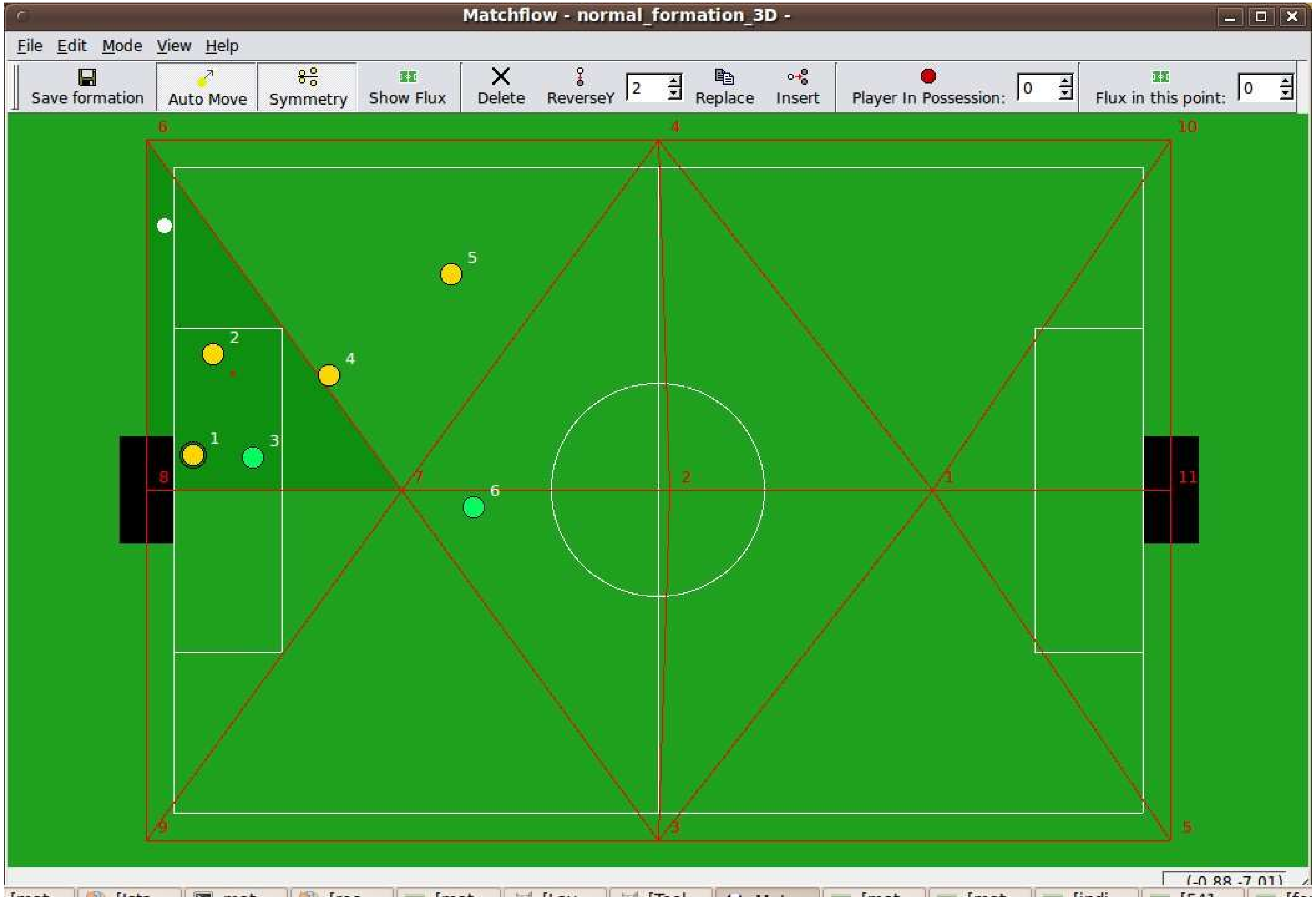
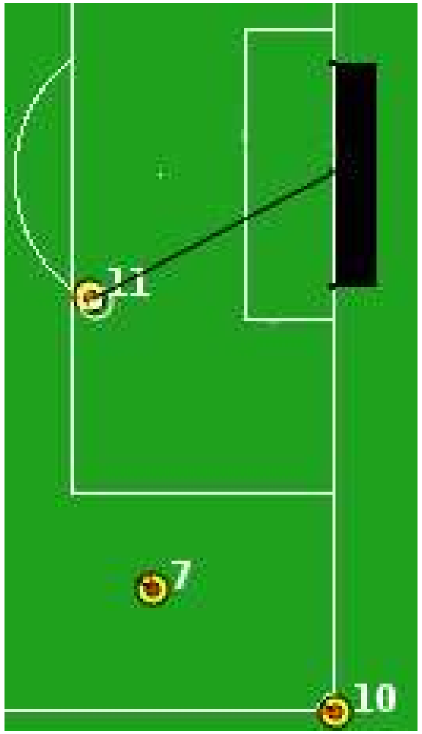


Formations in the MSL

Formations in the MSL

Setplay Example (Sim2D)

Simple, pre-defined but flexible plans, which describe cooperation and coordination between agents/robots



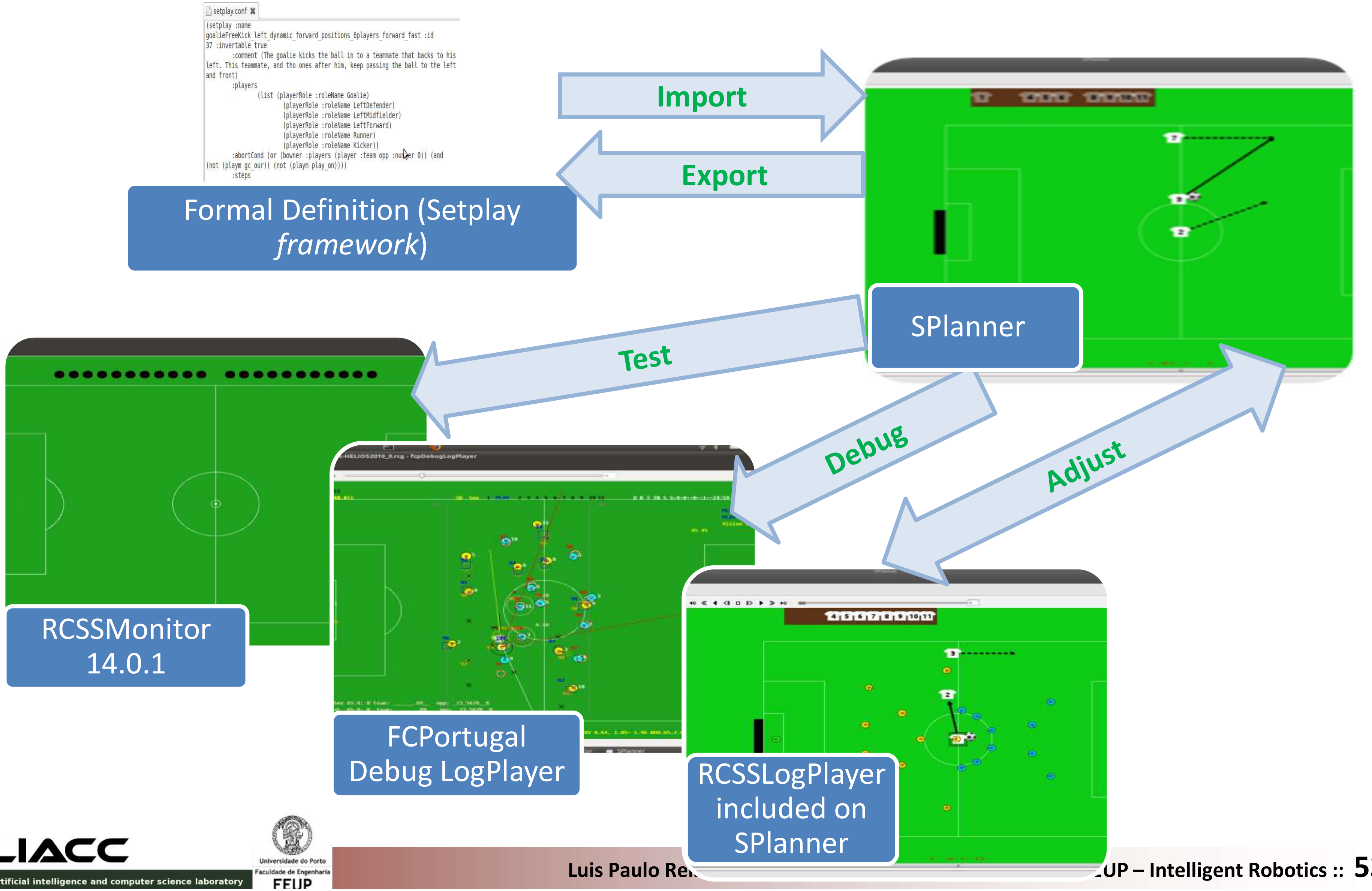
Setplay Definition

```
(setplay :name simpleCorner
    :players (list (playerRole :roleName CornerP)
    (playerRole :roleName receiver) (playerRole
 :roleName shooter))
:steps (seq (step :id 0 :waitTime 15 :abortTime 70
:participants
    (list (at CornerP (pt :x 52 :y 34))
        (at receiver (pt :x 40 :y 25)) (at shooter (pt :x
     36 :y 2)))
:condition (playm fk_our)
:leadPlayer CornerP
:transitions (list
    (nextStep :id 1:condition (canPassPl :from CornerP
 :to receiver)
    :directives (list
        (do :players CornerP :actions (bto :players
     receiver))
        (do :players receiver :actions (receivePass))))))
```

