Development of an Augmented Environment and Autonomous Learning for Quadruped Robots

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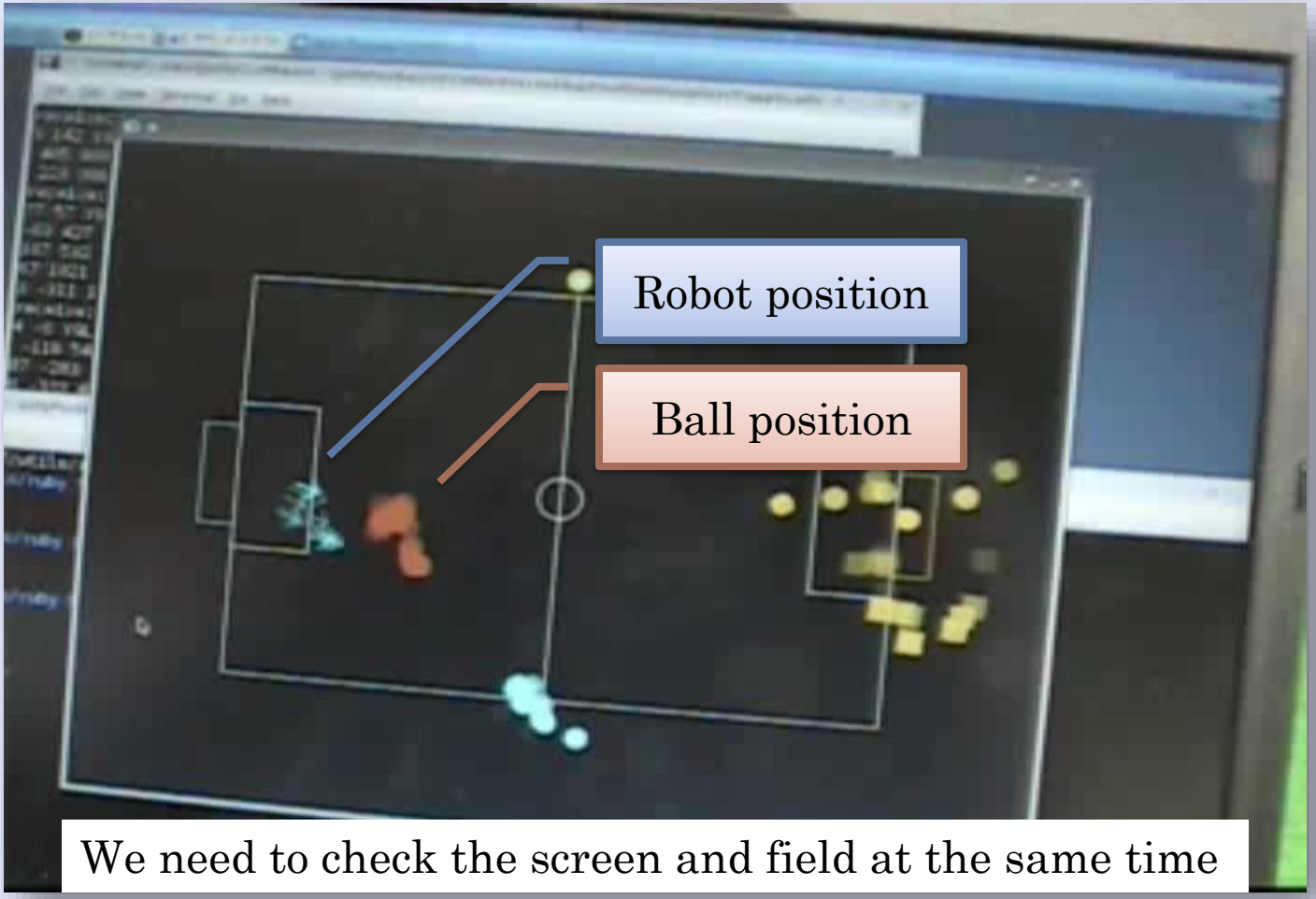
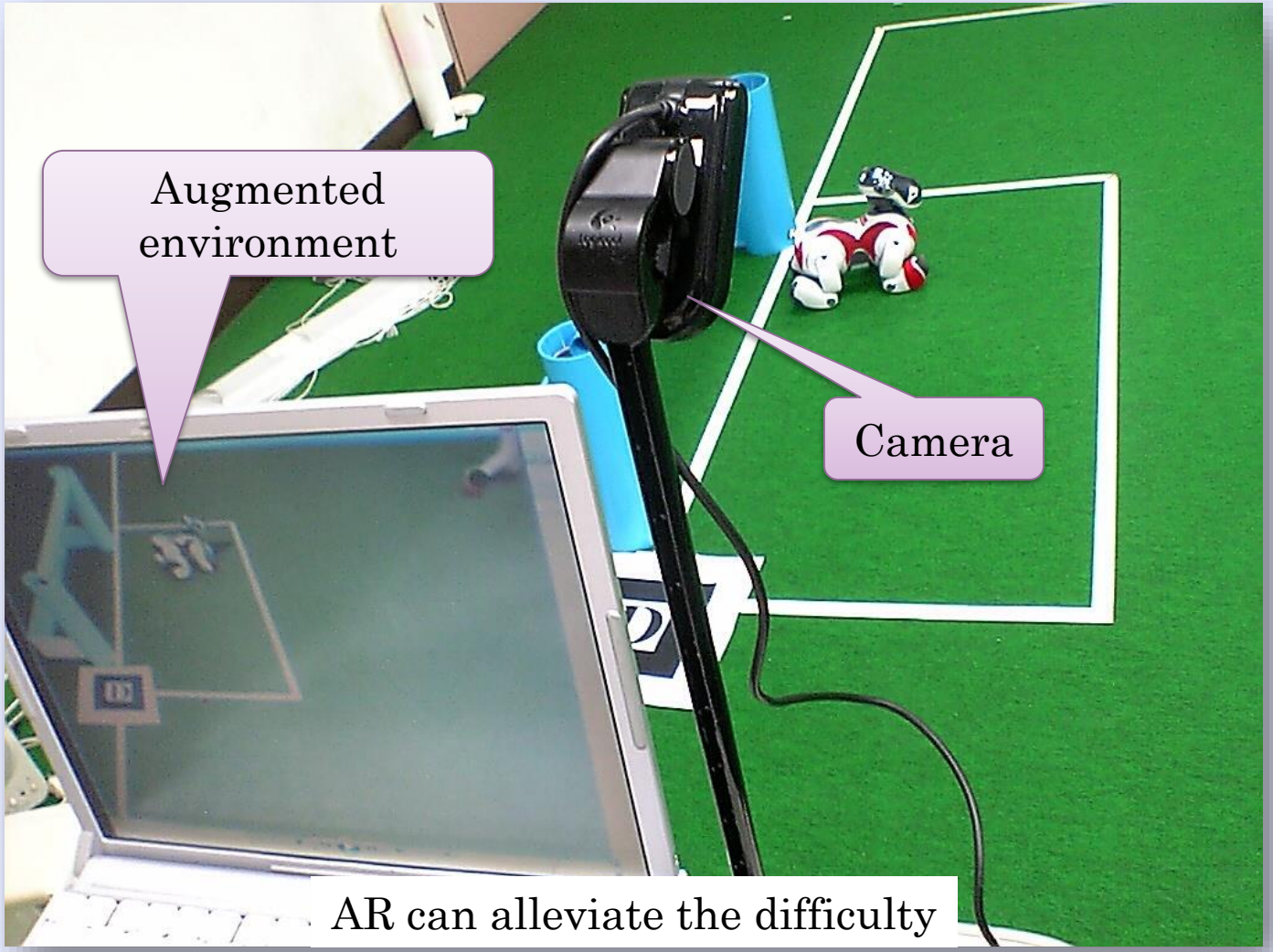
Difficulty of debugging using real robots



