Hierarchical Potential-based Reward Shaping from Task Specifications

Luigi Berducci\textsuperscript{1,}\textsuperscript{1}, Edgar A. Aguilar\textsuperscript{2,}, Dejan Ničković\textsuperscript{2}, Radu Grosu\textsuperscript{1}

Abstract—The automatic synthesis of policies for robotic-control tasks through reinforcement learning relies on a reward signal that simultaneously captures many possibly conflicting requirements. In this paper, we introduce a novel, hierarchical, potential-based reward-shaping approach (HPRS) for defining effective, multivariate rewards for a large family of such control tasks. We formalize a task as a partially-ordered set of safety, target, and comfort requirements, and define an automated methodology to enforce a natural order among requirements and shape the associated reward. Building upon potential-based reward shaping, we show that HPRS preserves policy optimality. Our experimental evaluation demonstrates HPRS’s superior ability in capturing the intended behavior, resulting in task-satisfying policies with improved comfort, and converging to optimal behavior faster than other state-of-the-art approaches. We demonstrate the practical usability of HPRS on several robotics applications and the smooth sim2real transition on two autonomous-driving scenarios for FITENTH race cars.

I. INTRODUCTION

Reinforcement learning (RL) is an increasingly popular method for training autonomous agents to solve complex tasks in sophisticated environments [1], [2], [3]. A key ingredient in RL is the reward function, a user-provided reinforcement signal, rewarding or penalizing the agent’s behavior. Autonomous agents are becoming increasingly complex and are expected to satisfy numerous, potentially conflicting requirements. Since the reward function must capture all the desired aspects of the agent’s behavior, a significant research effort has been invested in reward shaping over the past years [4], [5].

There are two major challenges in defining meaningful rewards, best illustrated with an autonomous-driving (AD) application. The first arises from mapping numerous requirements into a single scalar reward signal. In AD, there are more than 200 rules that need to be considered when assessing the course of action [6]. The second arises from the highly non-trivial task of determining the relative importance of the different requirements. In this realm, there are a plethora of regulations, ranging from safety and traffic rules, to performance, comfort, legal, and ethical requirements.

In order to address these challenges, we introduce HPRS, a novel, Hierarchical, Potential-based, Reward-Shaping technique to define the reward function from the formal requirements in a systematic fashion. We use an expressive language to formalize safety, target, and comfort requirements, and consider a task as a partially-ordered set of requirements.

In contrast to classical potential-based approaches, we exploit the partial order and the quantitative evaluation of the individual requirements in the HPRS function. Unlike multi-objective approaches, HPRS defines only one multivariate multiplicative objective, which optimizes all the requirements simultaneously. The potential formulation also allows us to provide theoretical guarantees on HPRS soundness [4]. Finally, in contrast to logic-based approaches, which compute the reward on transition sequences [7], [8], [9], we provide a reward in every time-step. This way, HPRS avoids delaying reward computation over time and mitigates the temporal credit-assignment problem, where a deferred reward is not efficiently propagated to the preceding transitions.

Our approach builds on top of three major components:

• An expressive formal specification language capturing classes of requirements that often occur in control tasks.
• An additional specification layer, allowing to group sets of requirements and define priorities among them.
• An automatic procedure for generating a reward, following the order relation among the different requirements.

The advantage of our approach is the seamless passage from task specifications to learning optimal control policies that satisfy the associated requirements, while relieving the engineer from the burden of manually shaping rewards.

We evaluated HPRS on three standard continuous-control benchmarks (lunar lander, bipedal walker classic and hardcore) and two autonomous driving scenarios (stand-alone and follow the leader). Our experimental results show that HPRS is very competitive compared to state-of-the-art approaches. Moreover, we deploy the resulting policies on FITENTH race cars [10], demonstrating the practical usability of HPRS in non-trivial real-world robotics systems.

II. MOTIVATING EXAMPLE

We motivate our work with an autonomous-driving task:

A car drives around a track delimited by walls by controlling its speed and steering angle. We say the car completes a lap when it drives around the track till its starting position.

The task has seven requirements: (1) the car shall complete 1 lap in bounded time; (2) the car shall never collide against the walls; (3) the car shall drive in the center of the track; (4) the car shall keep a speed above a minimum value; (5) the car shall keep a speed below a maximum value; (6) the car shall drive with a comfortable steering angle; (7) the car shall send smooth control commands to the actuators.

A moment of thought reveals that these requirements might interfere with each other. For example, a car always driving above the minimum speed (Requirement 4), while steering below the maximum angle (Requirement 6), would

\textsuperscript{1}Indicates authors with equal contributions
\textsuperscript{2}TU Wien, Cyber-Physical Systems Group
\textsuperscript{3}AIT Austrian Institute of Technology GmbH
have a limited-turn curvature. Any track layout containing a turn with a curvature larger than this limit would result in a collision, thus violating Requirement 2.

Furthermore, if the policy is bang-bang, that is, it drives with high-frequency saturated actuation only, the resulting behavior is uncomfortable to passengers and not transferable to real hardware because of actuator limitations. In Figure 1 we show various intended and unintended behaviors.

In this example, it also becomes evident that some requirements must have precedence over others. We consider safety as those requirements that fundamentally constrain the policy behavior, such as a catastrophic collision against the walls. Therefore, we interpret a safety violation as one compromising the validity of the entire episode. Lap completion (Requirement 1) is also a unique requirement that represents the agent’s main objective, or target, and in essence, its whole reason to be. After the safety requirement, this comes next in the hierarchy of importance. Explicitly, it means that we are willing to sacrifice the rest of the requirements (Requirements 3-7) in order to complete a collision-free lap around the track. These requirements are, therefore, soft constraints that should be optimized as long as they do not interfere with safety and target. We call them comfort.

In summary, we pose the following research question in this paper: Is there a principled way to shape an effective reward that takes into account all the task requirements in the order of importance mentioned above? In the rest of this paper, we will illustrate the necessary steps leading to a positive answer, on hand of the motivating example.