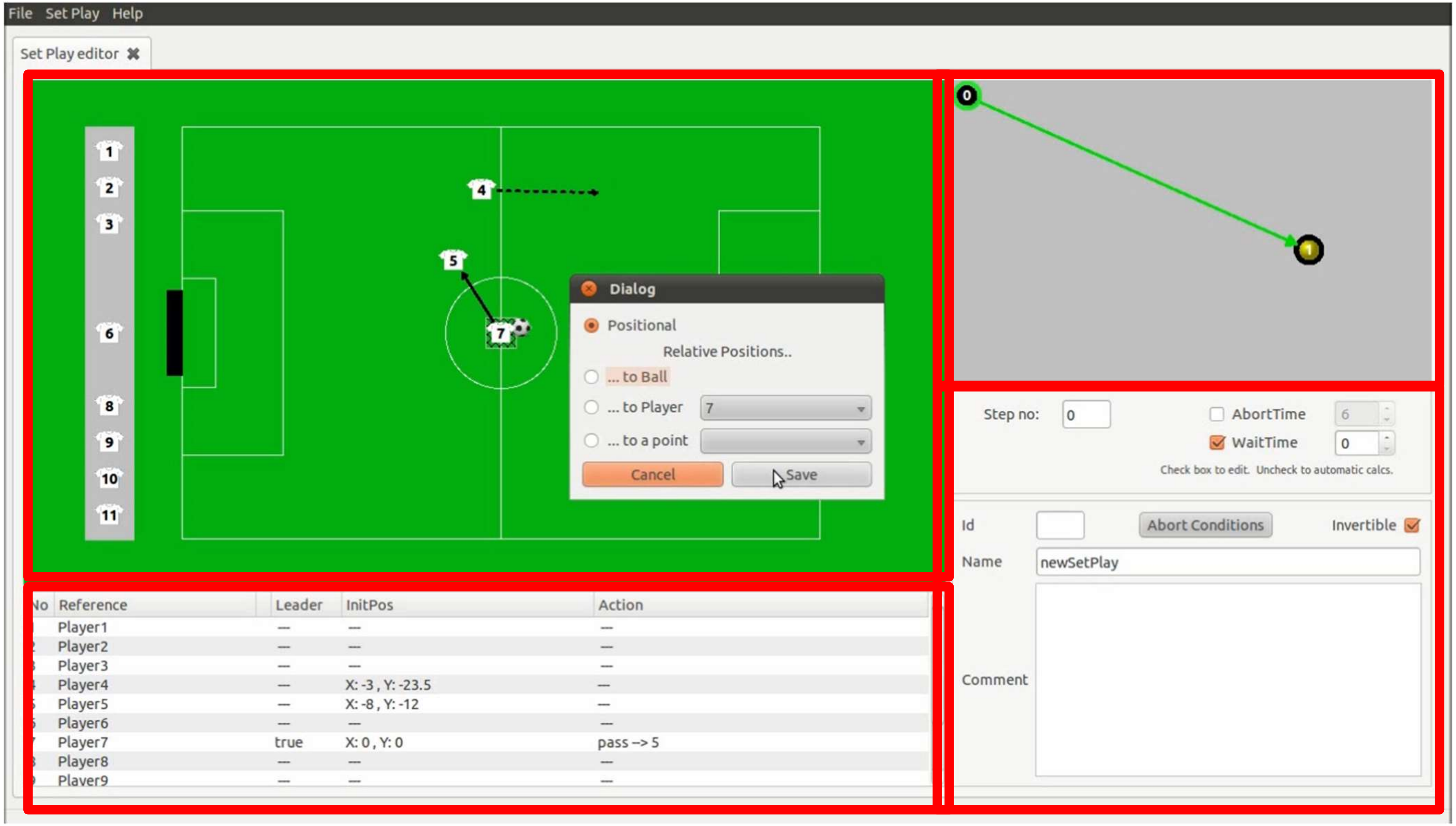
Setplay Definition

```
(step :id 1 :waitTime 5 :abortTime 70
:participants (list (at CornerP (pt :x 52 :y 34)) (at receiver (pt
:x 40 :y 25))
     (at shooter (pt :x 36 :y 2)) )
:condition (and (bowner :players receiver) (playm play_on))
:leadPlayer receiver
:transitions (list
    (nextStep :id 2
        :condition (canPassPl :from receiver :to shooter)
        :directives (list
            (do :players receiver :actions (bto :players shooter))
            (do :players shooter :actions (receivePass))))))
(step :id 2 :abortTime 70
:participants (list (at CornerP (pt :x 52 :y 34)) (at receiver (pt
:x 40 :y 25)) (at    shooter    (pt  :x 36 :y 2)) )
:condition (and (bowner :players shooter) (playm play_on) )
:leadPlayer shooter :transitions (list
    (nextStep :id 3 :condition (canShoot :players shooter)
        :directives (list
            (do :players shooter :actions (shoot))))))
```

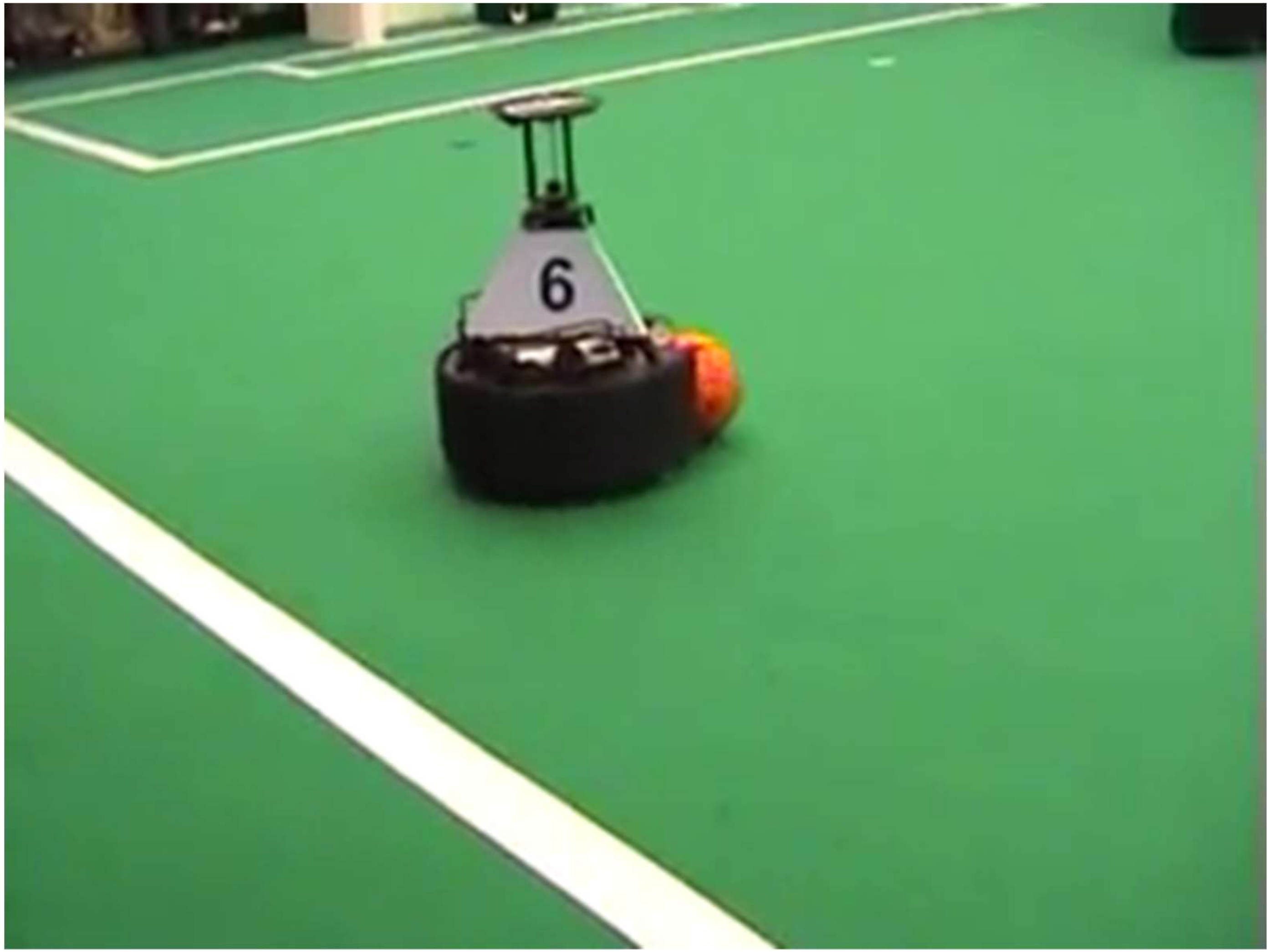
Setplays: Graphical Definition



Setplays: Graphical Definition



SetPlays in the MSL



Machine Learning Motivation

Programming Robots is a hard task:

- **No high-level programming language**
- **Sensors and actuators are noisy**
- **Robotics is moving towards increasingly unstructured environments**

If only robots could learn how to perform tasks by themselves…

$\Rightarrow$ **Machine Learning in Robotics**

Machine Learning in Robotics can be used for:

- Robot **Perception**
- Robot **Decision**
- Robot **Actuation** (Behaviors)
- Multi-robot **Coordination**
- Adapt **Human-Robot Interaction**