We need to check the screen and field at the same time

https://youtu.be/mB5MuDy9GFw

Augmented Reality



AR can alleviate the difficulty

https://youtu.be/yGzA6hC9YY8

Augmented soccer field system

Perceptible

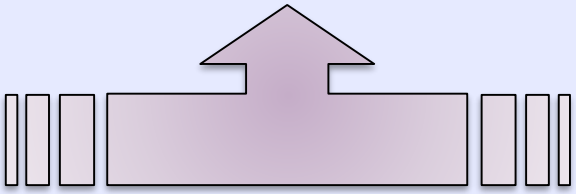
Virtual ball

Real robot

Virtual robot

Touchable

Augmented environment

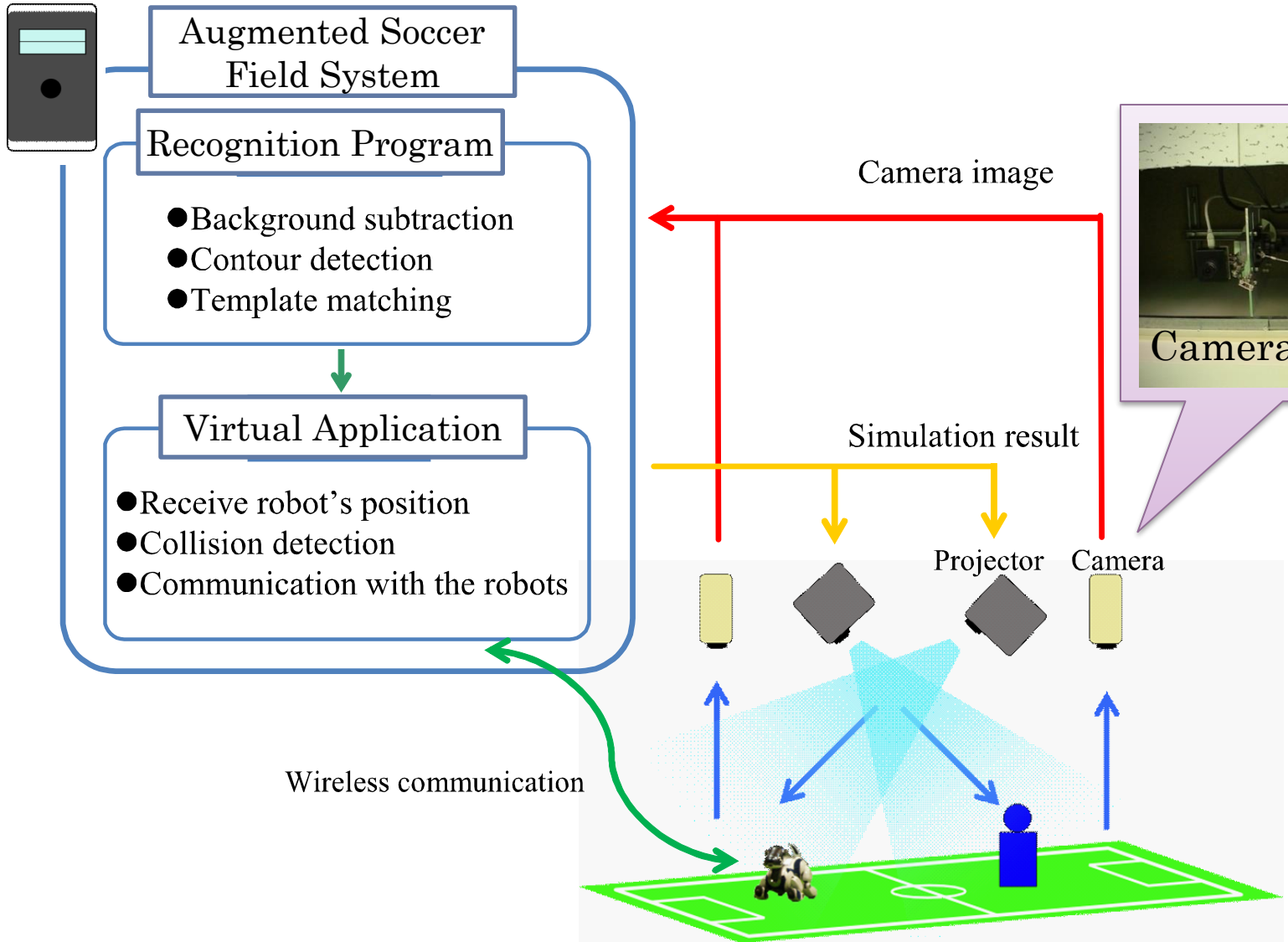


Intermediate role

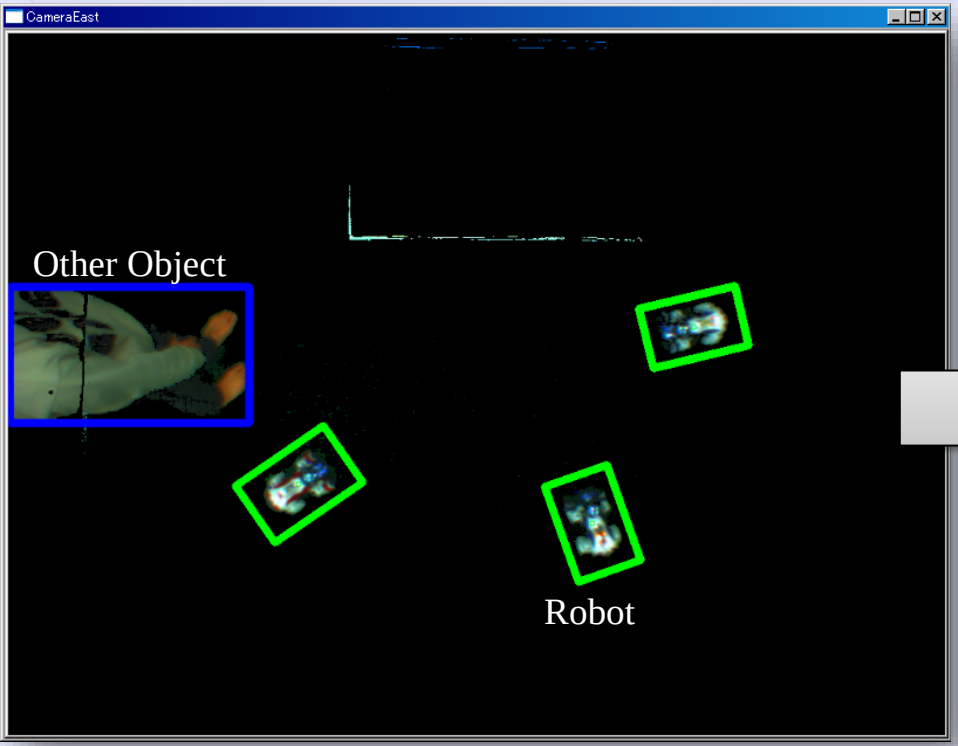
Simulated environment
in “Haribote” developed by team ARAIBO