III. RELATED WORK

Specifying reward functions for decision-making algorithms is a long-studied problem in the RL community. A poorly designed reward might not capture the actual objective and result in problematic or inefficient behaviors [11]. Therefore, shaping the reward helps to effectively steer the RL agent towards favorable behaviors [4], [5].

1) RL with Temporal Logic: Much prior work adopts temporal logic (TL) in RL. Some of it focuses on the decomposition of a complex task into many sub-tasks [12], [13]. Other formulations are tailored to tasks specified in TL [14], [8], [15], [16]. We consider the problem of reward shaping in the standard cumulative RL setting. Several works exploit the quantitative semantics of TL (i.e., STL and its variants) to systematically derive a reward [7], [17], [9]. However, they describe the task as a monolithic formula and compute the reward by either looking at the complete past sequence [7], or a sub-sequence [9]. Thus, they construct sparse rewards and suffer from the credit-assignment problem. In contrast, we interpret a task as the composition of different requirements and provide a reward at every step. This approach is more in-line with cumulative RL formulations used in robotics and completely agnostic to the learning algorithm.

2) Multi-Objective RL: Multi-Objective RL (MORL) studies the optimization of multiple and often conflicting objectives. MORL algorithms learn single or multiple policies [18], [19]. There exist several techniques to combine multiple reward signals into a single scalar value (i.e., scalarization), such as linear or non-linear projections [20], [21], [22]. Other approaches formulate structured rewards by imposing or assuming a preference ranking on the objectives and finding an equilibrium among them [23], [24], [25], [26]. We focus on the single-policy setting and propose a multivariate multiplicative way to combining requirements [27]. We exploit the natural interpretation of the requirement classes to provide an unambiguous interpretation of task satisfaction, without the need to deal with Pareto-optimal solutions.

A similar approach has been proposed in [28], where the authors show that decomposing the task specification in many requirements can improve the learning process. While these approaches still rely on the arbitrary choice of weights for each requirement, we focus on defining a systematic methodology to produce a reward signal. For completeness, in the experimental phase, we compare our approach to various instances of the linear-scalarization method adopted in [28], and show the negative impact of having an arbitrary choice of static weights.

3) Hierarchically Structured Requirements.: Partially ordering requirements has been proposed before but in different settings. The rulebook formalism uses a set of prioritized requirements for evaluating behaviors produced by a planner [6], or generating adversarial tests [29]. The complementary inverse RL approach in [30] learns dependencies among formal requirements from demonstrations. However, while they learn dependencies from data, we infer them from requirement classes and use them in reward shaping.

IV. MAIN CONTRIBUTION

In this section, we present our main contribution: A method for automatically generating a reward-shaping function from a plant definition and a set of safety, target, and comfort requirements. In order to make this method accessible, we
first introduce a formal language allowing to formulate the requirements mentioned above. Our method then:

- **Step 1**: Infers the priority among requirements and formulates a task as a partially-ordered set of requirements.
- **Step 2**: Extends the plant to an MDP by adding a sparse-reward signal and the episode-termination conditions.
- **Step 3**: Extends the reward with a continuous HPRS by hierarchically evaluating the individual requirements.

### A. Requirements-Specification Language

We formally define a set of expressive operators to capture requirements often occurring in continuous-control problems. Considering atomic predicates \( p \equiv f(s) \geq 0 \) over observable states \( s \in S \), we extend existing task-specification languages (e.g., SpectRL [12]) and define requirements as follows:

\[
\begin{align*}
\varphi &\equiv \text{achieve } p \mid \text{conquer } p \\
&\quad \text{ensure } p \mid \text{encourage } p
\end{align*}
\]

Commonly, a task can be defined as a set of requirements from three basic classes: safety, target, and comfort. Safety requirements, of the form ensure \( p \), are naturally associated to an invariant condition \( p \). Target requirements, of the form achieve \( p \) or conquer \( p \), formalize the one-time or respectively the persistent achievement of a goal within an episode. Finally, comfort requirements, of the form encourage \( p \), introduce the soft satisfaction of \( p \), as often as possible, without compromising task satisfaction.

Let \( \tau = (s_0, a_1, s_1, a_2, \ldots) \) denote an episode of \( |\tau| = t \) steps, and let \( \mathbb{E} \) be the set of all such traces. Each requirement \( \varphi \) induces a Boolean function \( \sigma : \mathbb{E} \rightarrow \mathbb{B} \) evaluating whether an episode \( \tau \in \mathbb{E} \) satisfies the requirement \( \varphi \). We define the requirement satisfaction function \( \sigma \) as follows:

\[
\begin{align*}
\sigma(\text{achieve } p, \tau) &\quad \text{iff } \exists i \leq t \text{ s.t. } f(s_i) \geq 0 \\
\sigma(\text{conquer } p, \tau) &\quad \text{iff } \exists i \leq t \text{ s.t. } \forall j \geq i, f(s_j) \geq 0 \\
\sigma(\text{ensure } p, \tau) &\quad \text{iff } \forall i \leq t \text{ s.t. } f(s_i) \geq 0 \\
\sigma(\text{encourage } p, \tau) &\quad \text{iff } \text{true}
\end{align*}
\]

**Example 1:** Consider the motivating example, and let us formally specify its requirements. The state \( s = (x, y, \theta, v, \vartheta) \) consists of \( x, y, \theta \) for the car position and heading in global coordinates, \( v \) and \( \vartheta \) are the car speed and rotational velocities, respectively. The control action is \( a = (\nu, \alpha) \) where \( \nu \) denotes the desired speed, and \( \alpha \) the steering angle.