Machine Learning Motivation

Table-Tennis

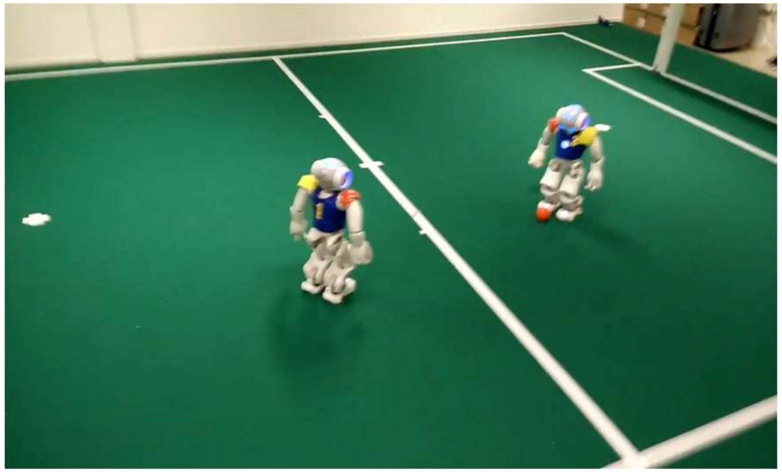
Robots

Mülling + Peters

Humans

Soccer Ball Passing

Robots



Erik Orjehag – LIU H1

Humans

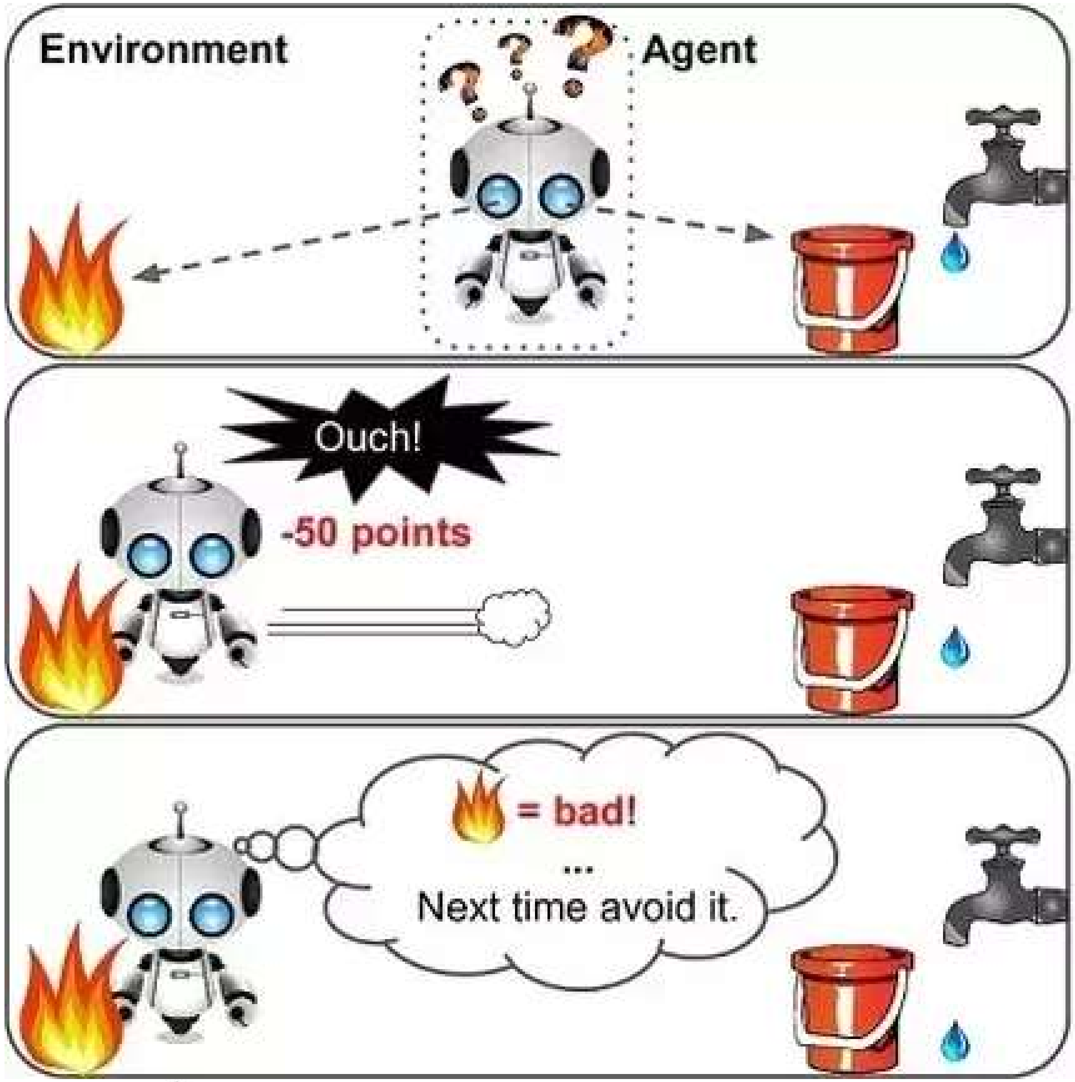
We need learning and adaptation to improve robot skills!

Machine Learning Motivation

Challenges in Robot Learning

- Cost of experimentation
- Cost of failure
- Limited data
- Generalization
- Curse of dimensionality
- Real time requirements
- Changes in environment
- Changes in task specification

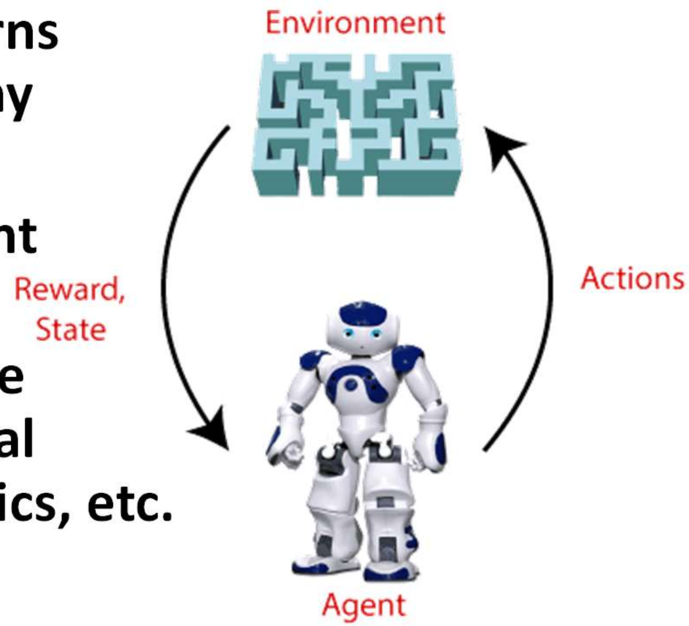
Reinforcement Learning



1. Observe
2. Select action using policy
3. Action!
4. Get reward or penalty
5. Update policy (learning step)
6. Iterate until an optimal policy is found

Reinforcement Learning

- Reinforcement Learning is a feedback-based Machine learning technique in which an agent learns to behave in an environment by performing the actions and seeing the results of actions.
- For each good action, the agent gets positive feedback, and for each bad action, the agent gets negative feedback or penalty.
- In Reinforcement Learning, the agent learns automatically using feedbacks without any labeled data
- Since there is no labeled data, so the agent is bound to learn by its experience only.
- RL solves a specific type of problem where decision making is sequential, and the goal is long-term, such as game-playing, robotics, etc.



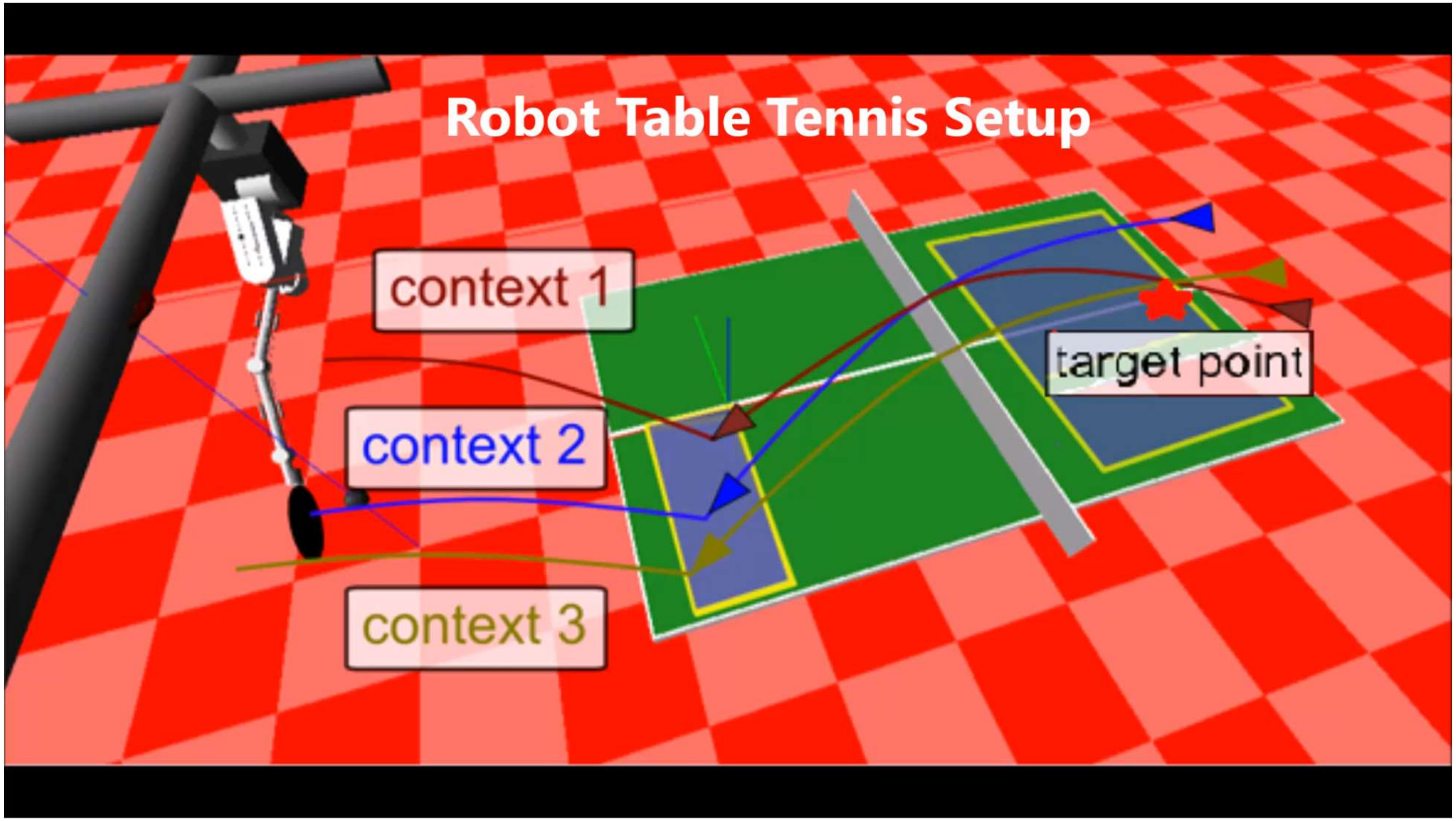
Reinforcement Learning

- The agent interacts with the environment and explores it by itself
- The primary goal of an agent in reinforcement learning is to improve the performance by getting the maximum positive rewards
- The agent learns with the process of hit and trial, and based on the experience, it learns to perform the task in a better way
- *"Reinforcement learning is a type of machine learning method where an intelligent agent (computer program) interacts with the environment and learns to act within that."*
- We do not need to pre-program the agent, as it learns from its own experience without any human intervention
- The agent learns that what actions lead to positive feedback or rewards and what actions lead to negative feedback penalty.
- As a positive reward, the agent gets a positive point, and as a penalty, it gets a negative point

