ABSTRACT

Hindsight Experience Replay (HER) is a multi-goal reinforcement learning algorithm for sparse reward functions. The algorithm treats every failure as a success for an alternative (virtual) goal that has been achieved in the episode. Virtual goals are randomly selected, irrespective of which are most instructive for the agent. In this paper, we present two improvements over the existing HER algorithm. First, we prioritize virtual goals from which the agent will learn more valuable information. We call this property the instructiveness of the virtual goal and define it by a heuristic measure, which expresses how well the agent will be able to generalize from that virtual goal to actual goals. Secondly, we reduce existing bias in HER by the removal of misleading samples. To test our algorithms, we built two challenging environments with sparse reward functions. Our empirical results in both environments show vast improvement in the final success rate and sample efficiency when compared to the original HER algorithm.

Keywords Sparse Reward Function · Hindsight Experience Replay · Virtual Goal

1 Introduction

Deep reinforcement learning, the combination of reinforcement learning [1] with deep learning [2] has led to many breakthroughs in recent years in generating goal-directed behavior in artificial agents ranging from playing Atari games without prior knowledge and human guidance [3], to teaching an animated humanoid agent to walk [4] [5] [6], and defeating the best GO player in the world [7], just to name a few. All reinforcement learning problems are based on the reward hypothesis, stating that any goal-directed task can be formulated in terms of a reward function. However, the engineering of such a reward function is often challenging. The difficulties in shaping suitable reward functions limit the application of reinforcement learning to real-world tasks, for example, in robotics [8]. One way to overcome the problem of reward shaping has been presented in Hindsight Experience Replay (HER) [9], which uses sparse reward signals to indicate whether a task has been completed or not. The algorithm uses failures to learn how to achieve alternative goals that have been achieved in the episode and uses the latter to generalize to actual goals. HER selects these virtual goals randomly in every episode.

In this paper, we provide two improvements over the original HER algorithm for the selection of virtual goals. First, we argue that the learning process will be more efficient if the algorithm will take into account that some virtual goals may be more instructive than others and will prioritize them accordingly. Towards this objective, we present a heuristic measure, which quantifies the instructiveness of each possible virtual goal. We call this method an Instructional-Based Strategy. Our strategy for selecting virtual goals will be applicable to environments for which the initial state distribution is not within the goal distribution. These conditions are given, for example, in robotic manipulators, where objects need to be moved between two different locations in a workspace. Our second contribution consists of the removal of misleading virtual goals. HER assumes that the achieved goals are the outcome of actions. However, this is not always
the case. Consider, for example, a soccer player that misses the ball in a penalty kick. Here, the ball is not affected by the action, and thus, the achieved goal is the outcome of the initial state rather than the action. These samples will induce bias and may hinder learning. A filtering process is applied to remove these misleading samples.

2 Background

2.1 Reinforcement Learning

Reinforcement learning consists of an agent learning how to solve a task via interaction with an environment \[^{[1]}\]. We assume that the environment is fully observable and defined by a set of states \(s \in \mathcal{S}\), set of actions \(a \in \mathcal{A}(s)\), initial state distribution \(P(s_0)\), reward function \(r : \mathcal{S} \times \mathcal{A} \to \mathbb{R}\) and a discount factor \(\gamma \in [0, 1]\). These components define a Markov Decision Process (MDP). The decisions of the agent are described by a policy \(\pi\) that maps states \(s\) to actions \(a\).

At the beginning of each episode, an initial state \(s_0\) is sampled from the distribution \(p(s_0)\). At every timestep, the agent chooses an action \(a_t\) using policy \(\pi(s_t)\), performs this action and receives a reward and the next state. The episode is terminated when the agent reaches a terminal state or exceeds the maximum number of timesteps. The agent’s goal is to find the policy that maximizes expected return, i.e., cumulative future discounted reward \(R_t = \sum_{i=t}^{\infty} \gamma^{i-t} r_i\).

2.2 Deep Deterministic Policy Gradient (DDPG)

RL algorithms can be implemented using temporal-difference learning, policy gradient or a combination of both in actor-critic methods. One of the most prominent actor-critic algorithms for continuous state- and action spaces is Deep Deterministic Policy Gradient (DDPG) \[^{[5]}\]. The DDPG architecture consists of two neural networks: an actor, which takes the state \(s_t\) as input and outputs the chosen action \(a_t\), and a critic, which approximates the Q-function, \(Q(s_t, a_t)\), for the chosen action. The critic network is trained using temporal-difference with the actions produced by the actor: \(\mathcal{L}_c = \frac{1}{N} \sum (y_i - Q(s_i, \pi(s_i)))^2\), where the target is \(y_i = r_i + \gamma Q'(s_{i+1}, \pi'(s_{i+1}))\) and \(Q', \pi'\) are provided by the target networks. The actor is trained using gradient descent on the loss \(\mathcal{L}_a = -\mathbb{E}_{s} Q(s, \pi(s))\).