We first define: (1) \( L : S \rightarrow [0, 1] \) a lap progress function which maps the car position to the fraction of track that has been driven from the starting position; (2) \( d_{\text{wall}} : S \rightarrow \mathbb{R} \) a distance function which returns the distance of the car to the closest wall; (3) \( d_{\text{center}} : S \rightarrow \mathbb{R} \) a distance function which returns the distance of the car to the centerline; (4) the maximum deviation from the centerline \( d_{\text{conf}} \) that we consider tolerable; (5) the maximum steering angle \( \alpha_{\text{conf}} \) that we consider being comfortable to drive straight; (6) the minimum and maximum speed \( v_{\text{min}}, v_{\text{max}} \) that define the speed limits; (7) the maximum tolerable change in controls \( \Delta \alpha \) that we consider to be comfortable; Then, the task can be formalized with the requirements reported in Table I.

### B. A Task as a Partially-Ordered Set of Requirements

We formalize a task by a partially-ordered set of formal requirements \( \Phi \), assuming that the target is unique and unambiguous. Formally, \( \Phi = \Phi_S \sqcup \Phi_T \sqcup \Phi_C \) such that:

\[
\begin{align*}
\Phi_S &:= \{ \varphi \mid \varphi \equiv \text{ensure } p \} \\
\Phi_C &:= \{ \varphi \mid \varphi \equiv \text{encourage } p \} \\
\Phi_T &:= \{ \varphi \mid \varphi \equiv \text{achieve } p \lor \varphi \equiv \text{conquer } p \}
\end{align*}
\]

The target requirement is required to be unique (\( |\Phi_T| = 1 \)). We use a very natural interpretation of importance among the class of requirements, which considers decreasing importance from safety, to target, and to comfort requirements.

Formally, this natural interpretation of importance defines a (strict) partial order relation \( \prec \) on \( \Phi \) as follows:

\[
\varphi \prec \varphi' \iff (\varphi \in \Phi_S \land \varphi' \notin \Phi_S) \lor (\varphi \in \Phi_T \land \varphi' \in \Phi_C)
\]

The resulting pair \( (\Phi, \prec) \) forms a partially-ordered set of requirements and defines our task. Extending the satisfaction semantics to a set, we consider a task accomplished when all of its requirements are satisfied:

\[
\sigma(\Phi, \tau) \iff \forall \varphi \in \Phi, \sigma(\varphi, \tau).
\]

### C. MDP Formalization of a Task

We assume that the plant (environment controlled by an autonomous agent) is given as \( E = (S, S_0, A, P) \), where \( S \) is the set of states, \( S_0 \) the set of initial states, \( A \) is the set of actions, and \( P(s' | s, a) \) is its dynamics, that is, the probability of reaching state \( s' \) by performing action \( a \) in state \( s \).

Given an episodic task \( (\Phi, \prec) \) over a bounded time horizon \( T \), our goal is to automatically extend the environment \( E \) to a Markov Decision Process (MDP) \( M = (S, S_0, A, P, R) \). To this end, we define \( R(s, a, s') \), the reward associated to the transition from state \( s \) to \( s' \) under action \( a \), to satisfy \((\Phi, \prec)\).

1. **Episodes:** An episode ends when its task satisfaction is decided: either through a safety violation, timeout, or goal achievement. The goal-achievement evaluation depends on the target operator adopted: for achieve \( p \) the goal is achieved when visiting at time \( t \leq T \) a state \( s_t \) that satisfies \( p \); for conquer \( p \) the goal is achieved if there is a time \( i \leq T \) such that \( p \) is satisfied for all \( s_i, i \leq t \leq T \).

2. **Base reward:** Given task \( (\Phi, \prec) \), we first define a sparse reward incentivizing goal achievement. Let the property of the unique target requirement be \( p \equiv f(s) \geq 0 \). Then:

\[
R(s, a, s') = \begin{cases} 
1 & \text{if } f(s') \geq 0 \\
0 & \text{otherwise}
\end{cases}
\]

The rationale behind this choice is that we aim to teach the policy to reach the target and stay there as often as possible.

### Table I

| Req Id | Formula Id | Formula |
|-------|------------|---------|
| Req1  | \( \varphi_1 \) | achieve \( L(s) = 1.0 \) |
| Req2  | \( \varphi_2 \) | ensure \( d_{\text{wall}}(s) > 0 \) |
| Req3  | \( \varphi_3 \) | encourage \( d_{\text{center}}(s) \leq d_{\text{conf}} \) |
| Req4  | \( \varphi_4 \) | ensure \( v \geq v_{\text{min}} \) |
| Req5  | \( \varphi_5 \) | encourage \( v \leq v_{\text{max}} \) |
| Req6  | \( \varphi_6 \) | encourage \( |\alpha| \leq \alpha_{\text{conf}} \) |
| Req7  | \( \varphi_7 \) | encourage \( |\alpha| \leq \Delta \alpha \) |
For achieve $p$, $R$ maximizes the probability of satisfying $p$. For conquer $p$, there is an added incentive to reach the target as soon as possible, and stay there until $T$.

The associated MDP is, in principle, solvable with any RL algorithm. However, while the sparse base reward $R$ can help solving simple tasks, where the target is easily achieved, it is completely ineffective in more complex control tasks.

D. Hierarchical Potential-based Reward Shaping

The main contribution is HPRS, our hierarchical potential-based reward shaping. This signal continuously provides feedback, guiding the agent towards the task satisfaction.

We assume the predicates $p(s) = f(s) \geq 0$ to be not trivially satisfied in all the states $s$, otherwise they can be omitted by the specification. Each signal is then bounded in $[l, u]$, for $l < 0 < u$. We also define the negatively saturated signal $f_-(s) = \min(0, f(s))$, and the following two signals:

$$c(p, s) = 1 - \frac{f_-(s)}{l}, \quad b(p, s) = 1_{\geq 0}(f(s))$$

where $1_{\geq 0}(\cdot)$ is an indicator function of non-negative numbers. Both $c$ and $b$ are bounded in $[0, 1]$ where 1 denotes the satisfaction of $p$ and 0 its largest violation. However, while $c$ is a continuous signal, $b$ is discrete, with values in $\{0, 1\}$.

