LongiControl: A Reinforcement Learning Environment for Longitudinal Vehicle Control

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Abstract: Reinforcement Learning (RL) might be very promising for solving a variety of challenges in the field of autonomous driving due to its ability to find long-term oriented solutions in complex decision scenarios. For training and validation of a RL algorithm, a simulative environment is advantageous due to risk reduction and saving of resources. This contribution presents an RL environment designed for the optimization of longitudinal control. The focus is on providing an illustrative and comprehensible example for a continuous real-world problem. The environment will be published following the OpenAI Gym interface, allowing for easy testing and comparing of novel RL algorithms. In addition to details on implementation reference is also made to areas where research is required.

1 INTRODUCTION

A large proportion of road traffic accidents are due to human error (Gründl, 2005). Autonomous vehicles and driver assistance systems are therefore promising ways to increase road safety in the future (Bertoncello and Wee, 2015). Moreover, global climate change and dwindling resources are increasingly contributing to raising society's awareness of environmental policy issues. In addition to vehicle electrification, advancing automation in transport promises a much more efficient use of energy. Assistance systems in particular which support the predictive longitudinal control of a vehicle can lead to significant energy savings (Radke, 2013).

A commonly chosen approach for energy-efficient optimization of the longitudinal control is based on the use of dynamic programming. Although this is basically capable of finding the discrete global optimum it requires in advance a comprehensive problem modeling, a deterministic environment and a discretization of the action space. Especially when considering other road users the conventional approaches therefore reach their limits (Ye et al., 2017). A priori, arbitrary traffic cannot be sufficiently modeled and thus no precise knowledge of the entire route can be given. Furthermore, the computing power available in the vehicle is not sufficient to perform new optimizations depending on the constantly changing environment. Online use in the vehicle is therefore unlikely.

The developments in the field of machine learning, especially deep reinforcement learning (DRL), are very promising. The learning system recognizes the relations between its actions and the associated effect on the environment. This enables the system to react immediately to environmental influences instead of just following a previously calculated plan. After proving in recent years to solve challenging video games (Mnih et al., 2013) on a partly superhuman level DRL has lately been increasingly used for engineering and physical tasks (Hinssen and Abbeel, 2018). Examples are the cooling of data centers (Gao, 2014), robotics (Gu et al., 2016), the energy management of hybrid vehicles (Liessner et al., 2018) or self-driving vehicles (Kendall et al., 2018) (Sallab et al., 2017). This motivates to apply such an approach also to the problem of optimizing longitudinal control.

In this contribution we propose LongiControl (Dohmen et al., 2019), a RL environment being adapted to the OpenAI Gym standardization. Even though LongiControl could be regarded as another simplified solution to the longitudinal control problem, the main focus, however, is rather to provide a stochastic and continuous RL environment being designed in such a way that RL agents can be trained with an ordinary notebook in a relatively short period of time. Furthermore, the longitudinal control problem has several easily comprehensible chal-

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lenges making it a suitable example to test and compare novel RL algorithms while also providing the possibility to investigate advanced topics like multi-objective RL (trade-off between conflicting goals of travel time minimization and energy consumption), safe RL (violation of speed limits may lead to accidents) or explainable RL (easy-to-follow actions and states). We aim to bridge real-world motivated RL with easy accessibility inside a highly relevant problem.

This publication is structured as follows. In section 2 overviews are given on the longitudinal control problem and on the basic principles of RL. In section 3 we present the LongiControl environment describing the route simulation, the vehicle model and its interaction with a RL agent. Thereafter, in section 4 we show exemplary results for different training phases and give a brief insight into the challenges with contrary reward formulations. This is followed by the conclusion in section 5 providing a basis for future working directions.

2 BACKGROUND

2.1 Longitudinal Control

Energy-Efficient Driving. In general terms, an energetically optimal driving corresponds to a global minimization of the input energy E in the interval $t_0 \leq t \leq T$ as a function of acceleration a, velocity v and power P:

$$E = \int_{t_0}^{T} P(t, a(t), v(t))\, dt \tag{1}$$

At the same time, according to external requirements, such as other road users or speed limits, the following boundary conditions must be met:

$$\begin{aligned} v_{lim,min}(x) &\leq v \leq v_{lim,max}(x) \\ a_{lim,min}(v) &\leq a \leq a_{lim,max}(v) \\ \dot{a}_{lim,min}(v) &\leq \dot{a} \leq \dot{a}_{lim,max}(v)\ . \end{aligned} \tag{2}$$

Where v is the velocity, a is the acceleration and $\dot{a}$ is the jerk, with $(\cdot)_{lim,min}$ and $(\cdot)_{lim,max}$ representing the lower and upper limits respectively.