2.3 Hindsight Experience Replay (HER)

DDPG can be extended to multi-goal tasks using Universal Value Function Approximators (UVFA) \[^{[10]}\]. The key idea behind UVFA is to augment action-value functions and policies by goal states, and thus, every transition contains also the desired goal. This enables generalization not only over states but also over goals when using neural networks as function approximators. In multi-goal tasks with sparse rewards, it is challenging to learn the task and achieve any progress. HER addresses this problem by taking failure as a success to an alternative (or virtual) goal. HER applies UVFA and includes additional transitions with virtual goals. Thus, the agent can learn from failures through generalization to actual goals. It has been demonstrated that HER significantly improves the performances in various challenging simulated robotic environments.

3 Method

3.1 Instructional-Based Strategy (IBS)

3.1.1 Motivation

HER is based on generalizing from previous failures to the desired target. In this paper, we address the question of how these failures should be taken into consideration in the learning process. Is every failure equally instructive as any other as has been proposed by the original HER algorithm? To analyze this question, consider the following soccer scenario: a player takes two penalty kicks. In a first kick, the goal was missed by a small distance to the right, whereas in a second kick the goal was missed by far to the left. The question arises which of these experiences is more instructive to the soccer player for learning the task of hitting the goal. It seems that nearly missing the goal is more instructive for achieving the goal. However, it might be that the player has experienced many kicks of the first type whereas none of the second. In this case, the latter kick may be more instructive for learning the task. On this Instructional-Based Strategy (IBS), we based our heuristic approach towards virtual goal prioritization.

3.1.2 Definitions

Prioritizing virtual goals is guided by three heuristic principles, which define (i) what the agent needs to learn (ii) what the agent can learn from an individual virtual goal and (iii) what is unknown to the agent. These three principles define
the *instructiveness* of the virtual goal.

**What the agent needs to learn:** The task of the agent is to learn the behavior which achieves the actual goals. The goals are described by a goal distribution \( g(x) \), where \( \Pr(x \in G) = \int_G g(x)dx \) for any measurable set \( G \subseteq \tilde{G} \). In most cases the goal distribution can be described by a uniform distribution over the range \( \tilde{G} \):

\[
g(x) = \begin{cases} 
  \text{const}, & \text{if } x \in G \\
  0, & \text{otherwise}.
\end{cases}
\]  

(1)

**What can be learned from a virtual goal:** The selection of a virtual goal \( \tilde{g} \) teaches the agent of how to reach that goal as well as goals that are in the near surrounding of \( \tilde{g} \). The latter is due to the generalization capabilities of the underlying neural networks \([10, 11]\). To approximate the relevance of the virtual goal \( \tilde{g} \) to other neighboring goals \( \tilde{g}' \), we use a Gaussian radial basis function (RBF) kernel, \( k(\tilde{g}, \tilde{g}') \). Thus, the relevance of virtual goal \( \tilde{g} \) to point \( \tilde{g}' \) is defined by the Mahalanobis distance, where the covariance matrix \( \Sigma \) defines a hyperparameter. Using kernel regression we score virtual goals given the goal distribution:

\[
\mu(\tilde{g}|\Sigma) = \int_{x \in \mathbb{R}^n} k(\tilde{g}, x)g(x)dx.
\]  

(2)

For a uniform goal distribution equation (2) simplifies to

\[
\mu(\tilde{g}|\Sigma, G) = \text{const} \cdot \int_{x \in G} k(\tilde{g}, x)dx.
\]  

(3)

Thus, virtual goals that are closer to the goal distribution center receive a higher score. Scores can be turned into a probability distribution over the possible virtual goals by normalization, resulting in the target distribution \( q^* \) of virtual goals

\[
q^*(\tilde{g}|\Sigma, G) = \frac{\mu(\tilde{g}|\Sigma, G)}{\int_{\tilde{g}' \in \tilde{G}} \mu(\tilde{g}'|\Sigma, G)\,d\tilde{g}'},
\]  

(4)

where \( \tilde{G} \) denotes the range of all virtual goals.