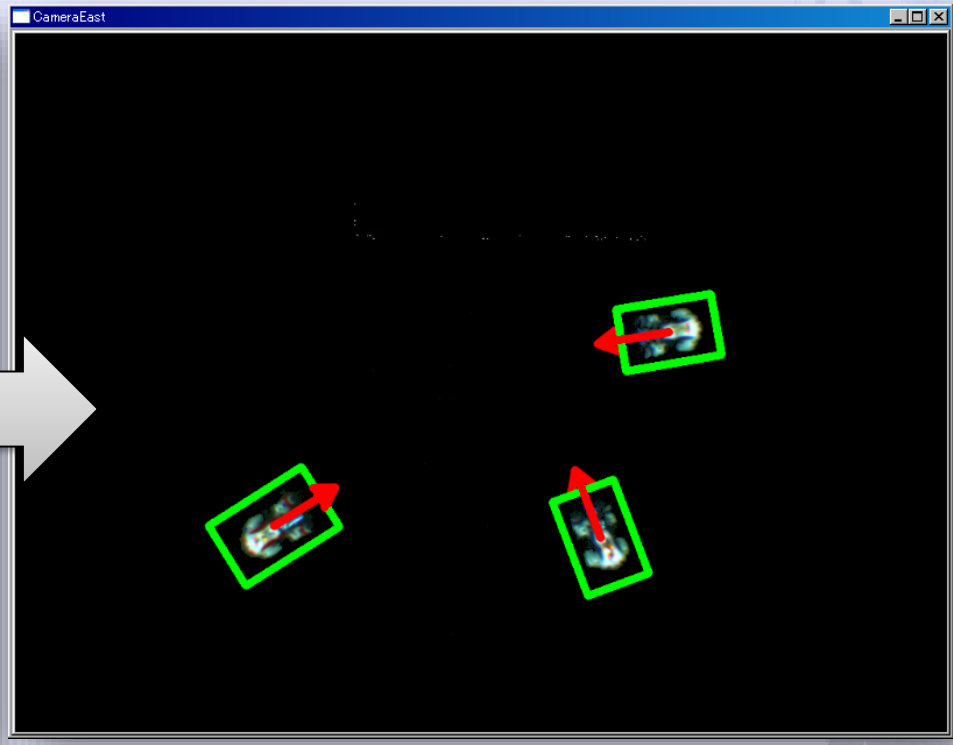
Real environment

Overview of our system



Recognition program



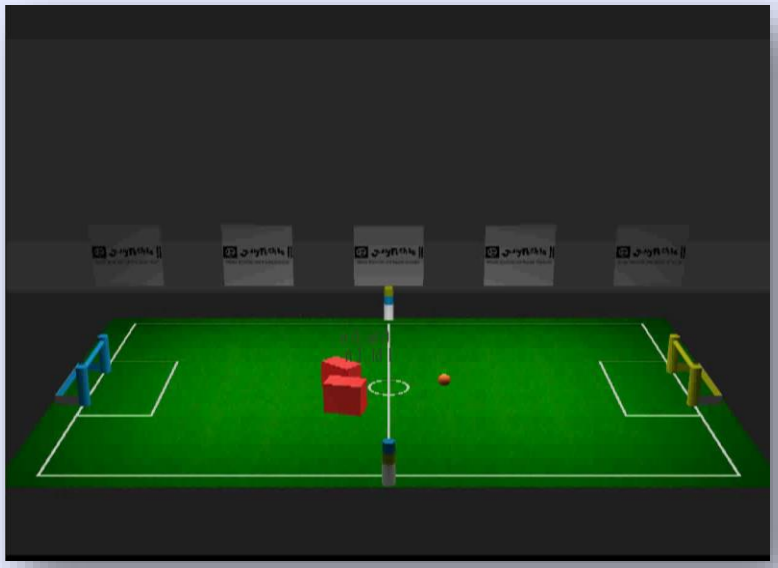


Extraction of contours
by a background subtraction method

Identification of robots' orientation
by a template matching method

Virtual application

Positions of virtual objects
e.g., virtual ball and robots



Virtual application

Real environment

Positions of real objects
e.g., real robots

Projection

Robots can interact the virtual ball

Learning of goalie strategies

- Essential for robot soccer
  - **No lost point, no lost game**

- Learning has been difficult so far

Difficulty of experiments in real environments

- Human intervention
- Time consuming
- Motor failure

Ex. Learning of goal saving skills in the real environment

Spank its head for failed saving

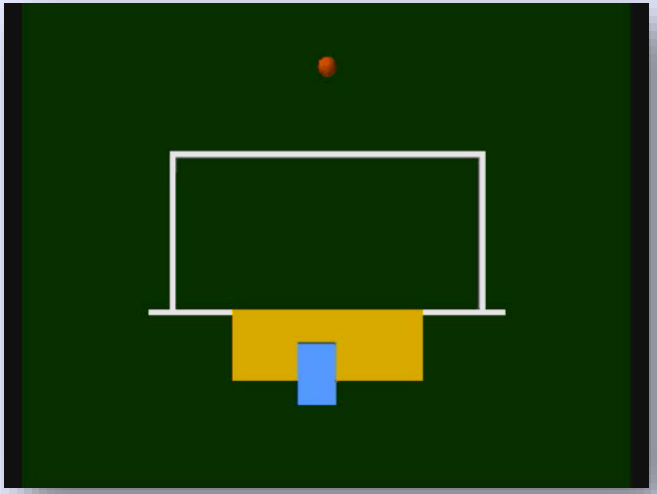
https://youtu.be/9oHA-GH9JT8

Stroke its head for successful saving

https://youtu.be/3Pluuk20xqs

Difficulty of experiments in simulated environments

- **Gap** from real environments
  - Serious, especially for **legged movements**



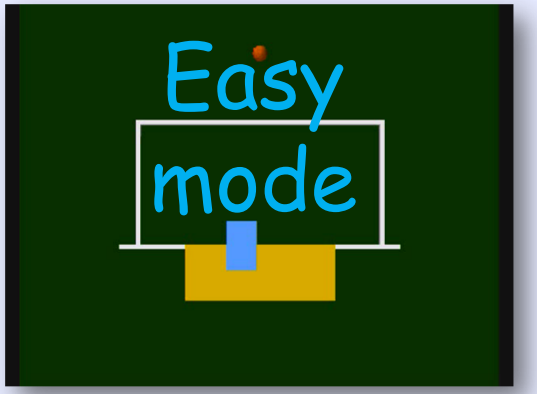
Simple simulator
without any difficulties

Gap

Real environment
with human intervention,
time consuming process,
and motor failure fear

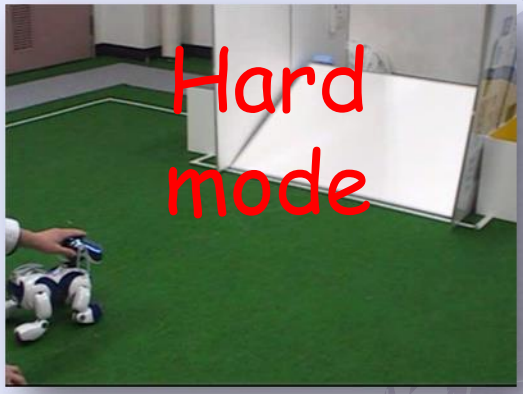
Our solution

- To bridge the gap
  - Using the **movements of real robots**
- To allow autonomous learning
  - Using the **convenience of virtual balls**



Simple simulator
without any difficulties

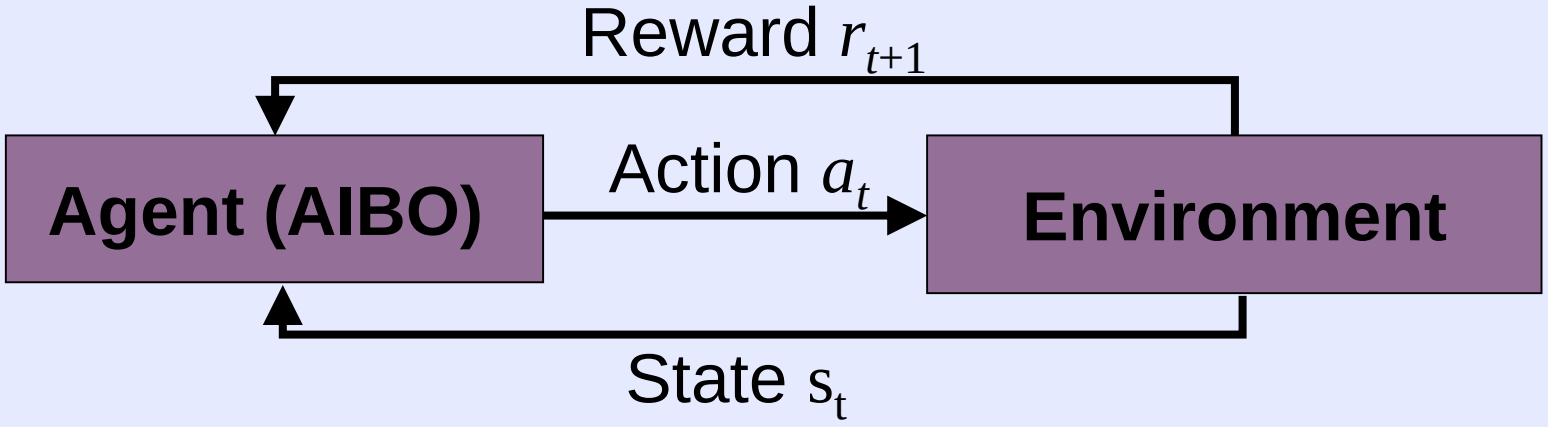
Augmented environment
without human intervention