Following Freuer (Freuer, 2015) the optimization can be divided roughly into four areas:

1. optimization of the vehicle properties,
2. optimization of traffic routing,
3. optimization on an organizational level,
4. optimization of vehicle control.

This paper deals with the last point. In various contributions (Barkenbus, 2010) (Uebel, 2018) an adapted vehicle control system is assigned an enormous savings potential. In addition to the safety aspect, assistance systems supporting vehicle control are becoming increasingly important for this reason as well. This trend is made possible by comprehensive sensor technology and the supply of up-to-date route data. In terms of longitudinal control, energy-saving driving modes can thus be encouraged:

- driving in energy-efficient speed ranges,
- keeping an appropriate distances to vehicles in front,
- anticipatory deceleration and acceleration.

Simulation. Simulations become more and more important in automotive engineering. According to Winner et al. (Winner and Wachenfeld, 2015), in the context of the automotive industry the overall system is composed of three parts: the vehicle, the driving environment and the vehicle control. These three components interact through an exchange of information and energy.

Within the simulation a vehicle model is needed which indicates the energy consumption. In general, physical and data-based approaches are suitable for modeling those (Isermann, 2008).

External influences are represented by the driving environment. This includes for example information about other road users and route data such as traffic light signals or speed limits. These information are used then by the vehicle control as boundary conditions for the driving strategy.

While in reality with increasing automation the information content of the sensor system in vehicles is increasing (Winner et al., 2015), this information can be easily generated in the simulation. Considering the modeling of the driving environment a distinction must be made between deterministic and stochastic approaches. In the deterministic case it is assumed that the driving environment behaves the same in every run. Changes during the simulation are not allowed. This means that reality can only be represented in a very simplified way. For example a sudden change of a traffic light signal or an unforeseen braking of the vehicle in front is not represented by such a model. In contrast, the stochastic approach offers the possibility to vary external influences during the simulation. Therefore, this type of modeling is much closer to the real driving situation.

Optimization. The aim of the RL environment is to train an agent to drive an electric vehicle a singlelane route as energy-efficient as possible. This corresponds to the minimization of Equation 1 while considering the corresponding boundary conditions in Equation 2.

Examples for state-of-the-art approaches for the optimization of the longitudinal control problem are Dynamic Programming (Bellman, 1954), Pontryagin's Maximum Principle (Pontryagin et al., 1962) or a combination of both (Uebel, 2018). As previously mentioned these approaches have two basic limitations: they are based on deterministic models and suffer from the curse of dimensionality.

According to (Sutton and Barto, 2018) and (Bertsekas and Tsitsiklis, 1999) RL approaches are a solution to this dilemma. The main difference between Dynamic Programming and RL is that the former assumes to know the complete model. RL approaches on the other hand only require the possibility of interaction with the environment model. Without knowing its inner structure solutions are learned. In modern deep RL (DRL), the use of neural networks for function approximation also allows to handle continuous state spaces and react to previously unknown states.

2.2 Reinforcement Learning

A standard reinforcement learning framework is considered, consisting of an agent that interacts with an environment (see Figure 1). The agent perceives its state $s_t \in \mathcal{S}$ in the environment in each time step $t = 0, 1, 2, \ldots$ and consequently chooses an action $a_t \in \mathcal{A}$. With this, the agent in turn directly influences the environment resulting in an updated state s_{t+1} for the next time step. The selected action is evaluated using a numerical reward $r_{t+1}(s, a)$. The sets $\mathcal{S}$ and $\mathcal{A}$ contain all possible states and actions that can occur in the description of the problem to be learned.

The policy $\pi(a \mid s)$ specifies for each time step which action is to be executed depending on the state. The aim is to select actions in such a way that the cumulative reward is maximized.

Policy gradient methods are probably the most popular class of RL algorithms for continuous problems. Currently very relevant examples for such methods are Proximal Policy Optimization (PPO) (Schulman et al., 2017), Deep Deterministic Policy Gradient (DDPG) (Lillicrap et al., 2015) or Soft Actor-Critic (SAC) (Haarnoja et al., 2018).