**What is unknown to the agent:** The agent’s current knowledge about the goal distribution is represented by the proposal distribution \( q(\tilde{g}) \) of virtual goals and is initialized with zero. The mismatch between the proposal and target distribution is calculated using the local difference:

\[
w(\tilde{g}) = \text{clip}[q^*(\tilde{g}) - q(\tilde{g}), \min = 0],
\]  

(5)

which by normalization leads to the probability used for prioritization

\[
p(\tilde{g}) = \frac{w(\tilde{g})}{\sum_{\tilde{g}' \in \tilde{G}} w(\tilde{g}')}, \forall \tilde{g} \in \tilde{G},
\]  

(6)

where \( \tilde{G} \) denotes the set of virtual goals. In practice, we find it useful to clip the weights to some small value (we used 0.0005) instead of zero, so all virtual goals have some probability of getting sampled. This trick makes learning more stable.

**3.1.3 Implementation**

For the implementation of the algorithm we discretize the range of virtual goals \( \tilde{G} = S \) into \( M \times N \) grid cells and approximate the target and proposal distributions of virtual goals over the grid cells:

\[
q^*_ij(\Sigma, G) = \frac{\sum_{t=1}^{M,N} \mu(|i,j|,\Sigma), G)}{\sum_{t=1}^{M,N} \mu(|i,j|,\Sigma), G)}, \quad i = 1, \ldots, M, j = 1, \ldots, N,
\]  

(7)

\[
q_{ij} = \frac{1}{|R|} \sum_{\tilde{g} \in R} |g| \in \text{cell}(i,j)|, \quad i = 1, \ldots, M, j = 1, \ldots, N,
\]  

(8)

where \( (i, j) \) denotes the center of the grid cells, \( [\cdot] \) is the indicator function and \( R \) the replay buffer of virtual goals with size \( |R| \). To stabilize the learning, we start with a high variance, \( \Sigma = \sigma^2 I \), and gradually decrease it to its final value. The weight of the virtual goal \( \tilde{g} \) is the weight of its bin

\[
w(\tilde{g}) = \text{clip}[q^*_bin(\tilde{g}), \Sigma, G) - q^*_bin(\tilde{g}), \min = 0],
\]  

(9)

and the prioritization probability is defined as in equation (6). See Alg.1 for a more formal description of the algorithm.
Algorithm 1 Instructional-Based HER

Require:
• an off-policy RL algorithm \( A \), \( \triangleright \) e.g. DQN, DDPG
• a reward function: \( \mathcal{S} \times A \times \mathcal{G} \to \mathcal{R} \), \( \triangleright \) e.g. \( r(s,a,g) = -1 \) if fail, 0 if success
• real goal distribution \( \mathcal{G} \)
• cov matrix \( \Sigma \) for the target \( q \) distribution

1: Initialize \( A \)
2: Initialize replay buffer \( R \)
3: Initialize \( q \) \( \triangleright \) \( q_{ij} = 0 \) \( \forall i,j \in [1 \ldots M], [1 \ldots N] \)
4: Calculate \( q^* \) \( \triangleright \) Using equation (7)
5: while True do
6:   for Episode \( \leftarrow 1, M \) do
7:     Sample a goal \( g \) and an initial state \( s_0 \).
8:   for \( t \leftarrow 0, T - 1 \) do
9:     Sample an action \( a_t \) using the behavioral policy from \( A \): \( a_t \leftarrow \pi(s_t|g) \) \( \triangleright \) \( || \) denotes concatenation
10:    Execute the action \( a_t \) and observe a new state \( s_{t+1} \)
11:   for \( t \leftarrow 0, T - 1 \) do \( \triangleright \) IBS
12:      Calculate the priority \( p(\tilde{g}_t) \) via equation (6)
13:   for \( t \leftarrow 0, T - 1 \) do \( \triangleright \) standard experience replay
14:      \( r_t := r(s_t, a_t, g) \)
15:      Store the transition \( (s_t, a_t, r_t, s_{t+1}|g) \) in \( R \)
16:   Sample a set of virtual goals \( \tilde{G} \) for replay from the future state based on priority \( p^*(\tilde{g}) \)
17:   for \( \tilde{g} \in \tilde{G} \) do \( \triangleright \) HER
18:      \( \tilde{r} = r(s_t, a_t, \tilde{r}) \)
19:      Store the transition \( (s_t, a_t, \tilde{r}, s_{t+1}|\tilde{g}) \) in \( R \)
20:   Update \( q \)
21:   \( |R| \leftarrow |R| + 1 \)
22: end for
23: Sample a minibatch \( B \) from the replay buffer \( R \)
24: Perform one step of optimization using \( A \) and minibatch \( B \)

