Ensembling Deep Deterministic Policy Gradients trained networks in Torcs

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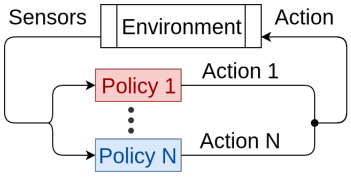
1 The controller

The principal component of our car controller consists in a feed forward neural network which uses 29 inputs (track angle, track position, speeds along 3 axis, RPM, 4 wheel spin velocities and 19 proximity sensors) to predict 2 values from -1 to 1 that represent the steering (-1=full right and 1=full left) and the acceleration/brace (-1=full brake and 1=full accelerate) respectively. We choose to merge both acceleration and brake into a single output in order to reduce the number of tunable parameters along with the action space size. Making acceleration and brake mutually exclusive experimentally led to comparable results.

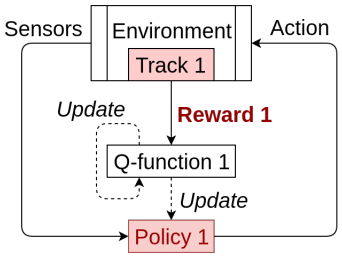
1.1 The training algorithm

In order to train our model we decided to use a state-of-the-art reinforcement learning algorithm rather than supervised ones. The DDPG (Deep Deterministic Policy Gradients) algorithm [3] resulted to be the best candidate for our problem since it grants the advantages of Deep Q-Learning techniques in a continuous action domain [4] (a brief explanation in appendix A).

Furthermore, the necessity of flexibility resulted in the creation of multiple smaller models, each one trained on a different kind of track with a specific reward function, rather than a single one. These trained model were merged into a better performing controller by combining the outputs during the race. Some genetic-tuned rule-based heuristics increase the robustness of our driver.



(a) Diagram of racing setup.



(b) Diagram of training setup for policy 1 on track 1 with reward function 1.

1.2 The implementation

Our implementation and adaptation of the DDPG algorithm relies on python Keras-rl module[1] which is built on top of the Keras framework[2] for Tensorflow[3]. After the implementation, we focused on finding the best reward function and hyper-parameters for the algorithm following basic guidelines from similar works [4]. Hardware, software and time limitations led to simplifications of the models and radical changes in the training phase. The introduction of *curriculum learning* [1] is just one of the strategies described in this section which we applied to decrease the training time.

The reward functions We used two different reward functions to train our neural networks (three out of five are trained with r_1, the other two with r_2). r_1 leads to a stable behavior by rewarding the speed of the car, its position and alignment with the track axis.

$$r_1 = \begin{cases} -500 & (if\ |p| > 0.99) \\ s \cdot (\cos\theta - |\sin\theta| - |p|) & (otherwise) \end{cases}$$

where θ is the angle between the car direction and the direction of the track axis, s is the current speed of the car in km/h and p is the distance between the car and the track axis normalized from -1 to 1.

Then r_2 allows the car to be near the edges of the track (up to -0.85 and 0.85) without being punished. This reward strategy is less safe but allows the car to learn to steer sharply and cut simple turns.

$$r_2 = \begin{cases} -5 & (if\ |p| > 0.99) \\ (d_t - d_{t-1}) \cdot (\cos\theta - |\sin\theta|) & (if\ |p| > 0.85) \\ (d_t - d_{t-1}) \cdot (\cos\theta - |\sin\theta| - (|p| - 0.85)^2/0.0225) & (otherwise) \end{cases}$$

where the factor 0.0225 is just $1/(1-0.85)^2$ which is needed to normalize the off-track-center factor from -1 to 1 and d_t is the distance from the start in time instant t in meters.

Both of the rewards punish the controllers with a negative value if the car goes off the track. A negative reward is given if the car bumps into guardrails in order to remove the unwanted behavior of using them to finish the track.

DDPG Hyper-parameters In order to tune the convergence factor τ and both the learning rates for the ADAM optimizer [2] we followed the original values described in the cited DDPG paper. In our specific case, we used Ornstein-Uhlenbeck process to generate temporally correlated noise (using Brownian motion). The noise was centered in 0 for the steering and 0.2 for the acceleration/brake output to explore increases in speed values.