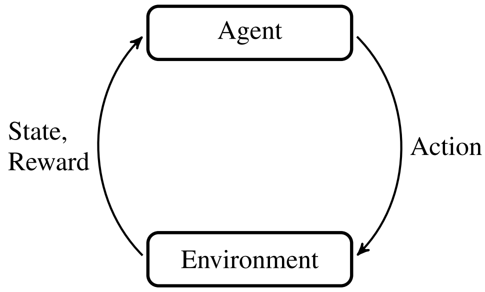


Figure 1: Agent environment interaction.

3 RL ENVIRONMENT

3.1 OpenAI Gym

OpenAI Gym (Brockman et al., 2016) is a widely used open-source framework with a large number of well-designed environments to compare RL algorithms. It does not rely on a specific agent structure or deep learning framework. To provide an easy starting point for RL and the longitudinal control problem, the implementation of the LongiControl environment follows the OpenAI Gym standardization.

3.2 Route Simulation

Figure 2 shows an example of the simplified track implementation within the simulation.

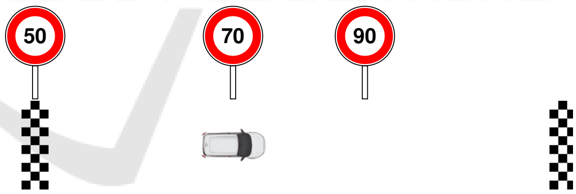


Figure 2: An example for the track visualization.

Equation of Motion. The vehicle motion is modeled simplified as uniform accelerated. The simulation is based on a time discretization of $\Delta t = 0.1\,\mathrm{s}$. The current velocity v_t and position x_t are calculated as follows:

$$
\begin{aligned}
v_t &= a_t\,\Delta t + v_{t-1} \\
x_t &= \frac{1}{2}\,a_t\,(\Delta t)^2 + v_{t-1}\,\Delta t + x_{t-1}
\end{aligned}
$$

The acceleration a_t must be specified through the agents action in each time step t. Since only the longitudinal control is considered the track can be modeled single-laned. Therefore, one-dimensional velocities v_t and positions x_t are sufficient at this point.

Stochastic Route Modeling. The route simulation is modeled in such a way that the track length may be arbitrarily long and that arbitrarily positioned speed limits specify an arbitrary permissible velocity. Here, it is argued that this can be considered equivalent to a stochastically modeled traffic.

Under the requirement that a certain safety distance to the vehicle in front must be maintained other road users are simply treated as further speed limits which depend directly on the distance and the difference in speed. For each time step the relevant speed limit is then equal to the minimum of the distance-related and traffic-related limit.

Restrictively, speed limits are generated in a minimum possible distance of 100 m. The permissible velocities are sampled from [20, 30, 40, 50, 60, 70, 80, 90, 100 km/h] while the difference of contiguous limits may not be greater than 40 km/h. It should therefore apply $x_{lim,j+1} - x_{lim,j} \geq 100\,\mathrm{m}$ and $|v_{lim,j+1} - v_{lim,j}| \leq 40\,\mathrm{km/h}$. The former is a good compromise to induce as many speed changes per trajectory as possible and to be able to identify anticipatory driving at the same time. The second is introduced as another simplification to speed up the learning process. Very large speed changes may be very hard for the agent to handle.

Up to 150 m in advance, the agent receives information about the upcoming two speed limits.

3.3 Vehicle Model

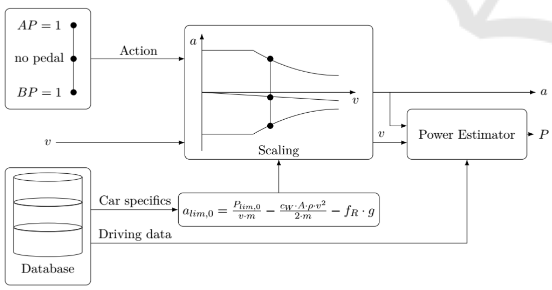


Figure 3: Assigning the action to an acceleration.

The vehicle model derived from vehicle measurement data (see figure 3) consists of several subcomponents. These have the function of receiving the action of the agent, assigning a physical acceleration value and outputting the corresponding energy consumption.

Assigning the Action to an Acceleration. The action of the agent is interpreted in this environment as the actuation of the vehicle pedals. In this sense, a positive action actuates the accelerator pedal. A negative analogous action actuates the brake pedal. The vehicle acceleration resulting from the pedal interaction depends on the current vehicle speed (road slopes are neglected) due to the limited vehicle motorization.

If neither pedal is actuated (corresponds to $action = 0$), the vehicle decelerates its speed by simulating the driving resistance. This means that to maintain a positive speed a positive action must be selected.