3.2 Comparison to Reward Shaping

At a first look, IBS may seem similar to reward shaping, which we aimed to avoid from the beginning. However, these two concepts are fundamentally different. While the objective of reward shaping is to find a feedback signal that describes how close the agent is to task goal completion [12], IBS relies on the same assumption as in UVFA, namely, that one goal can be generalized to another by using the generalization capabilities of neural networks. Under this assumption, IBS can be applied to any task with no further modifications.

3.3 Filtered-HER

3.3.1 Problem

In this section, we discuss a fundamental problem within the original HER algorithm. As mentioned in [13], HER may insert bias to the learning process. Using the achieved-goal as a virtual goal may lead in some cases to situations in which the agent performs poorly even though the agent receives repeatedly rewards indicating that it should continue to act in this way. To illustrate the problem consider the Push task in OpenAI Gym. In this environment, a manipulator needs to push a box to the desired location. In some cases, the manipulator does not touch the box at all, and thus, the achieved-goal (i.e., the box position) does not change throughout the entire game. Hence, when virtual goals for experience replay are sampled from these experiences, they all will be the same and identical to all the achieved-goals. This will result in positive virtual rewards (zero), and it will falsely indicate that all those actions were desired. This drawback of the original HER algorithm is similar to the role of terminal states in bootstrapping, in which the values of all states are gradually updated except for terminal states. Terminal states are, by definition, states for which the achieved goal is identical to the desired goal. However, no actions are assigned to terminal states in bootstrapping, nor is any next state observed (i.e., a tuple \( S, A, R, S' \)), because assigning actions to terminal states will disturb the
learning process. To illustrate the problem in more detail consider the following treasure hunting game: for every episode of the game a treasure box is placed randomly in a one-dimensional world. The pirate is also located at a random position, and his goal is to reach the treasure box by using the left and right actions (Fig. 1a). The pirates’ optimal policy is straightforward and shown in Fig. 1b. Assigning (random) actions to states which are equal to the goal will hinder the learning process, in particular, when using function approximation methods such as neural networks. However, the latter is an inherent feature of the HER algorithm, and thus, will generate misleading samples.

### 3.3.2 Solution

To resolve this problem, we apply a filter to remove misleading samples. Before storing the virtual sample in the replay buffer, the filter checks if the virtual goal has been already achieved in the current state. If so, the sample will be deleted, and the next virtual goal will be generated. See Alg. 2 for the pseudo-code of the Filtered-HER algorithm.

#### Algorithm 2 Filtered-HER

Require:
- an off-policy RL algorithm $A$,
- a reward function: $S \times A \times G \rightarrow \mathcal{R}$, $\triangleright$ e.g. DQN, DDPG
- $r(s, a, g) = -1$ if fail, 0 if success

1: Initialize $A$
2: Initialize replay buffer $R$
3: while True do
4:   for Episode $\leftarrow 1, M$ do
5:     Sample a goal $g$ and an initial state $s_0$.
6:     for $t \leftarrow 0, T - 1$ do
7:       Sample an action $a_t$ using the behavioral policy from $A$:
8:       $a_t \leftarrow \pi(s_t || g)$ $\triangleright$ || denotes concatenation
9:       Execute the action $a_t$ and observe a new state $s_{t+1}$
10:  for $t \leftarrow 0, T - 1$ do
11:    Store the transition $(s_t || g, a_t, r_t, s_{t+1} || g)$ in $R$ $\triangleright$ standard experience replay
12:   Sample a set of virtual goals $\tilde{G}$ for replay $\tilde{G} := S$ (current episode)
13:   for $\tilde{g} \in \tilde{G}$ do
14:     $\tilde{r} = r(s_t, a_t, \tilde{g})$
15:     if $r(s_{t-1}, a_{t-1}, \tilde{g}) < 0$ then
16:       Store the transition $(s_t || \tilde{g}, a_t, \tilde{r}, s_{t+1} || \tilde{g})$ in $R$ $\triangleright$ Filtered-HER
17:   for $t \leftarrow 1, N$ do
18:     Sample a minibatch $B$ from the replay buffer $R$
19:     Perform one step of optimization using $A$ and minibatch $B$