[1] https://github.com/matthiasplappert/keras-rl
[2] https://keras.io/
[3] https://www.tensorflow.org/
[4] https://yanpanlau.github.io/2016/10/11/Torcs-Keras.html

Curriculum Learning The neural network size and its training time resulted to be the strictest limitations of our implementation. While training the networks using general purpose laptops, we experimentally verified that the training time could be reduced by limiting the maximum allowed speed. Starting from 80 km/h, we gradually increased the upper limit by 10 km/h for every completed lap. Following this procedure, the networks quickly learned how to brake and turn properly. Picture 1.2 shows the effect of our training methodology on the average speed of the car in different episodes during the training phase. The x axis represents the iteration number while y values show the average speed of the car for that episode. The collected data underlines the effectiveness of the curriculum approach while showing the 2 different phases in the process (blue line in Picture 1.2). The average speed gradually increases while the controller is learning with a fixed speed limit, then it drops rapidly as soon as the speed limit is incremented to stabilize again after a few episodes. The final achieved speed is almost doubled if compared to the standard approach.

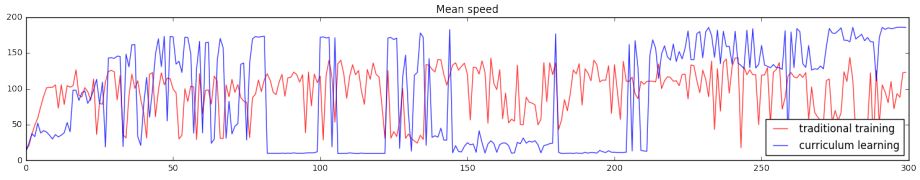


Fig. 2: Effect of curriculum learning on average speed in the first 300 iterations.

Ensemble methods Instead of training a single network on different tracks, we chose to train multiple models on a representative sample of them using 2 different reward functions. This option suited best our needs since it allowed us to train multiple models at the same time (each of them can be trained independently on different machines) while reducing the variance of the resulting model and making it less prone to over-fitting.

Every predicted action is the result of a weighted average of different trained networks. The steering is calculated by taking the average of the steering values, however, the acceleration/brake action is driven towards a more safe behavior. If at least one of the model predicts to brake, its weight is increased, along with every other agreeing model. If no models predict a brake action, we take a simple average of the suggested accelerations. Each weight has been tuned in order to find a balance between safer behaviors (r_1) and dangerous but better performing ones (r_2).

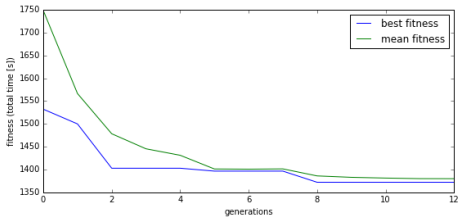
Rule based heuristics In order to to increase the stability of the controller and make it perform better, we added some basic rules:

1. if the car is too slow or not moving at all, then the acceleration is set to the maximum value and the brake is regulated to the minimum (the threshold for triggering this behavior were properly tuned). This rule has been added to force a movement when the car is blocked.

2. if the distance between the car and the border of the track is less than the braking distance, we do not allow the car to accelerate anymore and we increase the braking force ($brake_{Force}$) by a fixed factor. In order to do so, we empirically computed the value of the minimum distance required to completely stop when driving at the current speed [5]) and we added a tunable offset o to regulate the braking distance.
3. if the speed exceeds a fixed threshold the car steering is elevated to the power of 2 (this operation increases the stability when the car is racing in a high speed track).

2 Parameters tuning with genetic algorithm

Fig. 3: Results of the genetic algorithm run.



Since the rules created to regulate the acceleration/brake actions resulted to have a major impact on the performance of the controller (allowing it to cut corners cleanly or avoiding going out of track when performing sharp turns), we decided to tune only the two parameters that have the highest influence. The two most influential parameters were experimentally seen to be the offset o, and the $brake_{Force}$ from heuristics rule 2 (see section 1.2). This optimization problem has been approached by implementing a single objective genetic algorithm using The Watchmaker Framework[6]. The fitness function is the sum of one lap times for a subset of 6 tracks, namely alpine-1, alpine-2, b-speedway, corkscrew, aalborg and e-track-4. As the time needed to calculate each individuals fitness is moderately large, we found a compromise between evaluation time and search space: each generation is composed by 15 individuals, that produce off-springs via a 1 point crossover and random mutation (2% probability). In order to get a reasonable convergence time we used elitism (of 1 individual) and we used a stagnation termination of 10 generations (if no improvements have been made in the last 10 generations the algorithm stops) to leave the algorithm enough time to search for better solutions. Results of this operation can be seen in Figure 3.

3 Racing against opponents

Since opponent sensors had not been considered during the training phase, our controller ignored other cars. Since this lack of perception resulted in unwanted

[5] the value has been calculated experimentally with data form Torcs, and resulted to be $0.851898 \cdot 10^{-3} \cdot s^2 + 0.104532 \cdot s - 2.03841$

[6] http://watchmaker.uncommons.org

outcomes, we added simple rules to the controller in order to avoid hitting opponents which resulted in a simple overtake procedure and a triggered behavior that aims to avoid being overtaken by the opponents. The amount and complexity of the rule-based strategies has been carefully reduced since they override the behavior of the controller, potentially compromising its stability.