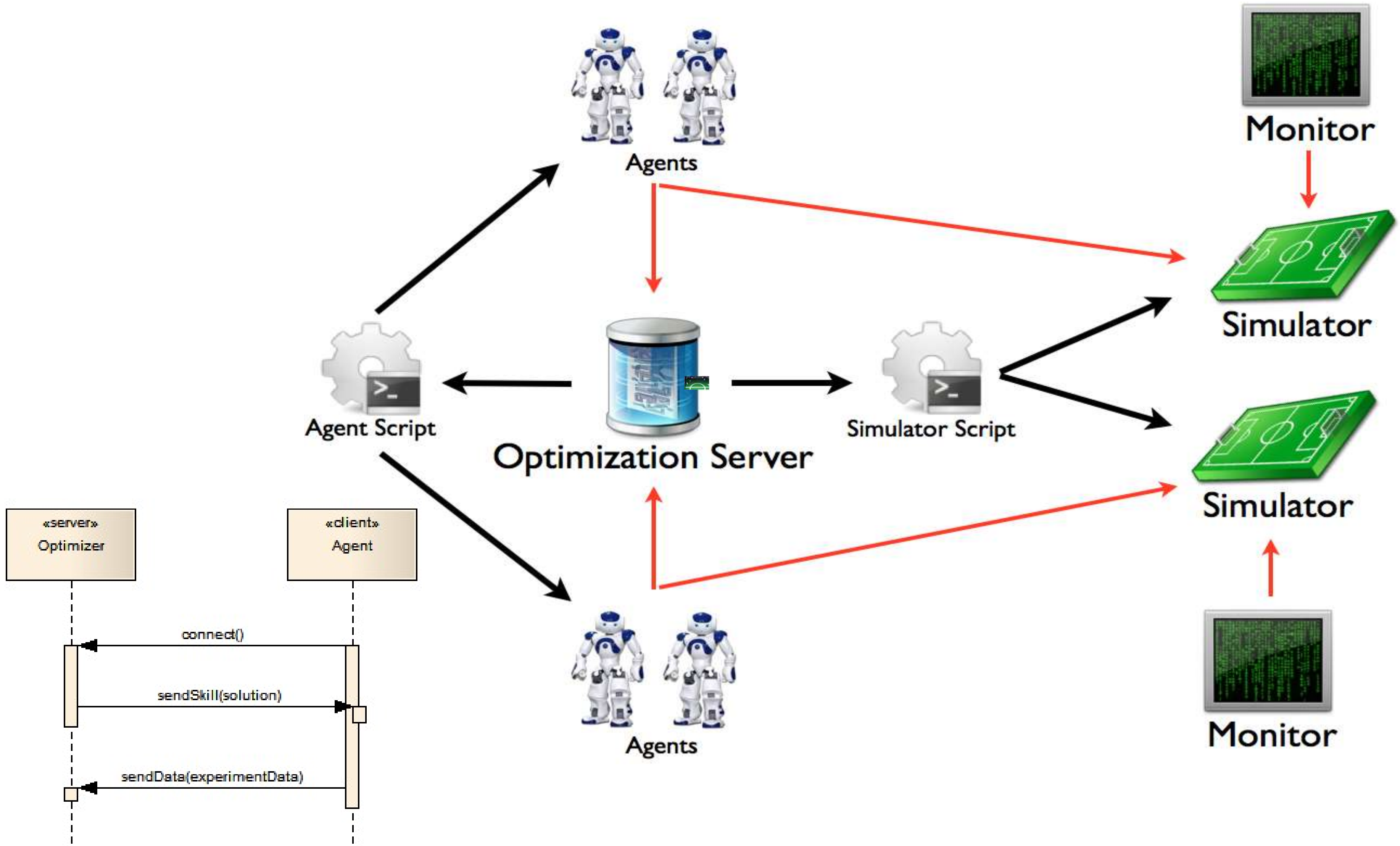
Reinforcement vs. Supervised Learning

Reinforcement Learning	Supervised Learning
RL works by interacting with the environment	Supervised learning works on the existing dataset
The RL algorithm works like the human brain works when making some decisions	Supervised Learning works as when a human learns things in the supervision of a guide
There is no labeled dataset is present	The labeled dataset is present
No previous training is provided to the learning agent	Training is provided to the algorithm so that it can predict the output
RL helps to take decisions sequentially	In Supervised learning, decisions are made when input is given

Experiments: Table Tennis

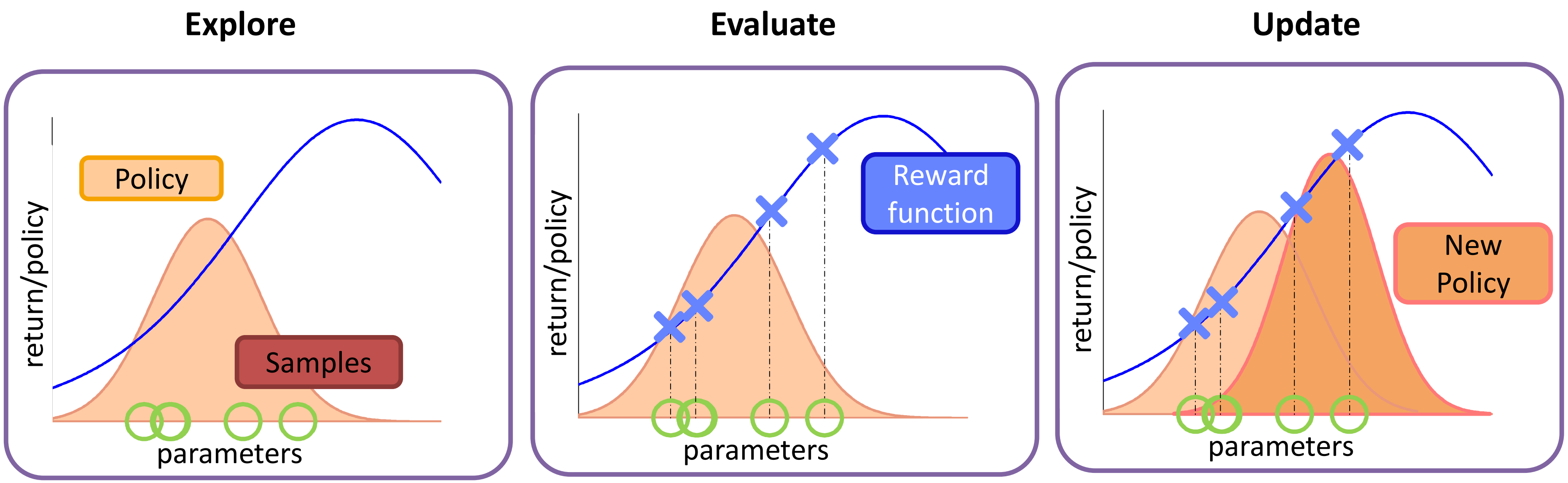


Generic Optimization



Stochastic Search

- **Use Search-Distribution:** $\pi(\boldsymbol{w}) = \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$
- **Objective: Find search distribution** $\pi(\boldsymbol{w})$ **that maximizes** $J_\pi = \int \pi(\boldsymbol{w}) R(\boldsymbol{w}) d\boldsymbol{w}$