### 4 Experiments

#### 4.1 Environments

For the standard multi-goal environments provided by OpenAI Gym ([13], [14]), the manipulator’s state-space is contained within the goal-space, and thus, is incompatible with our condition of having separated goal- and initial-state distributions. We have therefore built two new environments in Python using Pygame ([15]). Our environments have
similar properties to the manipulator environments from OpenAI but are two-dimensional. Both environments contain the following objects: (I) a hand, which can move in $x$- and $y$-directions with different velocities. The hand can be either open or closed. (II) A ball, which the hand can pick up and throw. To grab the ball, the hand must hover over the ball while closing the hand. A constant gravity field is applied in $-y$ direction. (III) A black-hole, which represents the target.

In both environments, the goal is to pick up the ball with the hand and throw it into the black hole.

We tested the algorithms on two tasks:

1. **Hand**: In this task the hand needs to pick up the ball and throw it to the target (Fig.2a).
2. **Hand-Wall**: Same as the Hand task, but in addition a wall is placed in-between the agent’s workspace and the target. The agent needs to throw the ball above the wall (Fig.2b).

**State Space**: The state space $S$ is a concatenated vector of the hand position $(x_h, y_h)$, hand velocity $(u_h, v_h)$, hand state (open/closed), the ball position $(x_b, y_b)$ and ball velocity $(u_b, v_b)$, i.e., $S = \mathbb{R}^9$. The hand position is restricted to a workspace on the left-hand side of the screen (red dashed rectangle in Figures 2a, 2b). Note that the hand needs to pick up the ball within the restricted workspace and release it with a suitable velocity towards the target.

**Initial State**: The hand is initialized to a random position within the workspace with zero velocity. Similar to the Pick-and-Place OpenAI Gym environment, the ball is initialized inside the hand with 0.5 probability while the hand is closed. In the other case, the ball is initialized at the floor ($y = 0$) with zero velocity while the hand is open.

**Goal State**: The goal position represents the target position of the ball with some fixed tolerance of $\epsilon$, i.e., $G = \mathbb{R}^2$.

**Initial Goal**: The goal distribution is assumed to be uniform within a rectangular area on the right-hand side of the screen, beyond the reach of the hand (black dashed rectangle in Figures 2a, 2b).

**Reward Function**: For both environments we used sparse reward function. The agent receives -1 for every step where the ball is not in the desired place (with some tolerance $\epsilon$) and 0 otherwise, i.e., $r(s_t, a_t, g) = -[|g - s_{ball}| > \epsilon]$, where $[\cdot]$ is the indicator function.

**Observation**: The observation is a dictionary which contains

- **Observation**: The state vector concatenated with the goal.
- **Desired Goal**: The coordinates of the goal position.
- **Achieved Goal**: The coordinates of the current ball position.

**Action**: The action space $A$ contains the velocity of the hand $(u_b, v_b)$ and the open/close action i.e., $A \in \mathbb{R}^3$. All three values are in the range of $[-50, 50]$, where the velocity is in units of $\frac{m}{s}$ (scaled by the simulation), and the open/close
4.2 Algorithms Performances

Training is performed using the DDPG algorithm ([5]), in which the actor and the critic were represented using multi-layer perceptrons (MLPs). See Appendix B for more details regarding network architecture and hyperparameters. In order to test the performance of the algorithms, we ran on each environment (I) HER, (II) Filtered-HER, (III) HER with IBS and (IV) Filtered-HER with IBS. In all algorithms we used prioritized experience replay (PER) [16].

The results of the algorithms are evaluated using three criteria:

- Virtual goal distributions
- Success rate
- Distance-to-goal

The first criterion analyzes the differences in virtual goal selection for the different algorithms, and the last two evaluate the performances of the agent.

Table 1: Comparison between proposal and target distribution of virtual goals. The target distribution is calculated using $\sigma = 0.2$ (screen size is 1X1)

|            | HER         | HER-IBS     | Filtered-HER | Filtered-HER-IBS |
|------------|-------------|-------------|--------------|------------------|
| Hand       |             |             |              |                  |
| Hand-Wall  |             |             |              |                  |

Table 2: KL Distance

|            | HER         | HER-IBS     | Filtered-HER | Filtered-HER-IBS |
|------------|-------------|-------------|--------------|------------------|
| Hand       | 2.0317      | 1.6623      | 0.3436       | **0.1928**       |
| Hand-Wall  | 5.0574      | 4.6005      | 0.9606       | **0.5971**       |

4.2.1 Virtual Goal Distributions

Table 1 shows the effect of different selection strategies for virtual targets and the resulting distributions. The virtual goal distribution generated by Filtered-HER-IBS is the closest to the target distribution as indicated by the KL distance in Table 2. Notice that Filtered-HER reduces dramatically the number of samples on the floor ($y = 0$) by removing misleading samples.