It becomes clear from the explanations that three speed-dependent acceleration values determine the physical range of the agent. These are the maximum and minimum acceleration and the acceleration value for $action = 0$.

Determination of the Acceleration Values. The speed-dependent maximum and minimum acceleration can be determined from the measurement data and the technical data of the vehicle. In the RL environment, the maximum and minimum values for each speed are stored as characteristic curves. The resulting acceleration at $action = 0$ is calculated physically. Using the driving resistance equation and the vehicle parameters an acceleration value is calculated for each speed. This is stored in the environment as a speed-dependent characteristic curve, analogous to the other two acceleration values.

Once the action, the current vehicle speed and the three acceleration values are available the resulting acceleration can be calculated as follows:

$$a_t = \begin{cases} (a_{max} - a_0) \cdot action + a_0 & \text{if } action > 0 \\ a_0 & \text{if } action = 0 \\ -(a_{min} - a_0) \cdot action + a_0 & \text{if } action < 0 \end{cases}$$

Calculation of Energy Consumption. Knowing the vehicle speed and acceleration the energy consumption can be estimated from these two values. For this purpose measured values of an electric vehicle (Argonne National Laboratory, 2013) were learned using a neural network and the network was stored in the environment.

3.4 Agent Environment Interaction

In accordance with the basic principle of RL an agent interacts with its environment through its actions and receives an updated state and reward.

Action. The agent selects an action in the value range [-1,1]. The agent can thus choose between a condition-dependent maximum and minimum acceleration of the vehicle. This type of modeling results in the agent only being able to select valid actions.

State. The features of the state must provide the agent with all the necessary information to enable a goal-oriented learning process. The individual features and their meaning are listed in Table 1.

When training neural networks the learning process often benefits from the fact that the dimensions of the input variables do not differ greatly from one another. According to Ioffe et al. (Ioffe and Szegedy, 2015) the gradient descent algorithm converges faster if the individual features have the same order of magnitude. Since according to Table 1 different physical quantities with different value ranges enter the state a measure for normalization seems to be reasonable at this point. All features are scaled min-max for this purpose so that they are always in the fixed interval [0, 1].

Table 1: Meaning of state features.

Feature	Meaning
$v(t)$	Vehicles's current velocity
$a_{prev}(t)$	Vehicle acceleration of the last time step, s.t. the agent is able to have an intuition for the jerk
$v_{lim}(t)$	Current speed limit
$\boldsymbol{v}_{lim,fut}(t)$	The next two speed limit changes, as long as they are within a range of 150 m
$\boldsymbol{d}_{v_{lim,fut}}(t)$	Distances to the next two speed limit changes, as long as they are within a range of 150 m

Reward. In the following, the reward function that combines several objectives is presented. The explanations indicate the complexity of the multi-objective manner. The LongiControl Environment thus provides a good basis for investigating these issues and for developing automated solutions to solve them.

A reward function defines the feedback the agent receives for each action and is the only way to control the agent's behavior. It is one of the most important and challenging components of an RL environment. If only the energy consumption were rewarded (negatively) the vehicle would simply stand still. The agent would learn that from the point of view of energy consumption it is most efficient simply not to drive. Although this is true we still want the agent to drive in our environment. So we need a reward that makes driving more appealing to the agent. By comparing different approaches the difference between the current speed and the current speed limit has proven to be particularly suitable. By minimizing the difference the agent automatically sets itself in motion. In order to still take energy consumption into account the reward component is maintained with energy consumption. A third reward component is caused by the jerk. This is because our autonomous vehicle should also be able to drive comfortably. To punish finally also the violation of the speed limits a fourth reward part is supplemented. Since RL is designed for a scalar reward it is necessary to weight these four parts.

A suitable weighting is not trivial and poses a great challenge. For the combined reward we propose the following (see also Table 2):

$$\begin{aligned} r_t = &-\xi_{forward}\, r_{forward}(t) \\ &-\xi_{energy}\, r_{energy}(t) \\ &-\xi_{jerk}\, r_{jerk}(t) \\ &-\xi_{safe}\, r_{safe}(t)\ , \end{aligned}$$

while

$$\begin{aligned} r_{forward}(t) &= \frac{|v(t) - v_{lim}(t)|}{v_{lim}(t)} \\ r_{energy}(t) &= \hat{E} \\ r_{jerk}(t) &= \frac{|a(t) - a_{prev}(t)|}{\Delta t} \\ r_{safe}(t) &= \begin{cases} 0 & v(t) \le v_{lim}(t) \\ 1 & v(t) > v_{lim}(t) \end{cases} . \end{aligned}$$

ξ are the weighting parameters for all reward shares. In some cases, the terms are used as penalty so that the learning algorithm minimizes their amount. To make it easier to get started with the environment we have preconfigured a functioning weighting (see Table 3). In the next section we will show some examples of the effects of different weightings.