Real environment
with many difficulties

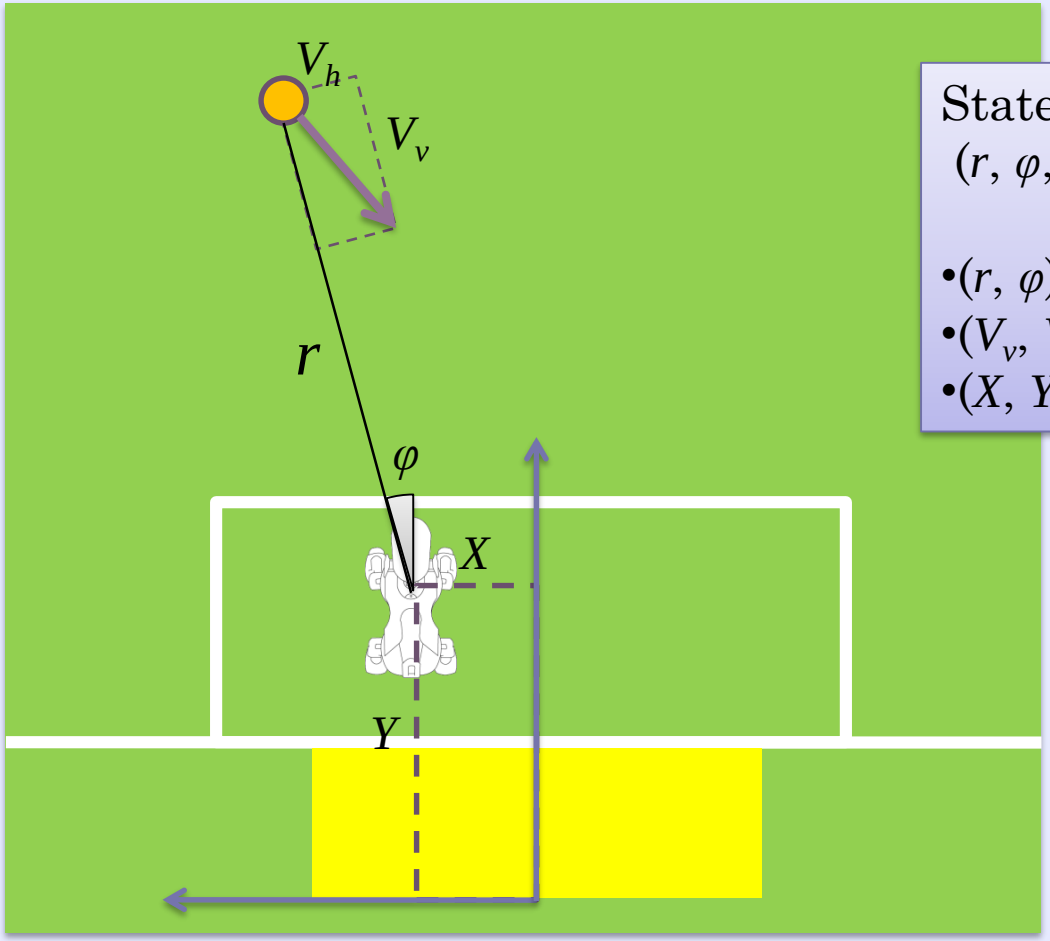
Reinforcement learning

- Acquire the map from **states** to **actions** maximizing the sum of **rewards**



- Sarsa(λ) [Rummery and Niranjan 1994; Sutton 1996]
  - Tile-coding (aka CMACs [Albus 1975])

State settings

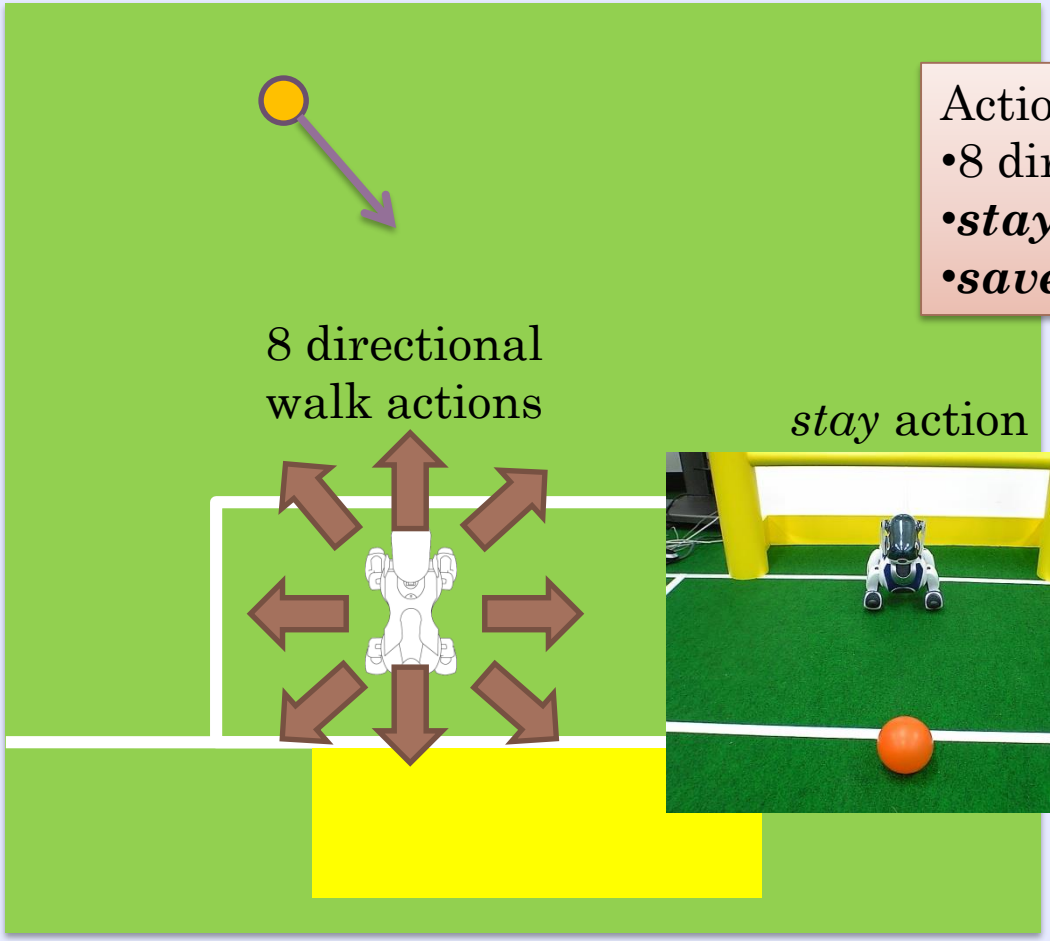


State representation
$(r, \varphi, V_v, V_h, X, Y)$

- (r, φ): Ball position
- (V_v, V_h): Ball velocity
- (X, Y): Robot position

(We removed the orientation of the robot by considering the PK situation only.)