4.2.2 Success Rate and Distance from Goal

As shown in Fig 3a and ??, the original HER algorithm fails to solve these tasks with nearly zero success rate and almost no improvements in the distance-to-goal measure. For both tasks, it is relatively hard to affect the achieved-goal in the first place. Without using Filtered-HER, the agent observes too many misleading samples and fails to learn. Although Filtered-HER improved the success rates in both tasks, the performances can be further increased by using the instructional-based selection strategy. Moreover, IBS leads to a more robust performance as indicated by the reduced range of the 33rd to 67th percentile.
Figure 3: Learning curves for the multi-goal hand task. Results are shown over 15 independent runs. The bold line shows the median and the light area indicates the range between the 33th to 67th percentile.

5 Related Work

Prioritizing samples over their relevance to the learning has been used in both Prioritized Experience Replay (PER) [16] and Energy-Based Hindsight Experience Prioritization (EBP) [17]. Similar to our algorithm, PER gives higher priority to samples that are unknown to the agent. However, unlike IBS, PER uses the TD-Error of the sample to measure the agent’s knowledge (i.e., a smaller error implies more acquaintance). PER receives the buffer as a given input set and prioritizes when sampling from it for experience replay. In contrast, IBS prioritizes when building the buffer during experiences. Another difference is that unlike IBS, PER only prioritizes over unfamiliar samples and does not take into consideration that some samples might be better towards task completion than others.

EBP applies a different prioritization scheme by calculating the amount of (translational and rotational) kinetic energy transferred to the object during an episode. Trajectories associated with a larger kinetic energy transfer are therefore preferred. The assumption behind EBP is that the agent can learn more from trajectories in which the object moved significantly. EBR does not differentiate between movement directions and is thus applicable for cases where all directions are equally informative for learning. Similar to PER, EBP gets the buffer as a given input set and prioritizes when sampling from it for experience replay. Since PER and EBP prioritize during experience replay, both methods can be applied with IBS.

6 Conclusion

In this paper we have introduced two novel techniques: an Instructional-Based Strategy (IBS) for virtual goal selection and a Filtered-HER for the removal of misleading samples. IBS is used for prioritizing more instructive virtual goals when collecting experiences while Filtered-HER is used to reduce bias that may occur when using HER. Both methods showed significant improvements in performances and sample efficiency when compared to vanilla-HER in the tested environments. Like HER, our methods can be applied using any off-policy RL algorithm, such as DDPG. Moreover, the presented methods can be easily combined with any experience replay prioritization technique as we have demonstrated in our experiments using PER.
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A Environments

The environments were built in Python using Pygame.
The simulation scales the objects coordinates and velocities to the range [0,1].

A.1 Screen

Screen height: 800 pxl ; Screen width: 1000 pxl ; Pixels per meter: 10 ;

A.2 Clock

Steps per second: 100 ; Steps per action: 10 ;

A.3 Hand

Hand height: 25 pxl ; Hand width: 25 pxl ; Hand col bound: [0,500] ; Hand row bound: [80,800] ; Hand col initialization: [0,500] ; Hand row initialization: [80,800] ;

A.4 Ball

Ball height: 40 pxl ; Ball width: 40 pxl ; Ball col bound: [0,1000] ; Ball row bound: [0,800] ; Ball col initialization: [0,500] ; Ball row initialization: [799,800] ;

A.5 Goal

Goal height: 80 pxl ; Goal width: 80 pxl ; Goal col bound: [700,920] ; Goal row bound: [400,720] ; Goal col initialization: [700,920] ; Goal row initialization: [400,920] ;

B Neural-Networks Architecture

For the training process we used the DDPG algorithm.
Hidden layers: 3 ; Number of neurons: 64 ; Activation function: Relu ; Learning rate: 0.001 ; Smoothing factor for target networks: 0.05 ; Discount factor: 0.98 ; Buffer size: 1e6 ; Gradient global norm clipping: 5 ; Epsilon decay rate: 0.95 every epoch.