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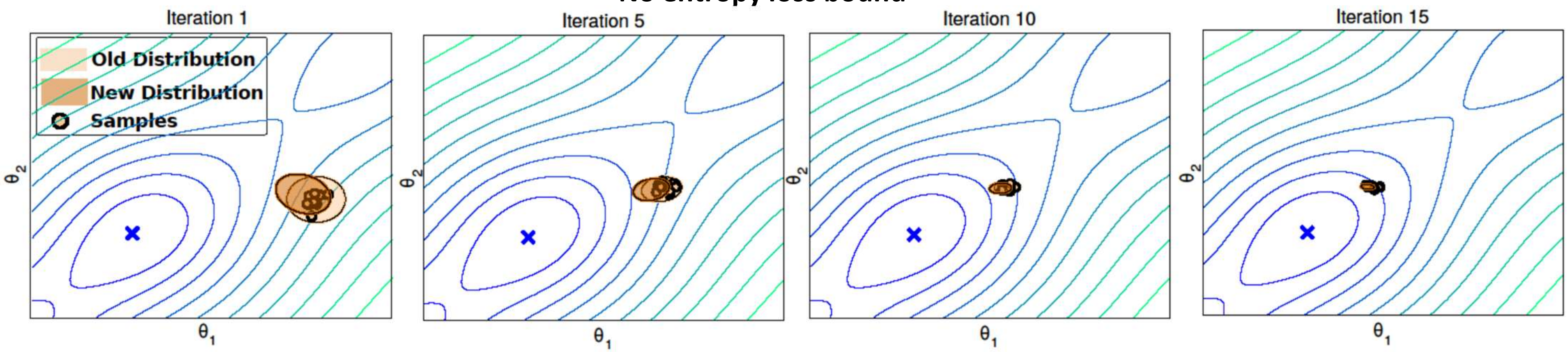
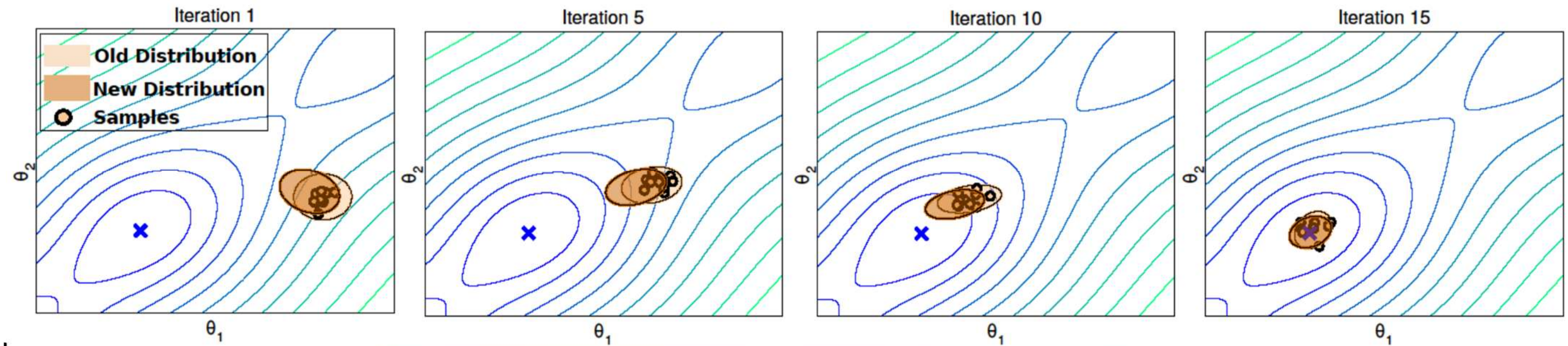
No entropy loss bound



With bounded entropy loss



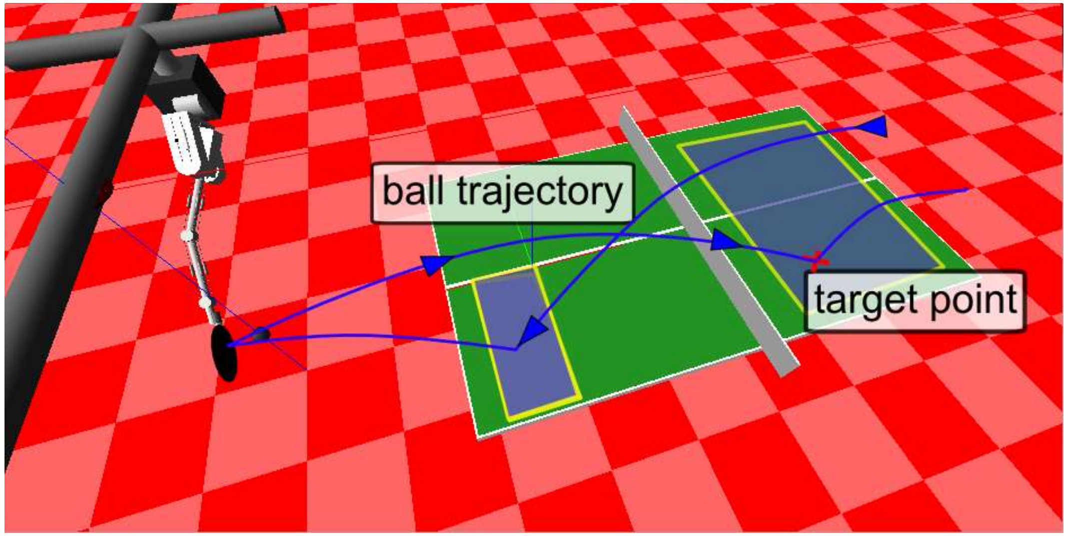
Contextual Stochastic Search

Goal: Adapt parameters w to different situations

- **Different ball trajectories**
- **Different target locations**

Introduce context vector s

- **Continuous valued vector**
- **Characterizes environment and objectives of agent**



Abdolmaleki, et. al, *Model-Based Relative Entropy Stochastic Search,* NIPS 2015

Learn contextual search policy $\pi(\boldsymbol{w}|\boldsymbol{s})$

Adaptation of Skills

Contextual distribution:

$$\pi(\boldsymbol{w}|\boldsymbol{s}) = \mathcal{N}(\boldsymbol{s}^T\boldsymbol{M} + \boldsymbol{m}, \boldsymbol{\Sigma})$$

Compatible Function Approximation:

$$R(\boldsymbol{s}, \boldsymbol{w}) \approx \boldsymbol{w}^T\boldsymbol{A}\boldsymbol{w} + \boldsymbol{s}^T\boldsymbol{B}\boldsymbol{w} + \boldsymbol{a}^T\boldsymbol{w} + a_0$$

Contextual distribution update:

1. Maximize **expected** return

$$\arg\max_{\pi} \mathbb{E}_{p(\boldsymbol{s})}\left[\int \pi(\boldsymbol{w}|\boldsymbol{s})R(\boldsymbol{s}, \boldsymbol{w})d\boldsymbol{w}\right]$$

2. Bound **expected** information loss

$$\text{s.t.:} \quad \mathbb{E}_{p(\boldsymbol{s})}\left[\mathrm{KL}\left(\pi(\cdot|\boldsymbol{s})||\pi_{\text{old}}(\cdot|\boldsymbol{s})\right)\right] \leq \epsilon$$

3. **Bound entropy loss – Controls Step Size of Covariance**

$$\underbrace{H(\pi_{\text{old}}) - H(\pi)}_{\text{loss in entropy}} \leq \gamma$$

New distribution:

$$\pi(\boldsymbol{w}|\boldsymbol{s}) \propto \pi_{\text{old}}(\boldsymbol{w}|\boldsymbol{s})^{\frac{\eta}{\eta+\omega}} \exp\left(\frac{R(\boldsymbol{s}, \boldsymbol{w})}{\eta + \omega}\right)$$

$$\propto \mathcal{N}(\boldsymbol{s}^T\boldsymbol{M}_{\text{new}} + \boldsymbol{m}_{\text{new}}, \boldsymbol{\Sigma}_{\text{new}})$$

Compatible Function Approximation

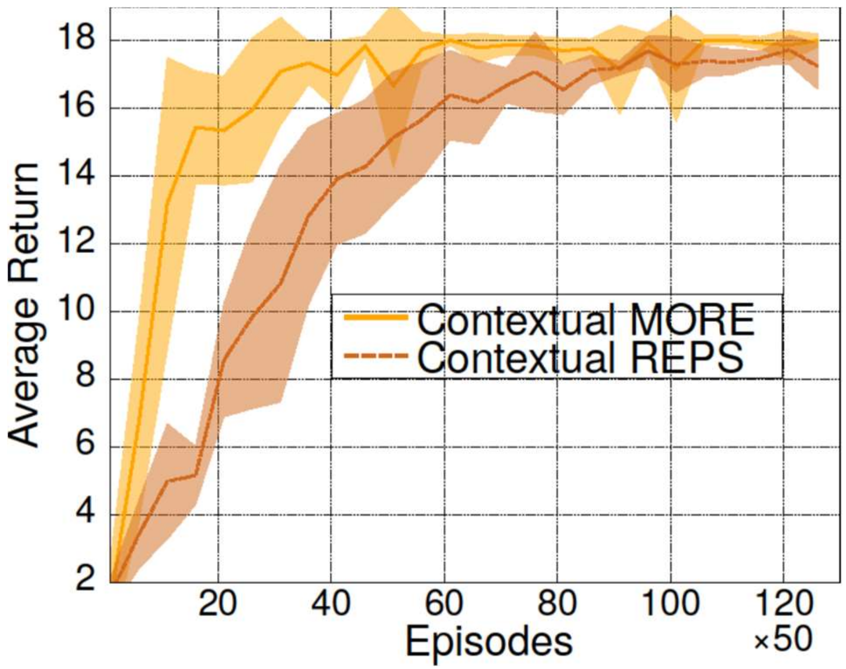
Adaptation of Skills: Table Tennis

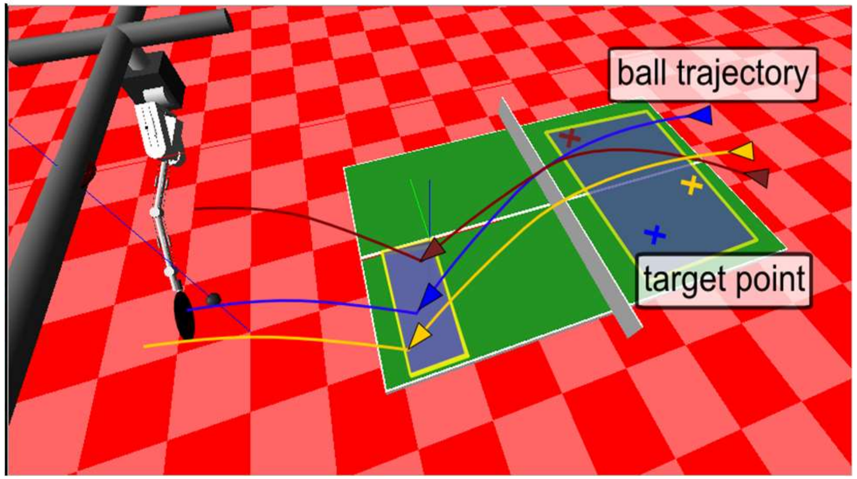
Contextual Stochastic Search:

- Context: Initial ball velocity

Reward:

- Hit ball
- Ball impacts at target position

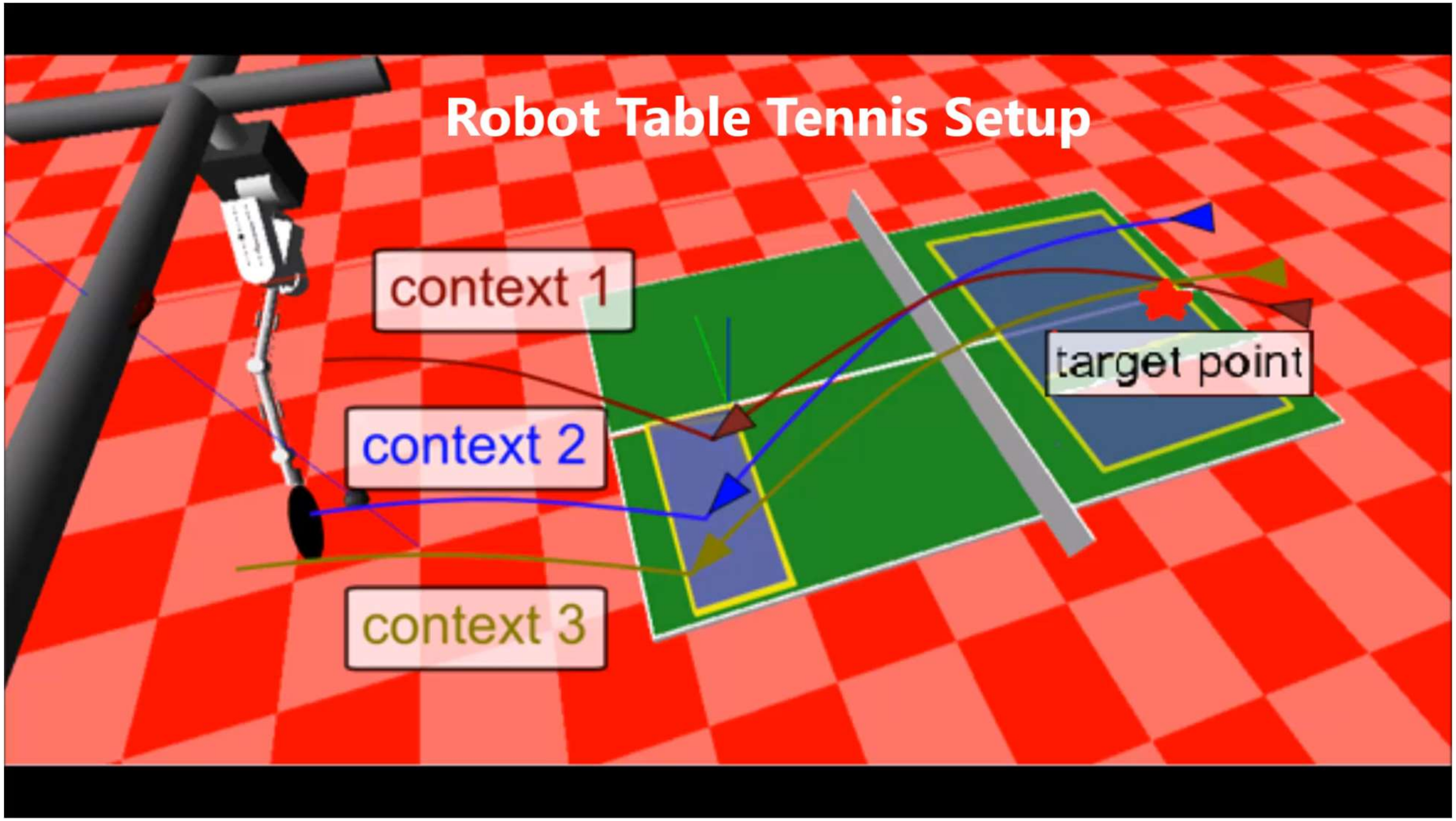




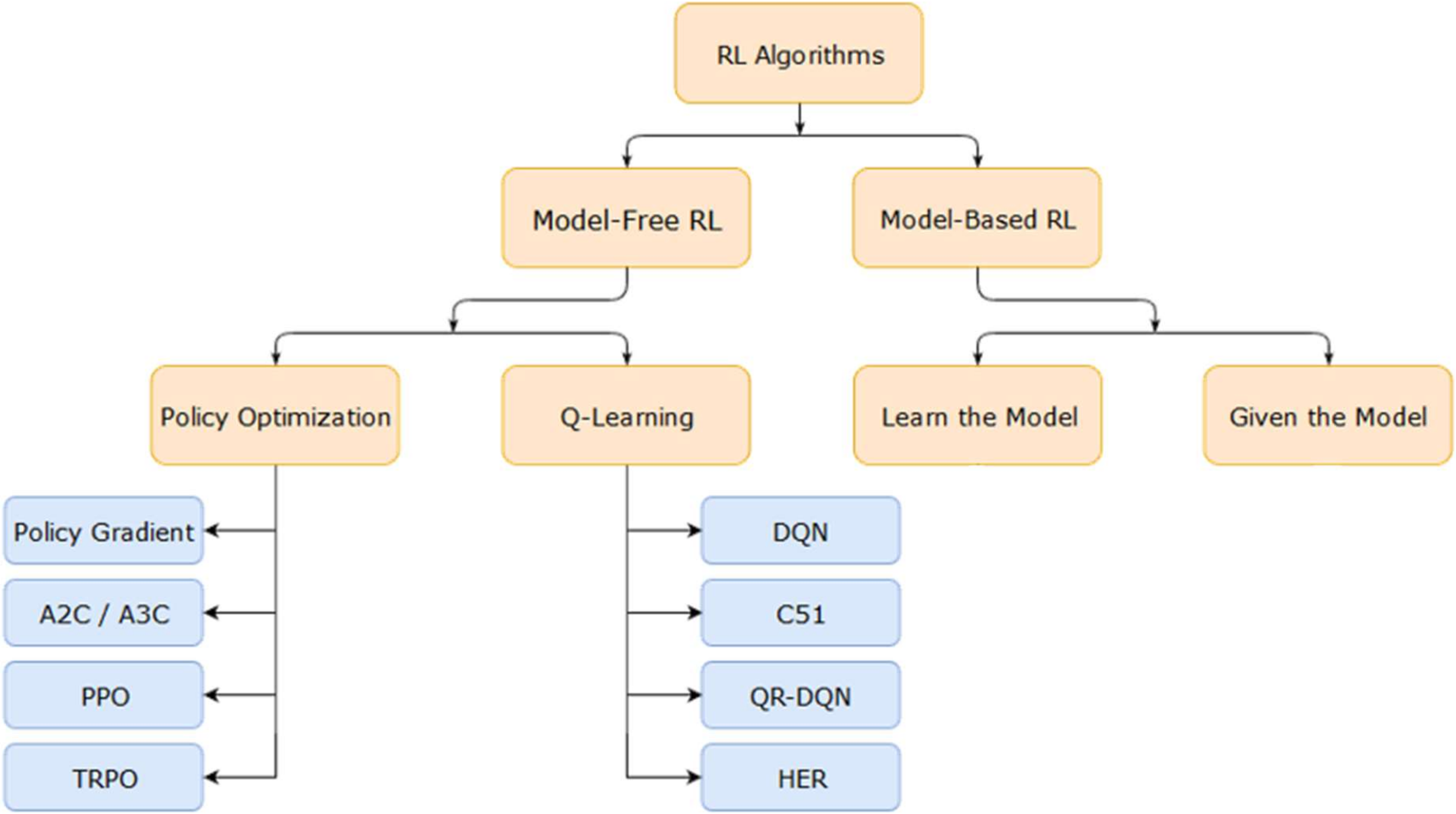
Skills Improvement:

- ✓ **Hot-start with imitation**
- ✓ **Continuous-valued decision making**
- ✓ **Low number of samples**
- ✓ **Adaptation**