Action settings



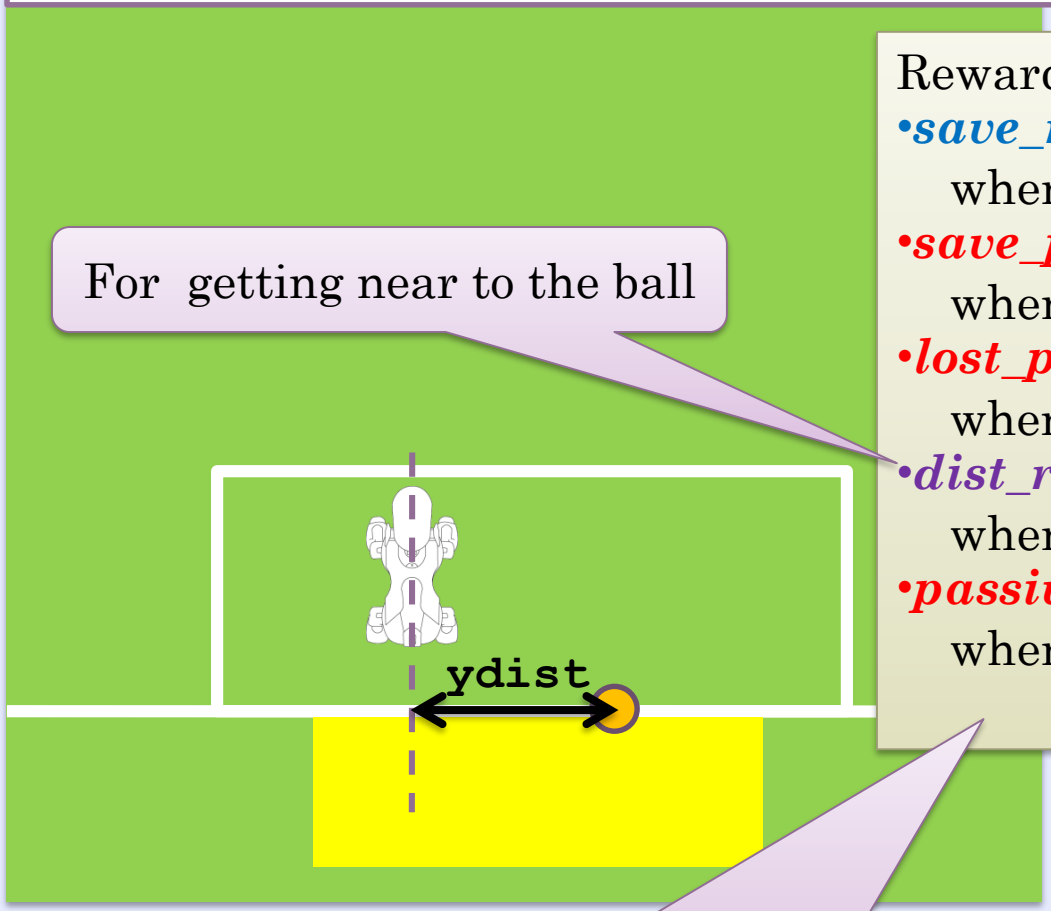
Actions (**10** kinds)
- 8 directional **walks**
- ***stay***; prepare enemy's kicks
- ***save***; interrupt enemy's goals

stay action

save action

Reward settings

Aim: To stop the ball using *save* action as safely as possible

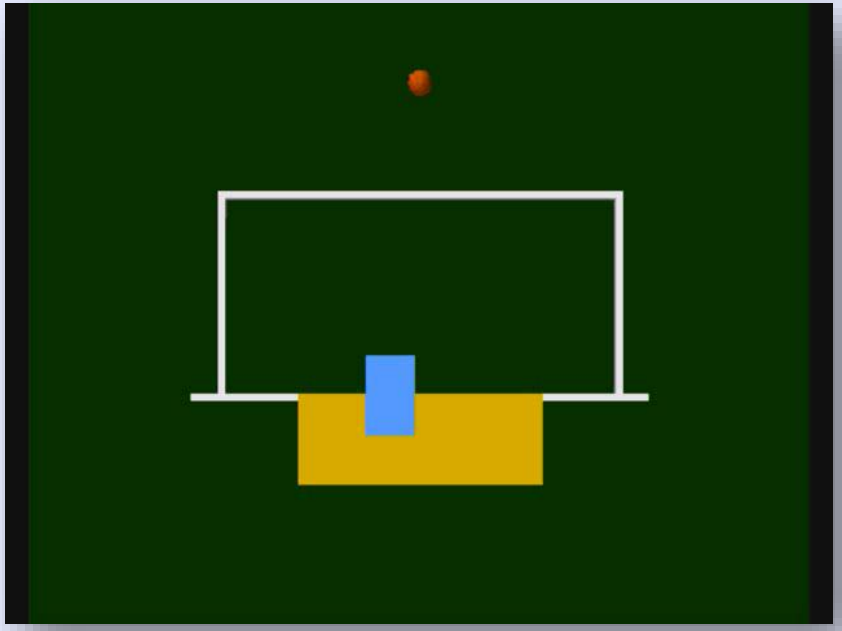


Rewards (punishments)

- ***save_rewared***: `0.5`
  when *save* is successful
- ***save_punishment***: `-0.02`
  when *save* is failed
- ***lost_punishment***: `-10`
  when a goal is scored
- ***dist_reward***: `1-|ydist|/112.5`
  when the game is over
- ***passive_punishment***: `-0.0000001`
  when *save* is not selected

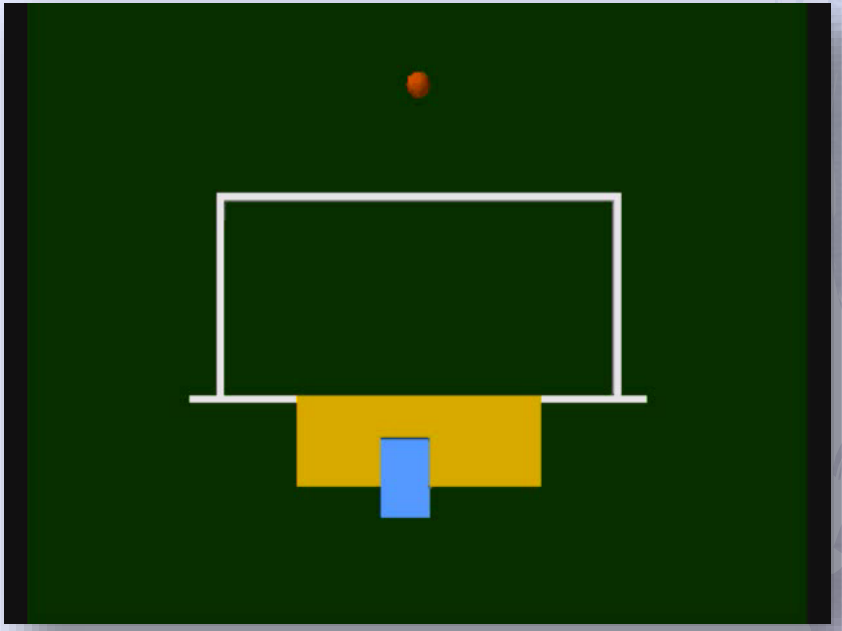
1 episode (game) is over,
when the ball is out,
when a goal is scored, or
when *save* is successful

