

# Interactive Reinforcement Learning for Table Balancing Robot



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Negative

feedback

non-target

action

Robot's

action

non-target

for

#### Introduction

- The need for anyone to easily train robots.
- Applying reinforcement learning(RL) to robot training.
- Giving verbal instruction is one of the important methods that humans have for teaching a task.
- Reward Shaping(RS): in RL, external trainer gives intermediate rewards to a learning agent to guide its learning proces
   Not exactly.
- Idea: allow the robot to learn a cooperative table balancing task from its interaction with human trainer through voice feedback.
  - by applying RS to RL.

#### Approach **State image** Converted feedback DQN String of value words Sentiment **ASR** Analysis **Voice "0.5752** signal Robot Good job action Next robot action

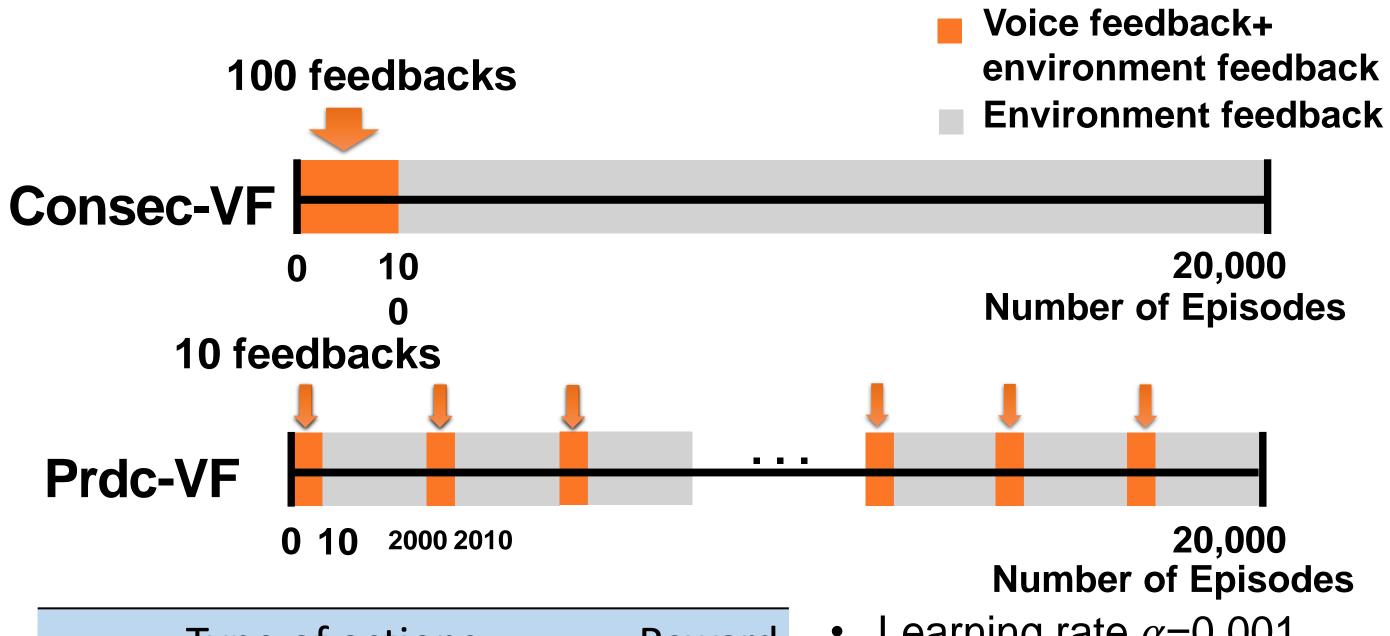
- 5 states and 5 actions are defined by the direction and degree of table movement and robot joint angle drive.
- State image taken by robot camera.
- After executing an action, the robot receives evaluative feedback from human on the action.
- The voice feedback is input via the robot's microphone, transcribed into character string by automatic speech recognition module.
- Then the transcribed feedback is converted to numeric value via sentiment analysis module.
- Converted feedback value is incorporated into the environmental rewards of the DQN algorithm.

"Well done" → 0.8

"That is not how you do it" → -0.699

"Try again" → -0.5

## **Experimental Settings**



| Type of actions            | Reward |
|----------------------------|--------|
| Reaching the target state  | +0.5   |
| Returning undefined action | -0.5   |
| Reaching non-target states | -0.3   |

- Learning rate  $\alpha$ =0.001
- Discount factor  $\gamma$ =0.9
- Epsilon  $\epsilon$ =20

Unbalanced

table

- Number of episodes: 20,000
- Number of voice feedbacks: 100 (50 positive and 50 negative)
- Training was mainly done in simulation, but also done on a physical robot as a proof of concept.

### Results

Table of 3 tested model's optimal policy convergence rate

| Optimizer     | Only environment reward (baseline) | Consec-VF | Prdc-VF |
|---------------|------------------------------------|-----------|---------|
| SGD           | 80%                                | 86%       | 80%     |
| Adam          | 73%                                | 96%       | 60%     |
| 2.00 Q-networ | k Q-network 1.75 -                 | 2.00 Q-   | network |

Loss graph of 3 tested models

| Optimizer | Baseline | Consec-VF |
|-----------|----------|-----------|
| SGD       | 80%      | 86%       |
| Adam      | 73%      | 96%       |
| Adagrad   | 43%      | 56%       |
| Adadelta  | 63%      | 76%       |



http://air.knu.ac.kr/index.php/evolutionary-cooperative-robot-development-using-distributed-deep-reinforcement-learning

- Consec-VF model learned optimal policies better than baseline and Prdc-VF model.
  - In all experiments Consec-VF showed improved optimal policy learning compared to the baseline DQN.