Experiments: Table Tennis

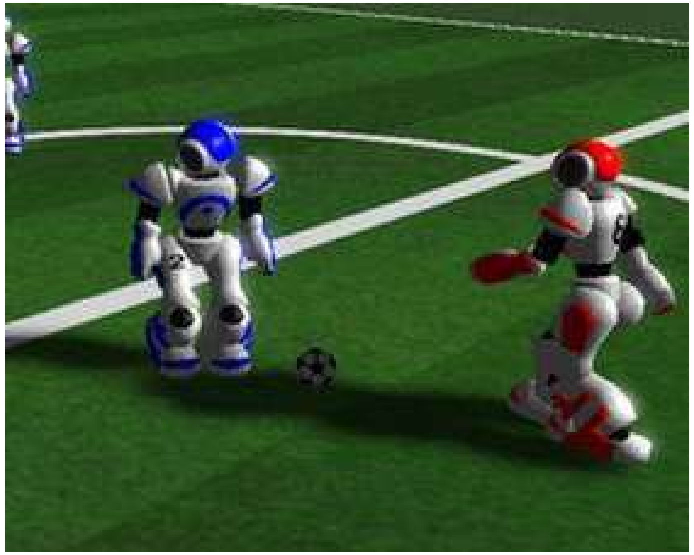


Reinforcement Learning

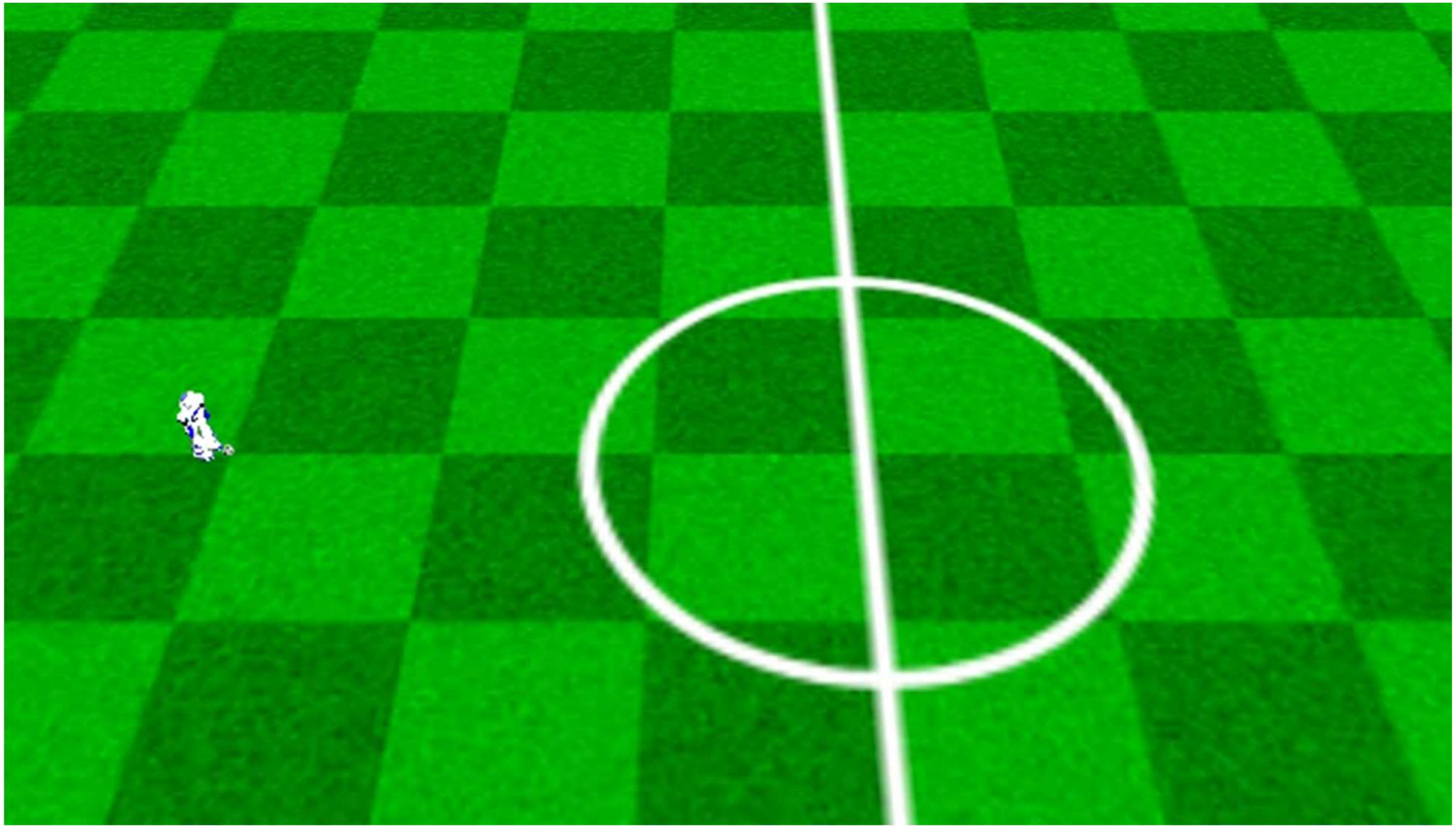


Skill Improvement: Controlled Kick

- **Task**
  - Develop a **kick with controlled kicking distance**
  - From 10 different positions in the soccer field (with distances ranging from 3m to 12m), kick the ball so that it stops in the center of the field
- **Classical approach**
  - Optimize for each distance
- **Contextual approach**
  - Optimize for all distances in a single process
  - Use all data to improve performance
  - Generalize for unknown contexts



Skill Improvement: 20 m Kick

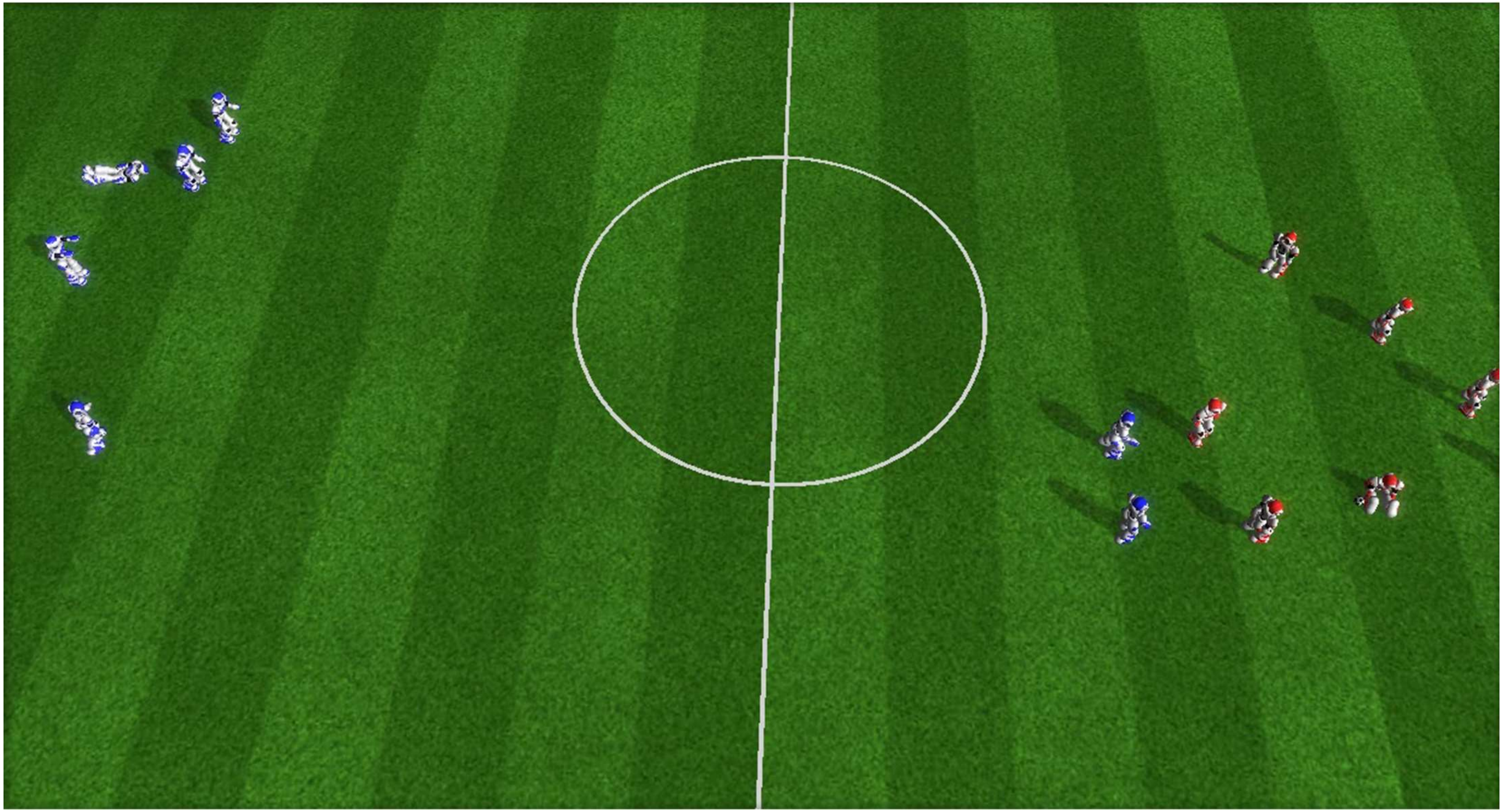


Skill Improvement: 20 m Kick

Skill Improvement: Controlled Kick

Abbas Abdolmaleki et al. Learning a Humanoid Kick With Controlled Distance. RoboCup 2016: Robot World Cup, Springer, July 2016