Table 2: Meaning of reward terms.

Reward	Meaning
$r_{forward}(t)$	Penalty for slow driving
$r_{energy}(t)$	Penalty for energy consumption
$r_{jerk}(t)$	Penalty for jerk
$r_{safe}(t)$	Penalty for speeding

4 EXAMPLES

In the following various examples of the environment are presented. For training the agent is confronted

Table 3: Weighting parameters for the reward.

Parameter	Value
$\xi_{forward}(t)$	1.0
$\xi_{energy}(t)$	0.5
$\xi_{jerk}(t)$	1.0
$\xi_{safe}(t)$	1.0

with new routes in each run using the stochastic mode of the environment. For validation it is always used the same deterministic route to compare like with like.

4.1 Learning Progress

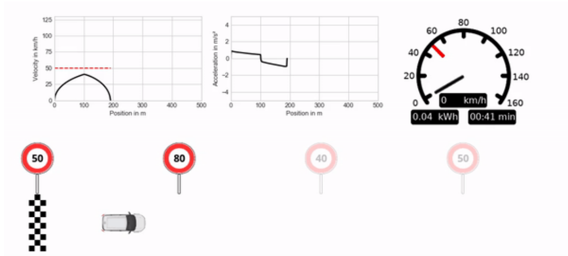
In the following different stages of an exemplary learning process are presented. An implementation of SAC (Haarnoja et al., 2018) was chosen as the deep RL algorithm. The used hyperparameters are listed in Table 4. Animated visualizations for the upcoming learning stages can be found on GitHub (Dohmen et al., 2019).

Table 4: SAC hyperparameter.

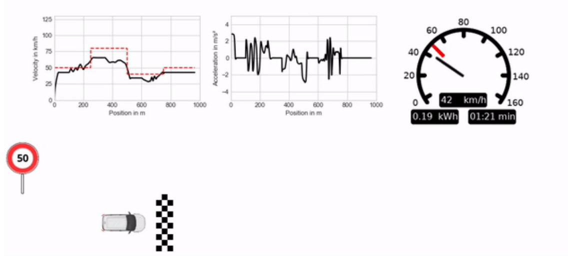
Parameter	Value
optimizer	Adam
learning rate	0.001
discount γ	0.99
replay buffer size	1000000
number of hidden layers (all networks)	2
number of hidden units per layer	64
optimization batch size	256
target entropy	$-\dim(\mathcal{A})$
activation function	ReLU
soft update factor τ	0.01
target update interval	1
gradient steps	1

Beginning of the Learning Process. At the very beginning of the learning process the agent remains in place and does not move at all. Then after a few more training epochs the agent starts to move but is not yet able to finish the track. Figure 4a shows this stage in the deterministic validation run.

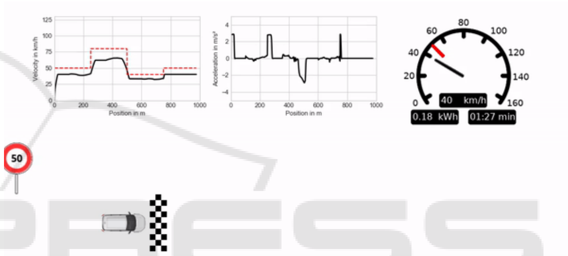
After Some Learning Progress. After some progress the agent is able to complete the course (see Figure 4b) but ignores speed limits while driving very



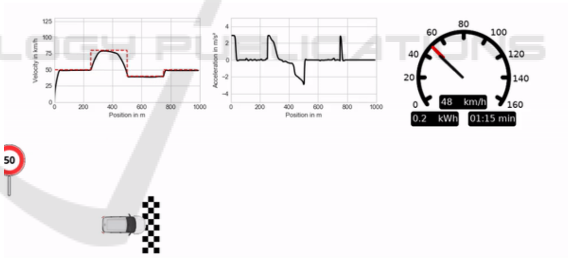
(a) Beginning of the learning process.



(b) After some learning progress.



(c) After a longer training procedure.