Using the signals $c$ and $b$, we now define the individual score $r$ for each requirement $\varphi \in \Phi$ as follows:

$$r(\varphi, s) = \begin{cases} b(p, s) & \text{if } \varphi \in \Phi_S \\ c(p, s) & \text{otherwise} \end{cases}$$

**Definition 1:** Let $(\Phi, \prec)$ be a task specification. Then the hierarchical potential function is defined as:

$$\Psi(s) = \sum_{\varphi \in \Phi} \prod_{\varphi' : \varphi' \prec \varphi} r(\varphi', s) \cdot r(\varphi, s)$$ \hspace{1cm} (3)

This potential function is a weighted sum over all requirements scores $r(\varphi, s)$. The weight of $r(\varphi', s)$ is the product of the scores $r(\varphi', s)$ of all the requirements $\varphi'$ that are strictly more important (hierarchically) than $\varphi$.

The potential is thus a multivariate signal that combines the scores with multiplicative terms [27], according to the ordering defined in the task $(\Phi, \prec)$. A linear combination of scores, as typical in multi-objective scalarization, would assume independence among objectives and would not be expressive enough to capture their interdependence [27]. Crucially, the weights dynamically adapt at every step, too, according to the satisfaction degree of the requirements.

**Corollary 1:** The optimal policy for the MDP $M'$, where its reward $R'$ is defined with HPRS as:

$$R'(s, a, s') = R(s, a, s') + \Psi(s') - \Psi(s)$$ \hspace{1cm} (4)

is also an optimal policy for the MDP $M$ with reward $R$.

This corollary shows that HPRS is preserving the policy optimality for the considered undiscounted episodic setting. It follows by the fact that $\Psi : S \rightarrow \mathbb{R}$ is a potential function (depends only on the current state), and by the results in [4].

E. Policy Assessment Metric

Since each reward formulation has its own scale, comparing the learning curves needs an external, unbiased assessment metric. To this end, we introduce a policy-assessment metric (PAM) $F$, capturing the logical satisfaction of various requirements. We use the PAM to monitor the learning process and compare HPRS to state-of-the-art approaches.

Let $\Phi = \Phi_S \cup \Phi_T \cup \Phi_P$ be the set of requirements defining the task. Then, we define $F$ as follows:

$$F(\Phi, \tau) = \sigma(\Phi_S, \tau) + \frac{1}{2} \sigma(\Phi_T, \tau) + \frac{1}{2} \sigma_{avg}(\Phi_P, \tau)$$

where $\sigma(\Phi, \tau) \in \{0, 1\}$ is the satisfaction function evaluated over $\Phi$ and $\tau$. We also define a time-averaged version for any comfort requirement $\varphi = \text{encourage } f(s) \geq 0$, as:

$$\sigma_{avg}(\varphi, \tau) = \sum_{i=1}^{\tau} 1_{\geq 0}(f(s_i)) / \tau.$$

Its set-wise extension computes the set-based average.

**Lemma 1:** Consider a task $(\Phi, \prec)$ and an episode $\tau$. Then, the following relations hold for $F$:

$$F(\Phi, \tau) \geq 1.0 \leftrightarrow \sigma(\Phi_S, \tau) \quad F(\Phi, \tau) \geq 1.5 \leftrightarrow \sigma(\Phi, \tau)$$

The proof follows from the construction of the PAM and the semantics of the task satisfaction defined in Equation 2.

V. EXPERIMENTAL RESULTS

A. Experimental Setup

To evaluate HPRS, we employ a state-of-the-art implementation of the SAC algorithm [31], [32] on five use cases: a custom driving task with single and multiple cars, respectively, the lunar-lander with an obstacle, and the bipedal-walker both in the classic and hardcore versions. In each use case, we formalize a set of requirements $\Phi = \Phi_S \cup \Phi_T \cup \Phi_P$ and derive their partially-ordered set formulation $(\Phi, \prec)$.

1) Use Cases: The safe driving task has already been presented as a motivating example. The follow leading-vehicle task consists of the extension with a non-controllable leading vehicle which the car aims to safely follow, keeping a comfortable distance to it. The agent does not access the full state but only the most-recent observations from LiDAR, noisy velocity estimates, and previous controls. The safety requirements are extended to consider the collision with the leading vehicle, and the comfort requirements consider the control requirements and encourage the car to keep a comfortable distance, without any constraints on the car speed. We formulate two safety, one target, and four comfort requirements. The lunar-lander agent’s objective is to land at the pad with coordinates $(0, 0)$. In this example, we assume infinite fuel. Landing outside of the pad is also possible. We allow continuous actions to control the lander and add an obstacle to the environment in the vicinity of the landing pad, which makes the landing task harder. We formulate two safety, one target, and two comfort requirements. The bipedal-walker robot’s objective is to move forward towards the end of the field without falling. We consider two variants of this case study: the classical one with the flat terrain; and
the hardcore one with holes and obstacles. We formulate one safety, one target, and four comfort requirements.

The formal specification of the safety, target, and comfort requirements in all use cases discussed above will be made available as an appendix of the full version of this paper.

2) Reward Baselines: We implemented HPRS as in Equation [3] We compared it with the original reward formulation, defined by experts in each environment, indicated as Shaped, and three additional baselines from state-of-the-art work:

- **TLTL** [7] specifies tasks in a bounded (Truncated) LTL variant, equipped with an infinity-norm quantitative semantics [33]. The quantitative evaluation of the episode is used as a reward. We employ the RTAMT monitoring tool to compute the episode robustness [34].

- **BHNR** [9] specifies tasks in a fragment of STL with the filtering semantics of [35]. The reward uses a sliding-window approach to produce more frequent feedback to the agent: at each step, it uses the quantitative semantics to evaluate a sequence of $H$ states.