Results – Formation and Kick

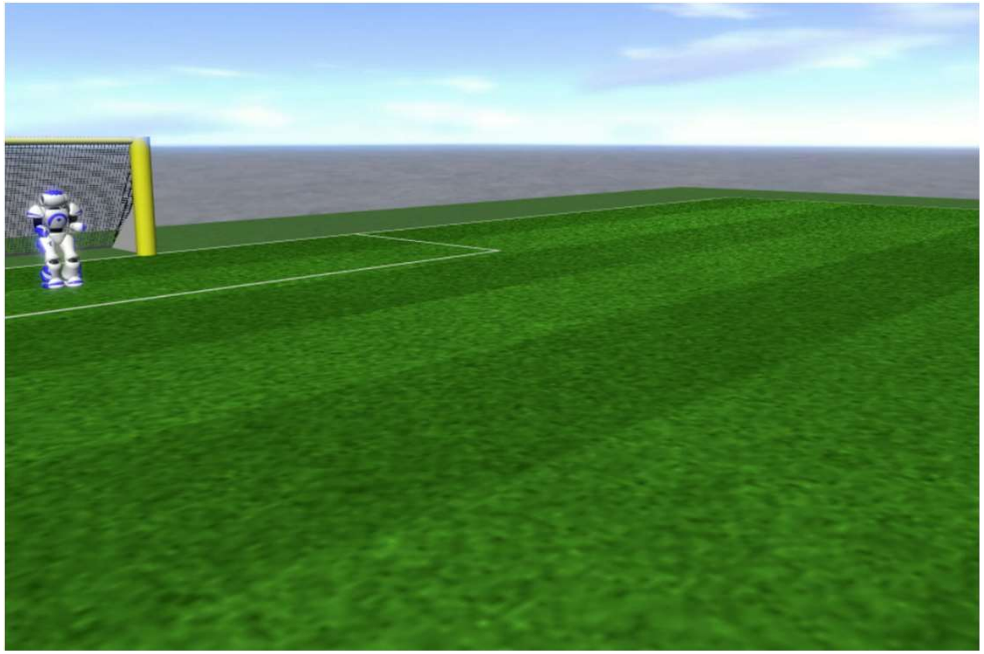


Results – Formation and Kick

Learning to Walk with PPO

Results

Top Sp.:1.5m/s v1 v2 Top Sp.:2.5m/s



Learning to Walk with PPO

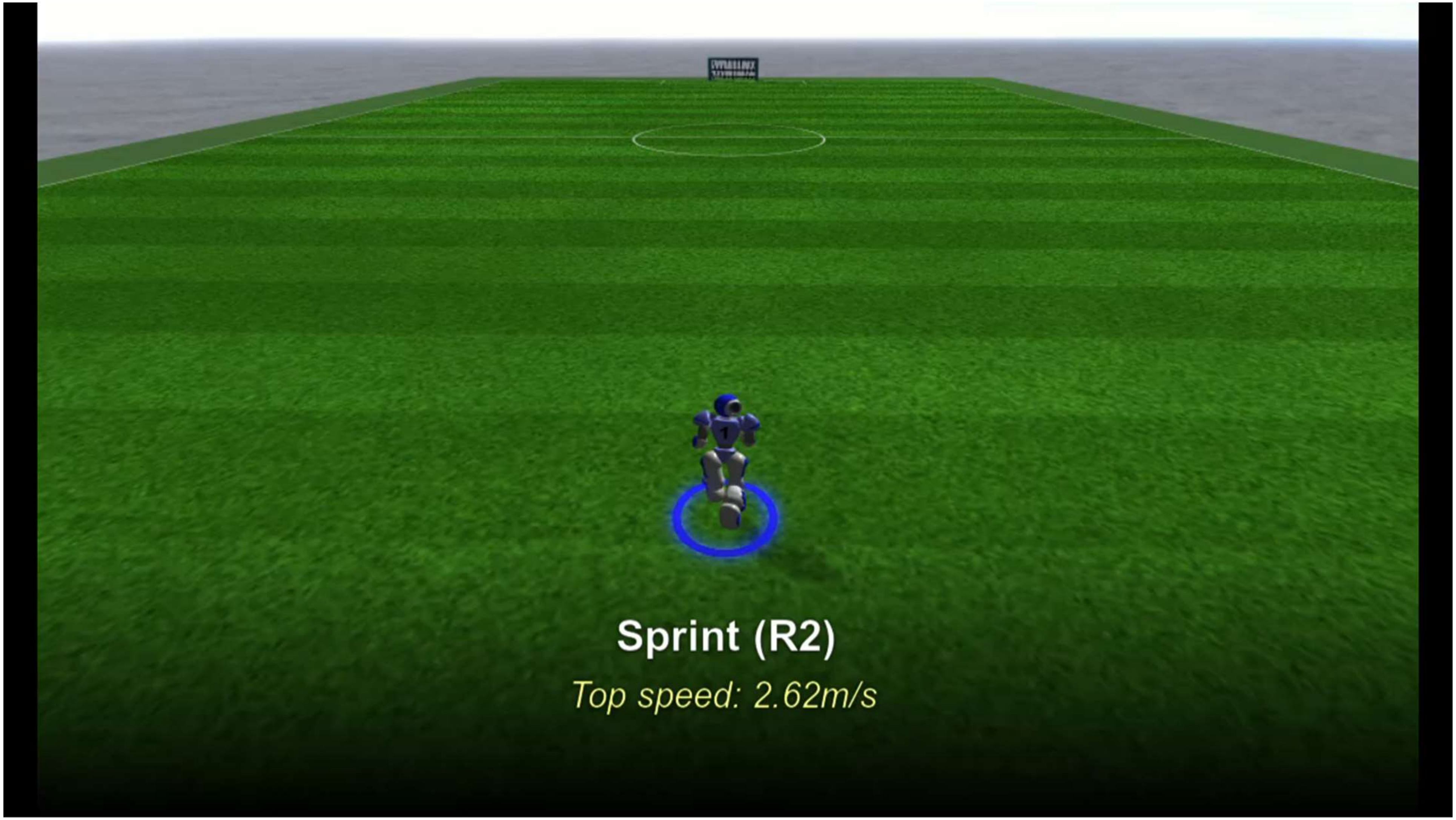
Results

v1

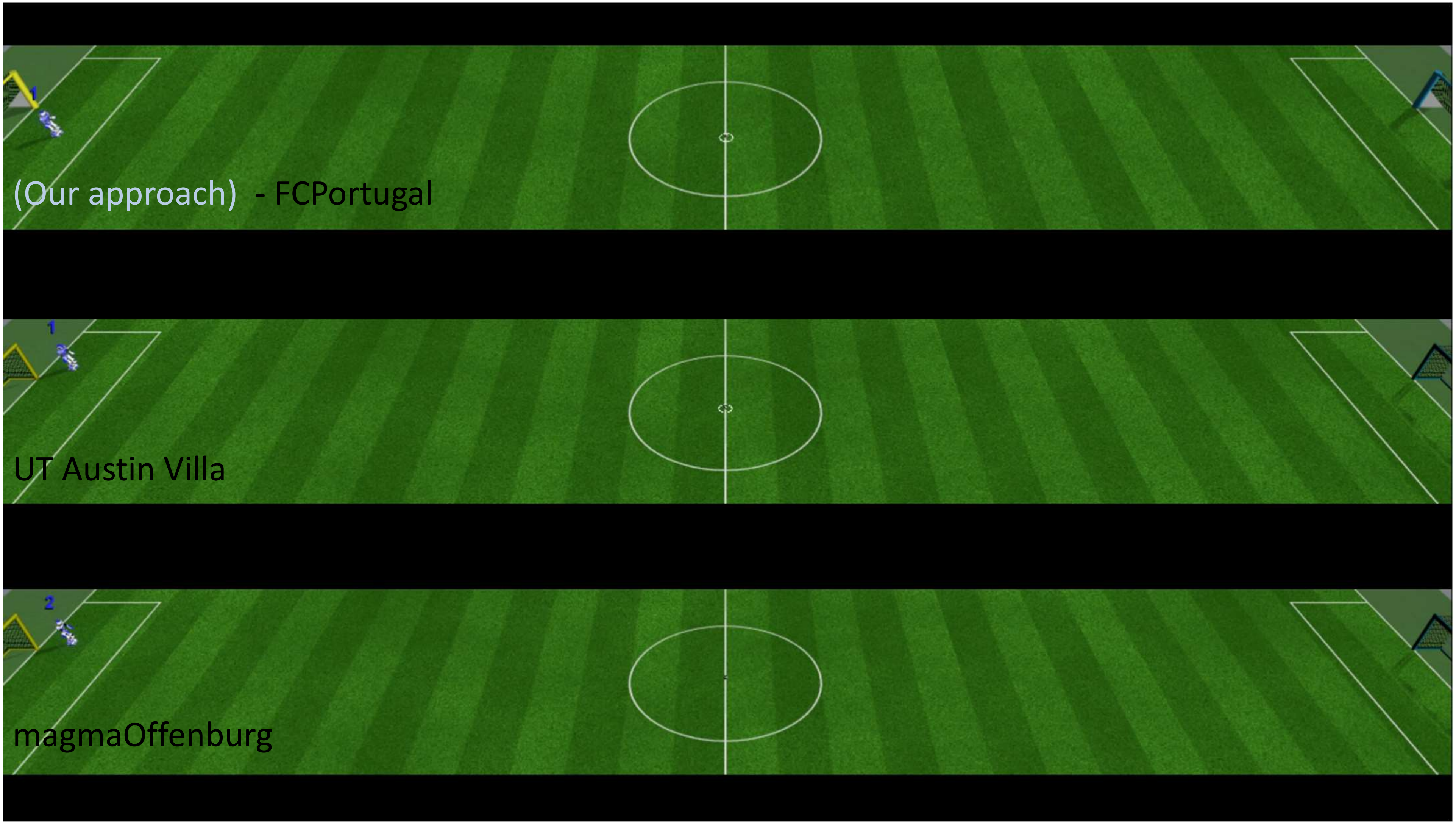
Turn & Run

Dribble

Learning to Walk with PPO2+



Learning to Walk with PPO2+

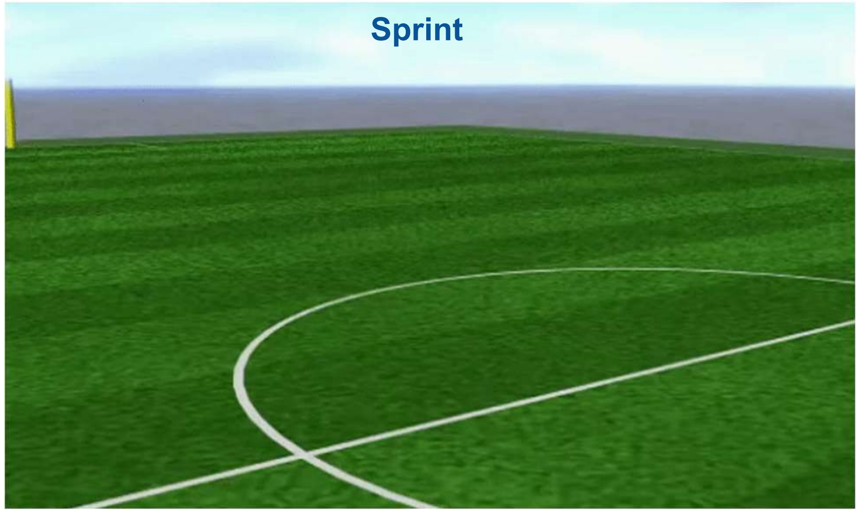


Learning to Walk with PPO

Learning with PPO

Kick in motion

Sprint



Sprint and kick

Conclusions

- **Coordination** of Teams in Adversarial Environments:
  - **Strategy, Formations (SBSP/DT), DPRE, Setplays**
- Complete **Tactical/Formation Framework and Setplay Framework** including graphical interfaces
- **Generic Coordination Framework/Library:**
  - May be used for coordinating any team:
    - World State -> High-Level Decision!
- Multi-Robot Coordination/Flexible and Adaptative Strategy
- Learning of Complex Robot/Multi-Robot Tasks
- Realistic Simulation and Bridging the Gap between Simulation and Robotics
- Methodologies with competition success
- **Different robots, distinct cooperative robotic** tasks and also to **other domains**: Rescue, surveillance, military apps

Simulators and Platforms: Robotic Soccer and FC Portugal

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