A possible solution we did not explored but which would be interesting for future work consists in taking into consideration opponents during the training phase. This approach would significantly slow down the training phase but it would allow the controller to learn how to behave among other cars by itself.

4 Performance evaluation

We evaluated our controller performances (both alone and with opponents) in all the 38 tracks available on the Torcs package. We checked whether the controller was able to perform at least one lap (with or without touching the border) and the sum of lap times all over the tracks. Table 1 shows the results obtained with a basic controller trained on only one track (alpine-1). With this configuration, the car was able to finish almost all the tracks but it hit the border in most of them. With the ensemble controller (5 networks) the controller performed worse considering the lap times. However, differently from the basic controller, the car was able to avoid hitting the border in more than half of the tracks. Adding heuristics the total lap time all over the tracks dropped of one third while increasing the number of completed tracks by 4. Lastly, the genetic parameters tuning allowed the controller to finish all the tracks without hitting the border in more than 80% of them. Moreover the controller gained more than 5 minutes in the total lap time.

Method	**Tracks**	**All tracks**	**alpine-2**	**spring**	**dirt-5**	**forza**
Basic	6-35/38	5339s	125.1s	(H) 619.8s	(H) 73.8 s	(H) 138.6s
Ensemble	25-33/38	5735s	118.9s	554.6s	(H) 43.0s	125.9s
Heuristics	22-37/38	4083s	116.3s	554.0s	(H) 47.8s	124.5s
Genetic	**31-38/38**	**3758s**	**111.9s**	**510.2s**	**53.6s**	**108.6s**

Table 1: Controller evaluation, 4 tracks and overall: (H) indicates whether the car hit the border of the track. The first number in the "Tracks" column represents in how many tracks the car finished without touching the border, the second the total number of finished ones.

5 Conclusions

Our work shows how the use reinforcement learning on continuous domains can lead to excellent results even with a relatively small feed-forward network and limited computational resources. We show how curriculum learning technique boosted the convergence of the training process and we highlight how averaging multiple networks can have a positive effect reducing the variance of the resulting model, increasing its precision and allowing parallel training. Heuristics and in-domain knowledge can help increasing stability and performances while the emerging complexity can be successfully handled by genetic algorithms.

A DDPG

The main idea behind the Deep Deterministic Policy Gradient is to use two different models for the reinforcement training phase.

The first model "*Actor*" represents a deterministic policy function $\mu : s \rightarrow a$ from the state s (values of all the sensors) to an action a (combination of values for steering and acceleration/brake), while the second one "$Critic$" takes as input both the predicted action and the state to compute the maximum discounted future reward R following the given deterministic policy $Q^{\mu} : s, a \rightarrow R$.

The total discount for future reward R is defined as:

$$R = r_1 + \gamma r_2 + \gamma^2 r_3 + \ldots + \gamma^n r_n$$

. Where $r_1 \ldots r_n$ represent the reward in states $s_1 \cdots s_n$ respectively. Since we want our policy μ to maximize the Q-function, we can compute the gradients with respect to the parameters θ^{μ} of the actor using the chain rule:

$$\Delta_{\theta^{\mu}} = \frac{\partial Q^{\mu}(s,a)}{\partial \theta^{\mu}} = \frac{\partial Q^{\mu}(s,a)}{\partial a} \frac{\partial a}{\partial \theta^{\mu}} = \frac{\partial Q^{\mu}(s,a)}{\partial a} \frac{\partial \mu(s)}{\partial \theta^{\mu}}$$

In order to update the critic model, we can use the SARSA (State-Action-Reward-State-Action) rule:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_{t+1} + \gamma Q(s_{t+1}, \mu(s_{t+1})) - Q(s_t, a_t) \right]$$

Since reinforcement learning algorithms make the assumption that samples are independently and equally distributed, instead of training directly on the sequence of states, the algorithm randomly samples from a replay buffer. Each entry of the buffer is a tuple (s_t, a_t, r_t, s_{t+1}) representing the current state s_t, the corresponding action a_t, the current reward r_t and the next observed state s_{t+1}. These values are first used to update the critic network and, then, the target one.

Since both networks are prone to divergence, instead of directly updating the weights during the back-propagation step, DDPG uses 2 copies ($targets$) of each network and updates the weights θ with a soft update equation:

$$\theta' \leftarrow \tau\theta + (1 - \tau)\theta'$$

The exploration of the neighborhood of the selected action policy is a fundamental part of the whole process, in fact, random noise $\mathcal{N}$ is added to the action of the *Actor* at every step during the training phase.

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