(d) After an even longer training period.

Figure 4: Learning progress.

jerky. Obviously, this is not desirable. Therefore the training continuous.

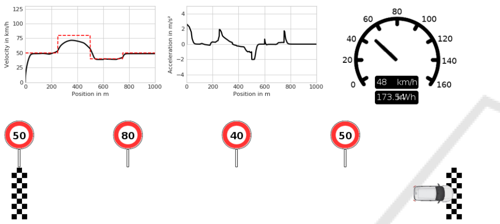
After a Longer Training Procedure. By letting the agent train even longer it learns to drive more comfortably and finally starts to respect the speed limits by an early enough deceleration. Though, in general it is driving quite slow in relation to the maximum allowed (see Figure 4c).

After an Even Longer Training Period. Finally after an even longer training, it drives very smooth, respects the speed limits while minimizing the safety margin to the maximum allowed (see Figure 4d).

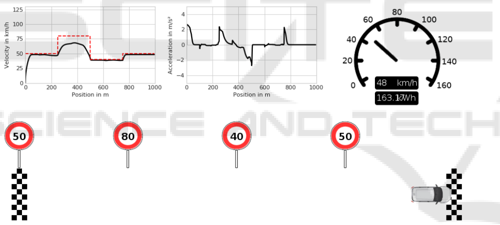
4.2 Multi-objective Optimization

As mentioned before, this problem has several contrary objectives. Thus also multi-objective investigations can be carried out. For a better understanding we present three examples.

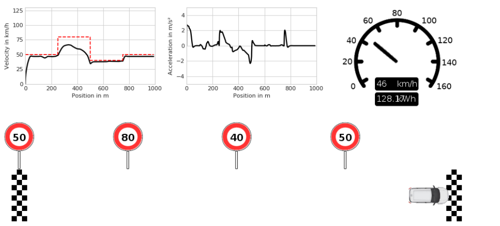
Reward Example 1. If only the movement reward – the deviation from the allowed speed – is applied (reward weighting $[\xi_{forward}(t) = 1,\ \xi_{energy}(t) = 0,\ \xi_{jerk}(t) = 0,\ \xi_{safe}(t) = 0]$) the agent violates the speed limits because being 5 km/h too fast is rewarded the same as being 5 km/h too slow (see Figure 5a).



(a) $\xi_{forward}(t) = 1,\ \xi_{energy}(t) = 0,\ \xi_{jerk}(t) = 0,\ \xi_{safe}(t) = 0.$



(b) $\xi_{forward}(t) = 1,\ \xi_{energy}(t) = 0,\ \xi_{jerk}(t) = 0,\ \xi_{safe}(t) = 1.$



(c) $\xi_{forward}(t) = 1,\ \xi_{energy}(t) = 0.5,\ \xi_{jerk}(t) = 1,\ \xi_{safe}(t) = 1.$

Figure 5: Reward weighting.

Reward Example 2. In the second example, the penalty for exceeding the speed limit is added (reward weighting $[\xi_{forward}(t) = 1,\ \xi_{energy}(t) = 0,\ \xi_{jerk}(t) = 0,\ \xi_{safe}(t) = 1]$). This results in the agent actually complying with the limits (see Figure 5b).

Reward Example 3. In the third example we add the energy and jerk reward (reward weighting $[\xi_{forward}(t) = 1,\ \xi_{energy}(t) = 0.5,\ \xi_{jerk}(t) = 1,\ \xi_{safe}(t) = 1]$). This results in the agent driving more energy-efficiently and also choosing smoother accelerations (see Figure 5c).

These examples illustrate that the environment provides a basis to investigate multi-objective optimization algorithms. For such investigations the weights of the individual rewards can be used as control variables and the travel time, energy consumption and the number of speed limit violations can be used to evaluate the higher-level objectives.

5 CONCLUSION

By means of the proposed RL environment, which is being adapted to the OpenAI Gym interface, we show that it is easy to prototype and implement state-of-art RL algorithms. The LongiControl environment is suitable for various examinations: In addition to the comparison of RL algorithms for continuous and stochastic problems, LongiControl provides an example for investigations in the area of multi-objective RL, explainable RL and safe RL. Regarding the longitudinal control problem itself, further possible research objectives may be among others the comparison with planning algorithms for known routes and the consideration of very long-term objectives like arriving at a specific time.

LongiControl is designed to enable the community to leverage the latest strategies of reinforcement learning to address a real-world and high-impact problem in the field of autonomous driving.

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