- **MORL** [28] implements the multi-objectivization of the task and solves the multi-objective problem by linear scalarization. To assess the sensitivity to the choice of weights, we consider two variants: uniform weights $MORL(unif)$; and decreasing weights $MORL(decr.)$ where safety is more important than target, and target is more important than comfort.

**B. Experimental Evaluation**

1) Comparison to baselines: We compare HPRS to the above baselines and empirically show its superior performance in properly capturing the desired requirements. We use PAM $F$ for a sound and unbiased comparison.

$F$ allows to categorize each episode $\tau$ as: (1) satisfying safety, if $F(\Phi, \tau) \geq 1$, (2) satisfying safety and target, if $F(\Phi, \tau) \geq 1.5$, and (3) additionally maximizing comfort, if $F(\Phi, \tau)$ is close to 1.75. We emphasize that $F$ is not used for training. Hence, it should not be used to evaluate the convergence of the RL algorithm in the training process.

Figure 2 shows that HPRS has superior performance and faster convergence to task-satisfying policies, even better than the shaped reward in most of the tasks. The other approaches are not competitive to learn a policy for tasks with a high number of requirements.

2) Offline evaluation of the learned behaviors: Despite the definition of a custom metric, capturing complex behaviors with a single scalar remains challenging. For this reason, we perform an extensive offline evaluation by comparing the policies (agents) trained with HPRS against the ones trained by using the other baseline rewards. We provide evidence of the emergent behaviors in the submitted video.

We evaluate each trained policy with respect to each class of requirements in 50 random episodes. Table II reports the Success Rate for incremental sets of Safety (S), Safety and Target (S+T), Safety, Target, and Comfort (S+T+C).

| Environment          | Reward  | S Succ. Rate (%) | S+T Succ. Rate (%) | S+T+C Succ. Rate (%) |
|----------------------|---------|-----------------|-------------------|----------------------|
| Safe Driving         | Shaped  | 0.74            | 0.74              | 0.20                 |
| Safe Driving         | TLTL    | 0.38            | 0.32              | 0.10                 |
| Safe Driving         | BHNR    | 0.00            | 0.00              | 0.00                 |
| Safe Driving         | $MORL(unif)$ | 0.99        | 0.89              | 0.35                 |
| Safe Driving         | $MORL(decr.)$ | 0.96       | 0.75              | 0.33                 |
| Safe Driving         | HPRS(ours) | 0.97        | 0.73              | 0.33                 |
| Follow Leading Vehicle | Shaped  | 0.97            | 0.96              | 0.94                 |
| Follow Leading Vehicle | TLTL    | 0.94            | 0.12              | 0.06                 |
| Follow Leading Vehicle | BHNR    | 0.31            | 0.00              | 0.01                 |
| Follow Leading Vehicle | $MORL(unif)$ | 0.74       | 0.73              | 0.45                 |
| Follow Leading Vehicle | $MORL(decr.)$ | 0.82       | 0.81              | 0.47                 |
| Follow Leading Vehicle | HPRS(ours) | 1.00        | 0.99              | 0.46                 |
| Lunar Lander         | Shaped  | 0.98            | 0.74              | 0.72                 |
| Lunar Lander         | TLTL    | 0.92            | 0.00              | 0.00                 |
| Lunar Lander         | BHNR    | 0.51            | 0.49              | 0.49                 |
| Lunar Lander         | $MORL(unif)$ | 0.91       | 0.91              | 0.90                 |
| Lunar Lander         | $MORL(decr.)$ | 0.94       | 0.91              | 0.91                 |
| Lunar Lander         | HPRS(ours) | 0.91        | 0.91              | 0.89                 |
| Bipedal Walker       | Shaped  | 0.99            | 0.99              | 0.53                 |
| Bipedal Walker       | TLTL    | 0.96            | 0.45              | 0.47                 |
| Bipedal Walker       | BHNR    | 0.21            | 0.00              | 0.00                 |
| Bipedal Walker       | $MORL(unif)$ | 0.40       | 0.10              | 0.19                 |
| Bipedal Walker       | $MORL(decr.)$ | 0.43       | 0.43              | 0.20                 |
| Bipedal Walker       | HPRS(ours) | 0.96        | 0.96              | 0.48                 |
| Bipedal Walker (Hardcore) | Shaped  | 0.98            | 0.99              | 0.11                 |
| Bipedal Walker (Hardcore) | TLTL    | 0.98            | 0.00              | 0.00                 |
| Bipedal Walker (Hardcore) | BHNR    | 0.55            | 0.00              | 0.00                 |
| Bipedal Walker (Hardcore) | $MORL(unif)$ | 0.07       | 0.03              | 0.02                 |
| Bipedal Walker (Hardcore) | $MORL(decr.)$ | 0.06       | 0.03              | 0.02                 |
| Bipedal Walker (Hardcore) | HPRS(ours) | 0.85        | 0.85              | 0.44                 |

**Table II**

Evaluation of trained agents over classes of requirements: Safety (S), Target (T), Comfort (C). Results $< 5\%$ close to the best-performing reward shaping are marked in bold.

and proving their ability in trading-off the different requirements. While other baselines struggle in capturing the correct objective and do not show consistent performance across different domains, we highlight that HPRS is $< 5\%$ close to the best-performing approach in all the tasks.

Logic-based approaches, such as TLTL and BHNR, consider the task as a unique specification and result in policies that either eagerly maximize the progress towards the target, resulting in unsafe behaviors, or converge to an over-conservative behavior that never achieves task completion. This observation highlights the weakness of these approaches when dealing with many requirements, because the dominant requirement could mask out the others, even if normalized adequately to the signal domain.

Multi-objective approaches are confirmed to be sensitive to weights selection. While their performance is competitive in some of the tasks, they perform poorly in more complex ones, such as those presented in the bipedal walker.

Finally, the Shaped reward results in policies capturing the desired behavior, confirming the good reward shaping proposed in the original environments. However, considering the current training budget, HPRS produces a more effective learning signal, resulting in better-performing policies.