Experiment in a simulated environment



Initial strategy

https://youtu.be/C2YTw6d7xPw

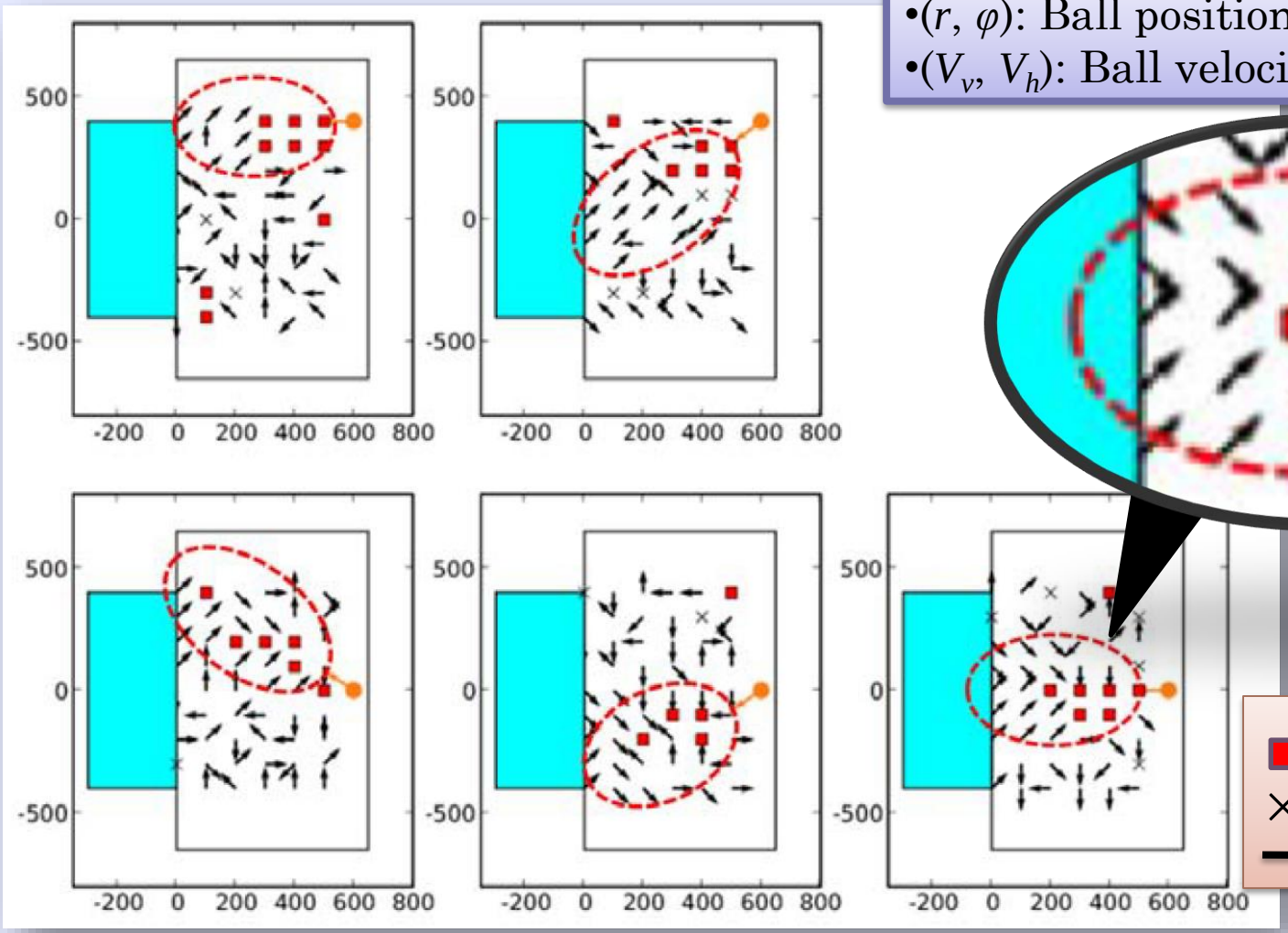


Learned strategy

https://youtu.be/xCoSGsQHkRY

Success: Blue screen
Failure: Red screen

Learned strategy in the simulated environment

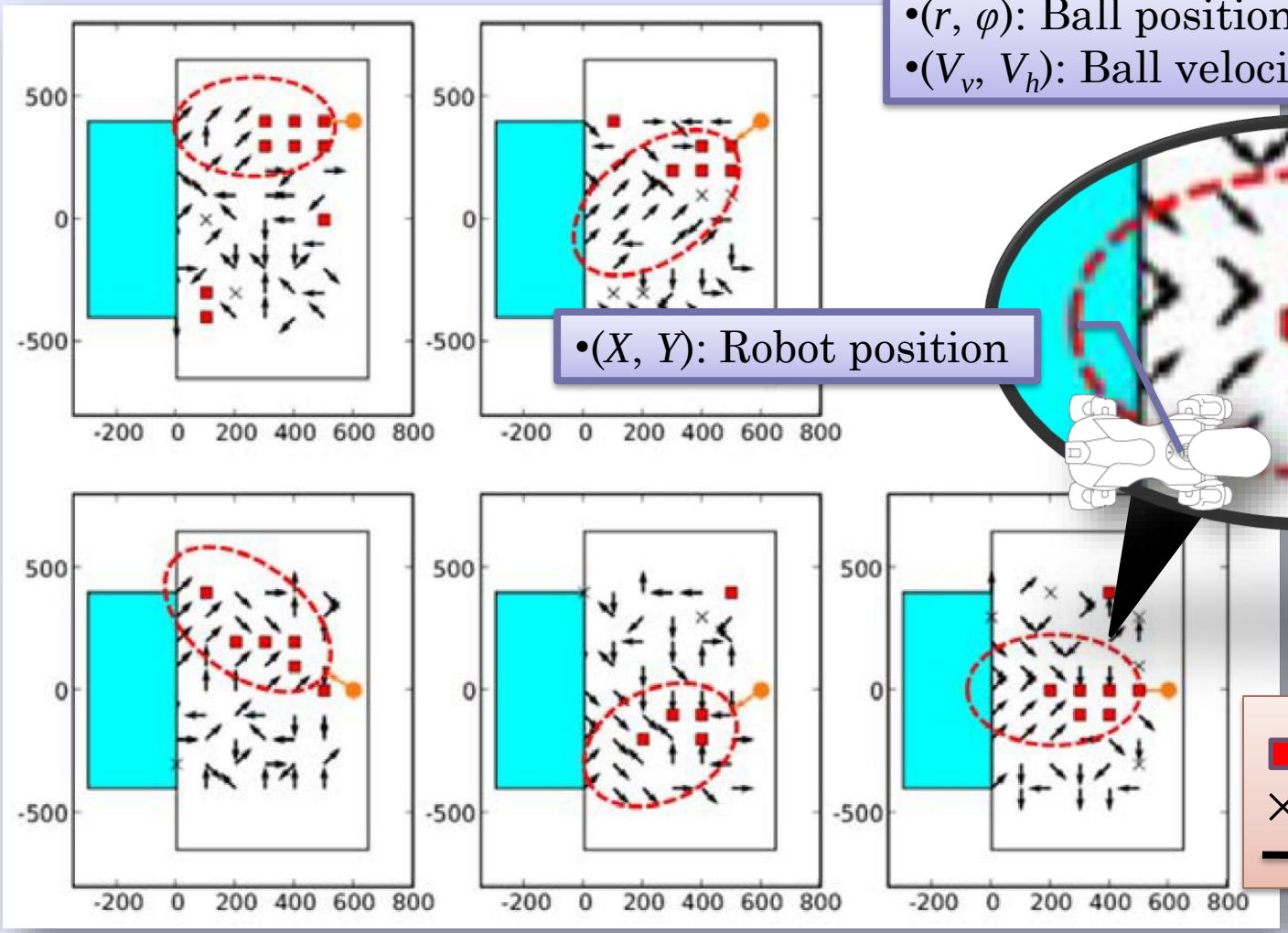


- (r, φ): Ball position
- (V_v, V_h): Ball velocity

Robot's actions

- *save* action
- × *stay* action
- → 8 walk actions

Learned strategy in the simulated environment



•(r, φ): Ball position
•(V_v, V_h): Ball velocity

•(X, Y): Robot position

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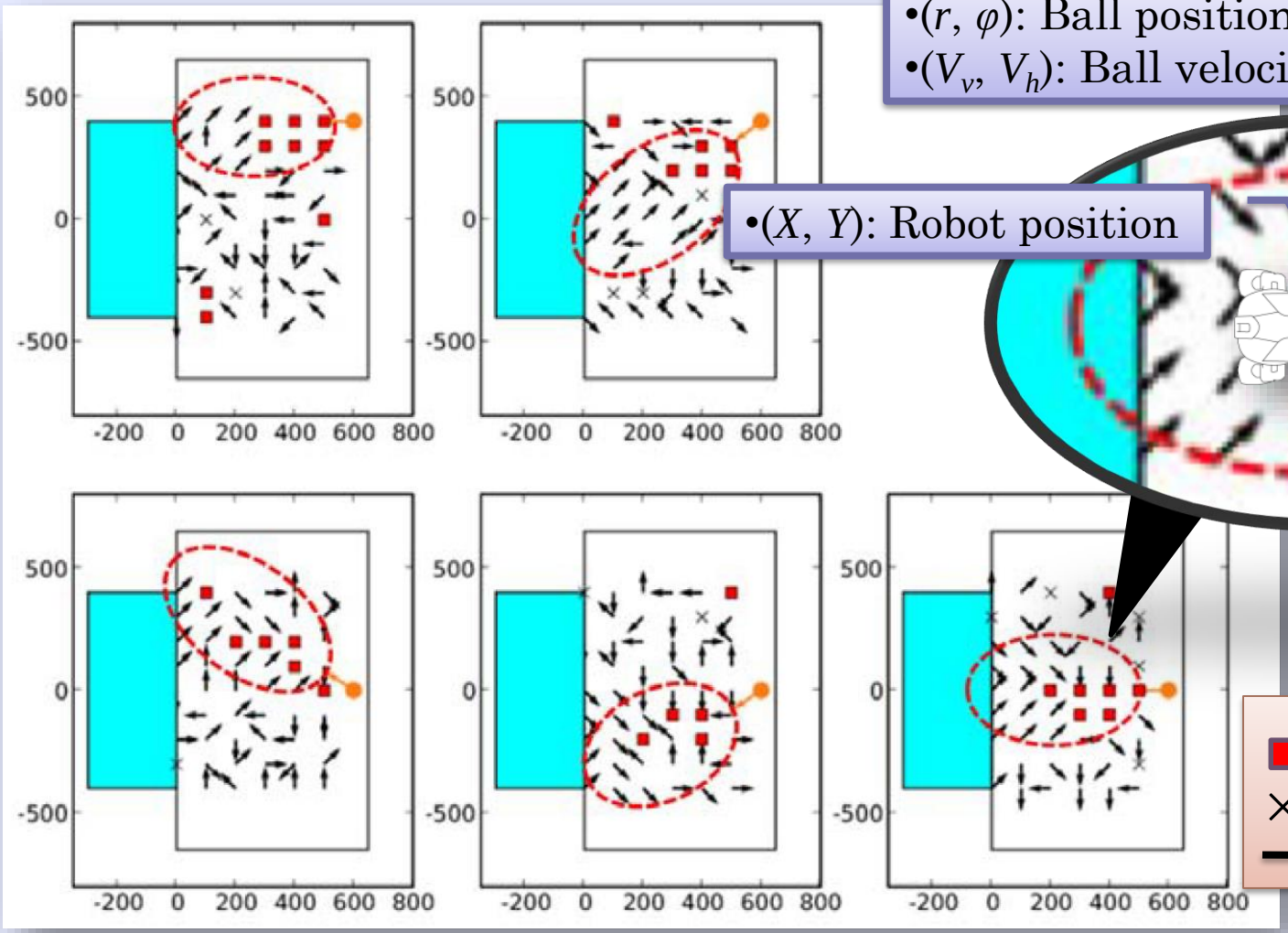
Learned strategy in the simulated environment