3) Ablation Study on Comfort Requirements: We evaluate the impact of individual requirements in the hierarchical structure of HPRS. We focus on the comfort requirements that have the least priority and thus the minor influence on the value of the final reward. Specifically, we study how the comfort requirements improve the observed comfort. We set up an ablation experiment on them and compare the performance of the resulting policies.

Table III reports the evaluation for policies trained with (+Comfort), and without (-Comfort) comfort requirements. For each seed, we collect 50 episodes and compute the ratio
of satisfaction of comfort requirements over each episode.

| Safe Driving                  | +Comfort | -Comfort |
|------------------------------|----------|----------|
| Keep the center              | 0.39 ± 0.12 | 0.33 ± 0.10 |
| Min Velocity                 | 0.48 ± 0.21 | 0.89 ± 0.06 |
| Max Velocity                 | 0.99 ± 0.01 | 0.36 ± 0.14 |
| Comfortable steering         | 0.27 ± 0.08 | 0.08 ± 0.04 |
| Smooth control               | 0.70 ± 0.07 | 0.32 ± 0.07 |

| Follow Leading Vehicle       |          |          |
|------------------------------|----------|----------|
| Min Distance                 | 0.55 ± 0.22 | 0.85 ± 0.16 |
| Max Distance                 | 0.90 ± 0.08 | 0.61 ± 0.18 |
| Comfortable steering         | 0.23 ± 0.05 | 0.15 ± 0.04 |
| Smooth control               | 0.78 ± 0.09 | 0.41 ± 0.11 |

| Lunar Lander                 |          |          |
|------------------------------|----------|----------|
| Hull angle                   | 0.99 ± 0.05 | 0.99 ± 0.02 |
| Hull angular velocity        | 0.97 ± 0.07 | 0.98 ± 0.05 |

| Bipedal Walker               |          |          |
|------------------------------|----------|----------|
| Hull angle                   | 0.80 ± 0.17 | 0.33 ± 0.27 |
| Hull angular velocity        | 1.00 ± 0.00 | 0.99 ± 0.01 |
| Vertical oscillation         | 0.98 ± 0.01 | 0.91 ± 0.11 |
| Horizontal velocity          | 0.95 ± 0.01 | 0.92 ± 0.03 |

| Bipedal Walker Hardcore      |          |          |
|------------------------------|----------|----------|
| Hull angle                   | 0.70 ± 0.13 | 0.29 ± 0.14 |
| Hull angular velocity        | 1.00 ± 0.00 | 0.99 ± 0.01 |
| Vertical oscillation         | 0.83 ± 0.06 | 0.75 ± 0.09 |
| Horizontal velocity          | 0.94 ± 0.05 | 0.81 ± 0.10 |

TABLE III
EVALUATION OF POLICIES TRAINED WITH AND WITHOUT COMFORT REQUIREMENTS (±COMFORT).

In all the tasks, introducing comfort requirements positively impacts the evaluation. While some of the requirements are almost always satisfied by both configurations, the satisfaction of other requirements significantly improves once comfort rules are introduced, denoted by an increase of the mean satisfaction and a reduction in its standard deviation. Especially in driving tasks, the smaller steering magnitude and smoother transition between consecutive controls make the policy amenable to transfer to the real-world applications.

VI. REAL-WORLD DEMONSTRATION

We validated the driving policies trained with HPRS in a real-world setting using the F1TENTH racing cars [10]. The hardware platform consists of an off-the-shelf model race car chassis Traxxas Ford Fiesta ST. Actuation is provided by a brushless DC electric motor Traxxas Velineon 3351R which is driven by a VESC 6 MkIV electronic speed controller (ESC). The distances to the walls are sensed by a Hokuyo UST-10LX LiDAR sensor and the velocity estimate is directly read from the VESC. The control loop is executed at a 10 Hz rate on a NVIDIA Jetson Xavier NX embedded computing platform. We integrate the trained agent (sim2real) in a ROS node within the F1TENTH software setup. The speed and steering commands are passed to the auxiliary nodes, which automatically compute motor rpm and servo position.

We train the policy in simulation [36], sampling the car position and the simulation parameters (e.g., mass, sensor noise, actuator gains) to robustly transfer it to the real world [37]. Figure 3 shows a successful deployment for the SafeDriving task. The attached video shows: (1) the car smoothly driving along the track, and (2) the car safely following a leading vehicle while keeping a comfortable distance.

VII. CONCLUSIONS

This paper introduced HPRS, a novel, hierarchical, potential-based reward-shaping method and tool for tasks (φ, ~), consisting of a partially-ordered set of safety, target, and comfort requirements. We showed that HPRS performs better than state-of-the-art approaches on five continuous-control benchmarks. We also demonstrated that HPRS facilitates a smooth sim2real transition on the two F1TENTH driving benchmarks. The idea of automatically shaping rewards from specifications possessing an evaluation procedure, is general, and agnostic to the plant and the RL algorithm adopted.

In subsequent work, we intend to consider more expressive operators and study the formalization of requirements beyond safety, progress, and comfort, such as the ethical, legal, and performance objectives. Both our code and the supplementary material are freely available at the following repository: [github.com/EdAlexAguilar/reward_shaping](https://github.com/EdAlexAguilar/reward_shaping)
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APPENDIX

In this appendix we provide our implementation details for the experiments and the training/evaluation. This includes the requirements and formal specifications for the lunar lander and bipedal walker studies. We also include the details of the environment modifications we did to all environments (mainly lunar lander).

Table IX includes the details of the training parameters used. For training, we evaluate the progress of the policy every 10,000 steps, and use 10 episodes for the evaluation. As mentioned in the main text, we use the SAC implementation from [32]. Table IX also reports the algorithm hyper-parameters, omitting the ones we keep to default values.

| Safe Driving | Follow Leading Vehicle | Lunar Lander + Obstacle | Bipedal Walker | Bipedal Walker (Hardcore) |
|--------------|------------------------|-------------------------|---------------|--------------------------|
| num_steps    | 1e6                    | 1e6                     | 1e6           | 2e6                      | 3e6                      |
| evaluate_every | 1e4                   | 1e4                     | 1e4           | 1e4                      | 1e4                      |
| num_eval_episodes | 10               | 10                      | 10            | 10                       | 10                       |

SAC Implementation Parameters

| buffer_size    | 3e5                    | 3e5                     | 3e5           | 1e6                      | 1e6                      |
| learning_starts | 1e2                   | 1e2                     | 1e4           | 1e2                      | 1e2                      |
| batch_size     | 256                   | 256                     | 256           | 256                      | 256                      |
| tau            | 0.005                 | 0.005                   | 0.01          | 0.005                    | 0.005                    |
| net_architecture | DEF                   | QT[256, 256], pi:[64, 64] | [400, 300] | DEF                      | DEF                      |

| Table IV | Parameters used for training all environments. Omitted values are default (DEF) and common across all environments, e.g. \( \gamma = 0.99 \), \( \text{LEARNING_RATE}=0.0003 \), \( \text{GRADIENT_STEPS}=1 \), \( \text{TARGET_UPDATE_INTERVAL}=1 \), \( \text{ENTROPY_COEFFICIENT}='\text{AUTO}' \). |

A. Safe Driving

As mentioned in the main text, the objective of this task is to complete 1 lap around the track in a safe manner. The requirements are in found in Table I of the main text, and the parameters used can be found in Table VIII. The training has been carried on in simulation using three different tracks. The cars’ starting positions and the simulation parameters have been randomly sampled at the beginning of each episode. The tracks reported in Figure 4 have been physically created in our facilities at the Technical University of Vienna: Getreidemarkt Circle (GM-C), Getreidemarkt (GM), and Treitlstrasse (TRT). For the accompanying video, we show the single-agent behavior in the GM circuit, and the follow-leading vehicle in GM-C.

B. Follow Lead Vehicle

The second driving task uses the same environment, shown in Figure 5. The agent’s objective is also to complete a single lap around a track, but this time it has to do so while following a leading vehicle. In this case, the comfort requirements are: encouraging a small steering angle \( \alpha \), encouraging smooth controls \( |a| \), and encouraging the agent to keep a distance between \([d_{\text{lead min comp}}, d_{\text{lead max comp}}]\). In contrast to the safe driving example, note that here there are no comfort requirements to keep a specific speed, nor are there comfort requirements for driving in the middle of the track. The requirements are found in Table IX and the parameters used can be found in Table X. The map used for this task is the Getreidemarkt circle (GMC), observed in Figure 4.
| Req Id | Formula Id | Formula |
|--------|------------|---------|
| Req1   | \( \varphi_1 \) | achieve \( L(s) = 1.0 \) |
| Req2   | \( \varphi_2 \) | ensure \( d_{\text{wall}}(s) > 0 \) |
| Req4   | \( \varphi_4 \) | encourage \( d_{\text{lead}}(s) \geq d_{\text{lead, min, conf}} \) |
| Req5   | \( \varphi_5 \) | encourage \( d_{\text{lead}}(s) \leq d_{\text{lead, max, conf}} \) |
| Req6   | \( \varphi_6 \) | encourage \( |a| \leq a_{\text{conf}} \) |
| Req7   | \( \varphi_7 \) | encourage \( |\alpha| \leq \alpha_{\text{comf}} \) |

**TABLE V**

**FOLLOW LEAD VEHICLE – FORMALIZED REQUIREMENTS**

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**C. Lunar-Lander with Obstacle:**

The lunar lander’s objective is to land at the pad with coordinates \((0, 0)\). In this example, we assume infinite fuel. Landing outside of the pad is also possible (as long as the impact velocity does not exceed a threshold). We allow continuous actions that allow firing the engine to the left or right, firing the main engine, and doing nothing. We add an obstacle to the environment, that makes the landing harder. The original state space of the lunar lander is the tuple \((x, y, \dot{x}, \dot{y}, \theta, \dot{\theta})\), where \((x, y)\) is the position of the lander, \((\dot{x}, \dot{y})\) is its velocity, \(\theta\) is the angle of the lander with respect to the direction of gravity \((y\text{-axis})\), and \(\dot{\theta}\) is its angular velocity. The lander also has contact sensors for both of its legs, and we further enhance the state space with the obstacle coordinates (left, right, top, bottom) and a flag variable on whether the pole has collided or not.

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**D. Bipedal-Walker:**

In this case study, the main objective for the robot is to move forward without falling. We consider two variants of this case study – the **classical** one with the flat terrain and the **hardcore** one with holes and obstacles. A state in this case study is the tuple \((\dot{x}, \dot{y}, \theta, \dot{\theta}, I)\), where \(\dot{x}\) is the horizontal velocity, \(\dot{y}\) is the vertical velocity, \(\theta\) is the hull angle, \(\dot{\theta}\) is the angular velocity and \(I\) is a vector of 10 LiDAR range-finder measurements. In the original environment, there are additional variables in the agent’s observation (e.g., joints position, joints angular speed), and we omit their definition because not used in the formalization. We did not alter the agent’s observation space for this environment. Since we wanted to showcase
the achieve specification, the environment terminates upon reaching the goal. Table XI (end of document) lists the used parameters. Figure 7 shows two frames of the normal environment, and two frames of the hardcore environment.