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•(V_v, V_h): Ball velocity

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Robot's actions
- *save* action
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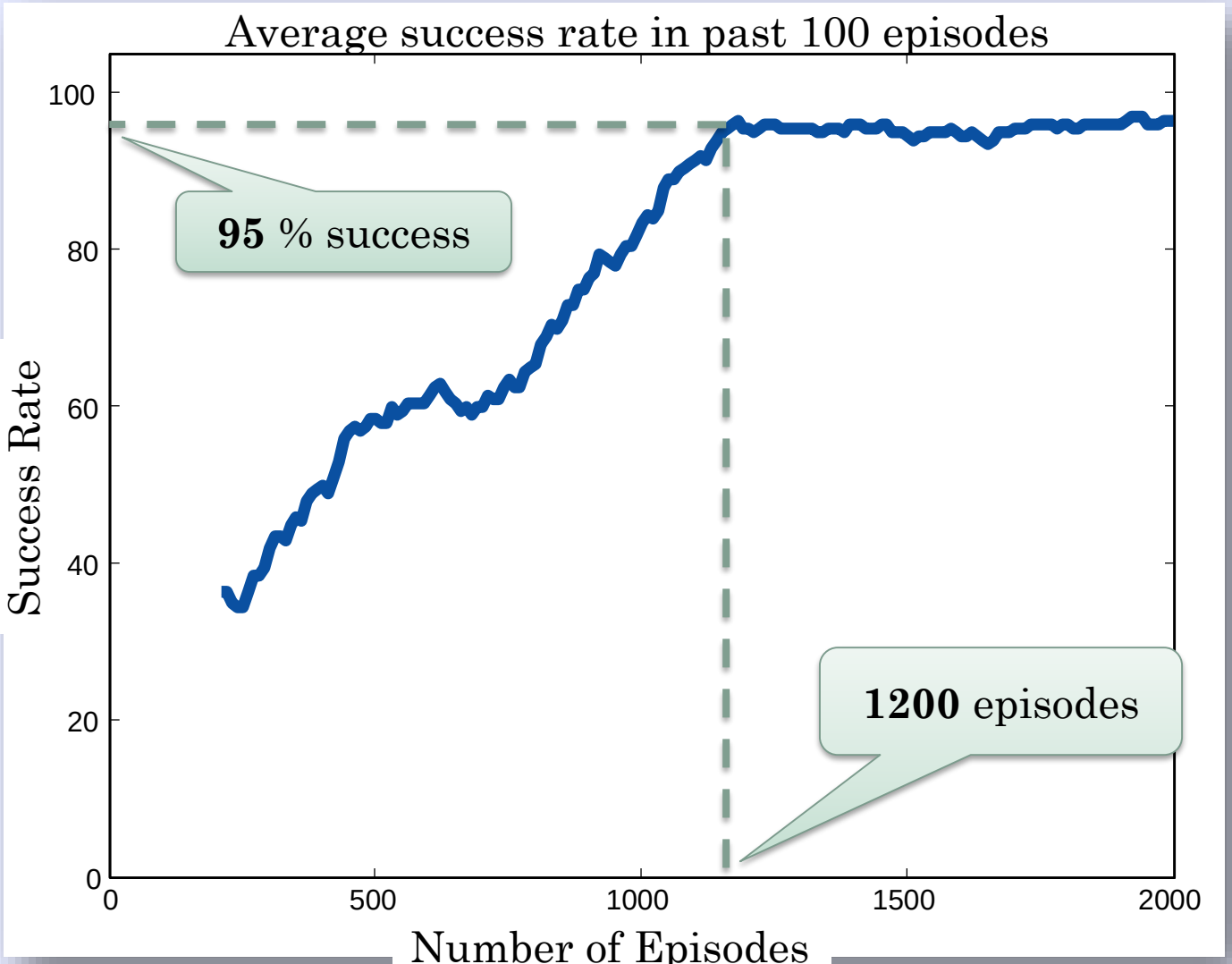
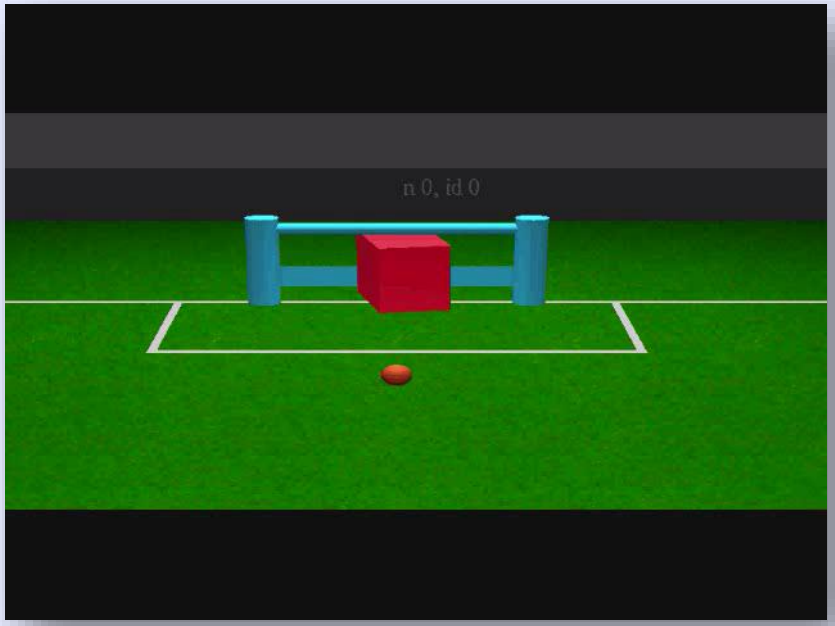
Learning result in the simulated environment