![Figure 7](image)

We define the following constants: (1) $O$ – the set of coordinates occupied by the static obstacle, (2) $\theta_{\text{conf}}$ – the maximum comfortable angle, (3) $\dot{\theta}_{\text{conf}}$ – the maximum comfortable angular velocity, and (4) $\dot{y}_{\text{conf}}$ – the maximum comfortable vertical velocity. Table VII lists the informal requirements collected for the bipedal walker example, and their formalization in STL.
### E. Tables of Environment Parameters

#### Safe Driving

| Parameter                  | Value                      |
|----------------------------|----------------------------|
| max_steps                  | 2500                       |
| track                      | GM                        |
| frame_skip                 | 10                        |
| terminate_on_collision     | True                       |
| dt                         | 0.01                       |

#### Reward Parameters

| Parameter                  | Value                      |
|----------------------------|----------------------------|
| comf_wall_dist             | 0.5                       |
| comf_min_vel               | 2.0                       |
| comf_max_vel               | 3.5                       |
| comf_max_steering          | 0.1                       |
| comf_max_action_norm       | 0.25                      |

#### Observation Parameters

| Parameter                  | Value                      |
|----------------------------|----------------------------|
| use_history_wrapper        | True                       |
| n_last_actions             | 3                          |
| obs_names                  | lidar_64, velocity_x      |

**TABLE VIII**

**Parameters used for the Safe Driving environment.**

#### Follow Lead Vehicle

| Parameter                  | Value                      |
|----------------------------|----------------------------|
| max_steps                  | 3000                       |
| track                      | GMC                       |
| comf_wall_dist             | 0.5                       |
| comf_min_dist_lead         | -2.0                      |
| comf_max_dist_lead         | -1.5                      |
| comf_max_steering          | 0.1                       |
| comf_max_action_norm       | 0.25                      |
| lead_min_speed             | 1.25                      |
| lead_max_speed             | 1.75                      |
| lead_observations          | lidar_64                  |

#### Leading Vehicle Parameters

| Parameter                  | Value                      |
|----------------------------|----------------------------|
| algorithm                  | “Follow the Gap”          |
| gap_threshold              | 2.0                       |
| lead_min_speed             | 1.25                      |
| lead_max_speed             | 1.75                      |

**TABLE IX**

**Parameters used for the Follow Lead Vehicle environment. Non-stated episode conditions and observation parameters are the same as the Safe driving example.**
### Lunar lander with obstacle

#### Episode Conditions

| Parameter                | Value |
|--------------------------|-------|
| max_steps                | 600   |
| terminate_on_collision   | True  |

Episode ends if lander collides with ground or with obstacle.

| Parameter                | Value |
|--------------------------|-------|
| x_limit                  | 1.0   |

Episode ends if $|x| \geq x_{\text{limit}}$.

Note: there is no $y_{\text{limit}}$.

#### Reward Parameters

| Parameter                | Value |
|--------------------------|-------|
| $x_{\text{target}}$      | 0.0   |
| $y_{\text{target}}$      | 0.0   |
| $x_{\text{target}}_{\text{tol}}$ | 0.15  |

Goal area. $G = \{ (x, 0) : |x - x_{\text{target}}| \leq x_{\text{target}}_{\text{tol}} \}$

| Parameter                | Value |
|--------------------------|-------|
| theta_target             | 0.0   |

The lander’s most comfortable angle.

| Parameter                | Value |
|--------------------------|-------|
| theta_comf                | $\pi/3$ |

Comfort limit. $|\theta - \theta_{\text{target}}| \leq \theta_{\text{comf}}$

| Parameter                | Value |
|--------------------------|-------|
| theta_dot_target         | 0.0   |

The lander’s most comfortable angular velocity.

| Parameter                | Value |
|--------------------------|-------|
| theta_dot_comf           | 0.5   |

Comfort limit. $|\dot{\theta} - \dot{\theta}_{\text{target}}| \leq \dot{\theta}_{\text{comf}}$

#### Initial Conditions

| Parameter                | Value |
|--------------------------|-------|
| $x_{\text{offset}}$      | 0.1   |

Lander’s starting $x$-position, $x_0 \in \pm x_{\text{offset}}$

| Parameter                | Value |
|--------------------------|-------|
| obstacle_left            | 0.0   |
| obstacle_right           | 0.2   |
| obstacle_bottom          | 0.53  |
| obstacle_top             | 0.46  |

Obstacle size and position is fixed.

### Table X

Parameters used for the lunar lander with obstacle environment. Non-stated parameters were not altered. Angles given in radians. Spatial coordinates normalized with default environment resolution.

### Bipedal Walker

#### Episode Conditions

| Parameter                | Value |
|--------------------------|-------|
| max_steps                | 500   |
| terminate_on_collision   | True  |

Episode ends if walker’s hull makes contact with the ground or an obstacle.

#### Reward Parameters

| Parameter                | Value |
|--------------------------|-------|
| lidar_offset             | 0.225 |

Since the LiDAR origin is inside the hull, a constant offset is considered. $l \leftarrow l_{\text{offset}}$

| Parameter                | Value |
|--------------------------|-------|
| theta_target             | 0.0   |

The hull’s most comfortable angle.

| Parameter                | Value |
|--------------------------|-------|
| theta_comf                | $0.0873$ |

Comfort limit. $|\theta - \theta_{\text{target}}| \leq \theta_{\text{comf}}$

| Parameter                | Value |
|--------------------------|-------|
| theta_dot_target         | 0.0   |

The hull’s most comfortable angular velocity.

| Parameter                | Value |
|--------------------------|-------|
| theta_dot_comf           | 0.25  |

Comfort limit. $|\dot{\theta} - \dot{\theta}_{\text{target}}| \leq \dot{\theta}_{\text{comf}}$

| Parameter                | Value |
|--------------------------|-------|
| y_dot_target             | 0.0   |

The hull’s most comfortable $y$-velocity.

| Parameter                | Value |
|--------------------------|-------|
| y_dot_comf                | 0.1   |

Comfort limit. $|\dot{y} - \dot{y}_{\text{target}}| \leq \dot{y}_{\text{comf}}$

### Table XI

Parameters used for the bipedal walker environments. Non-stated parameters were not altered. Angles given in radians. Spatial coordinates normalized with default environment resolution.