Experiment in the augmented environment

The true positions of the virtual ball and robot



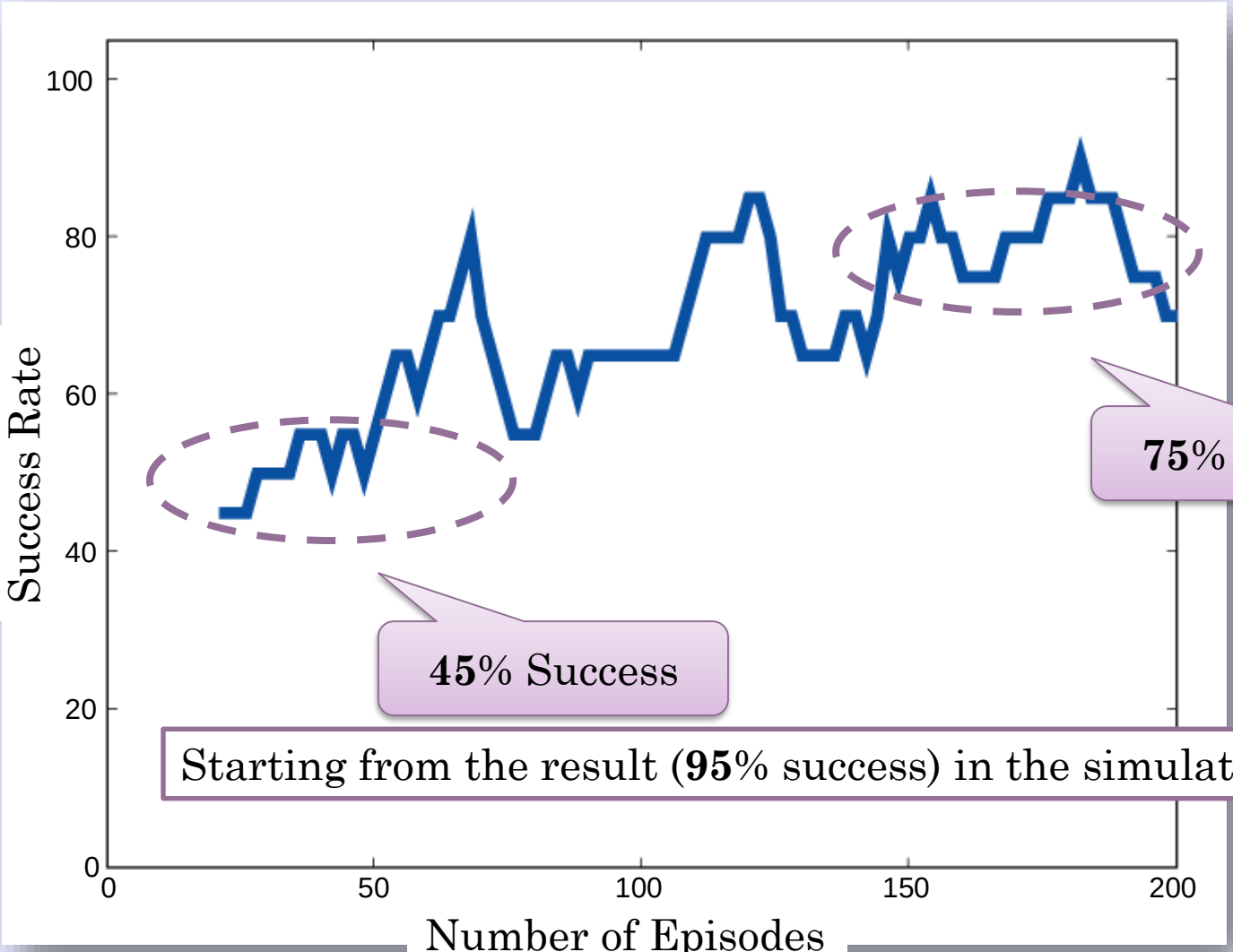
The action of the real robot

https://youtu.be/HVx6TlHkPgw

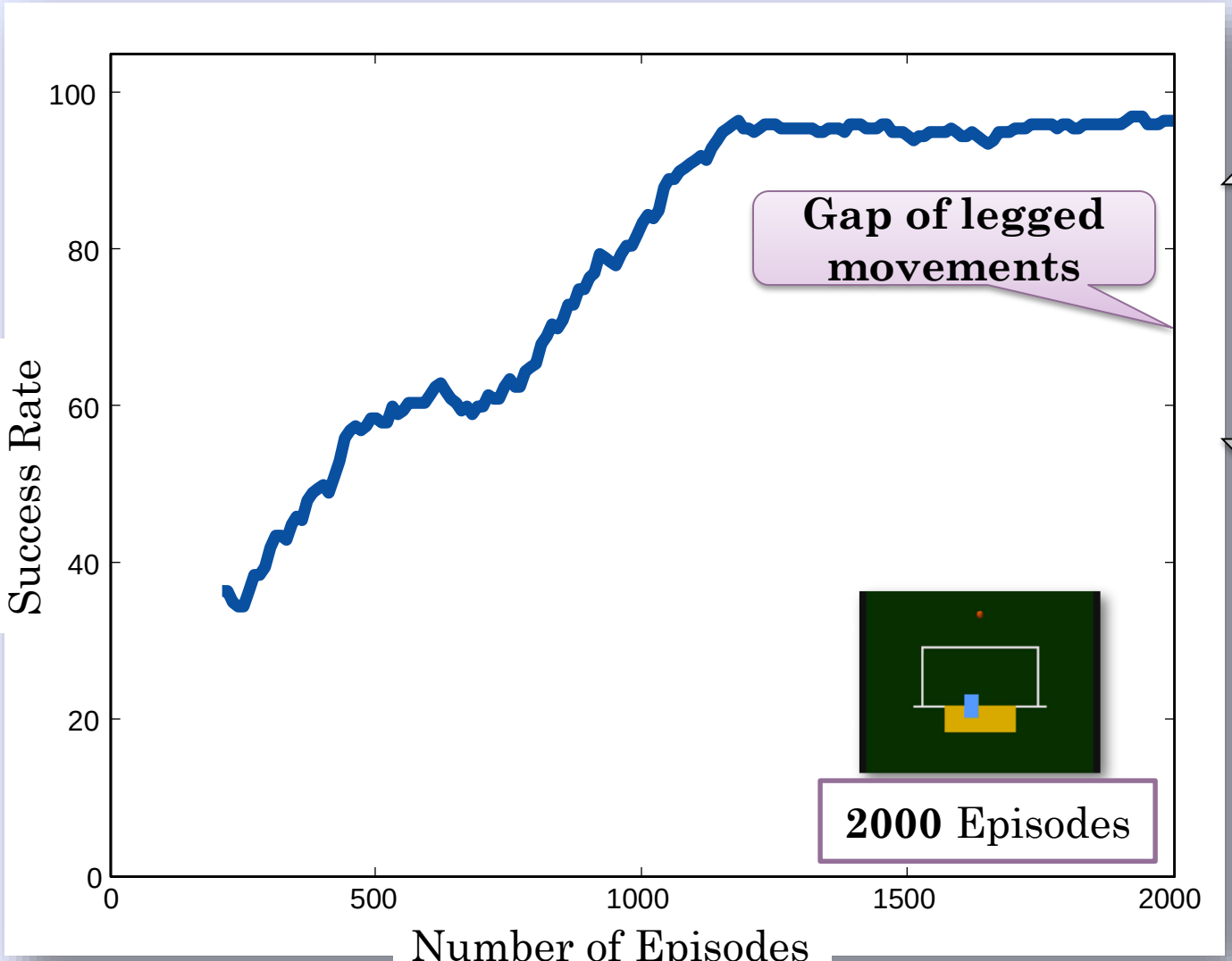
Experiment in the augmented environment

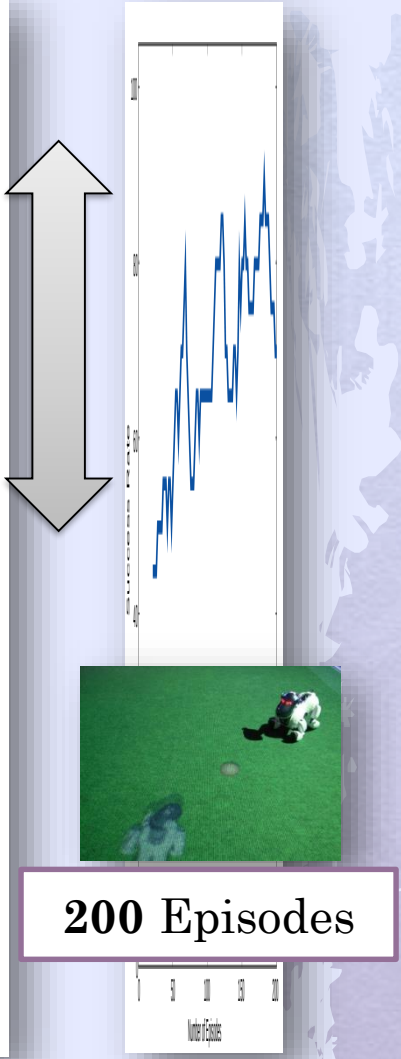
https://youtu.be/F3-3o2oCP14

Learning result in the augmented environment



Comparison with the simulator





Conclusions

- Augmented soccer field system
  - Intermediate role between simulated environments and real environments
- Autonomous learning of goalie strategies
  - Movements of real robots
  - Convenience of virtual balls

Thank you for your attention

Air hockey game using our system