Learning Quadruped Locomotion Policies with Reward Machines

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Abstract—Legged robots have been shown to be effective in navigating unstructured environments. Although there has been much success in learning locomotion policies for quadruped robots, there is little research on how to incorporate human knowledge to facilitate this learning process. In this paper, we demonstrate that human knowledge in the form of LTL formulas can be applied to quadruped locomotion learning within a Reward Machine (RM) framework. Experimental results in simulation show that our RM-based approach enables easily defining diverse locomotion styles, and efficiently learning locomotion policies of the defined styles.

I. INTRODUCTION

Legged robot platforms have been applied to navigation tasks, such as climbing stairs, and crossing uneven terrains, where wheeled platforms are less effective. The typical robotic locomotion problem is to find a sequence of actions the robot can take to efficiently reach its destination. In this paper, we are concerned with a quadruped setting consisting of finding the correct sequence of leg movements at the joint level.

One approach to finding a quadruped locomotion method is to use Model Predictive Control (MPC) [2], where we have access to an accurate dynamics model. This can be useful in controlled environments, such as factory assembly lines, where such dynamics models are readily available. Unfortunately, it is oftentimes unrealistic to assume access to an accurate dynamics model, particularly in uncontrolled real-world environments. Consider a scenario where a quadruped is walking down a rocky hill. An accurate dynamics model might need to include surface frictions, wind speed, temperature and humidity, and even more unpredictable human behaviors around the robot. In such a scenario, estimating a sufficiently accurate dynamics model is impractical.

Researchers have used Reinforcement Learning (RL) methods [20] for quadruped locomotion, e.g., [15, 21, 17]. In those RL approaches, desired behaviors are learned through trial and error experiences. Thus, RL algorithms have been developed such that agents can use these experiences to find a locomotion method without the need of a dynamics model. Despite the desirable learning capabilities, RL-based quadruped locomotion methods present a variety of challenges. This paper is motivated by the following two issues observed in current RL-based quadruped locomotion methods. First, current methods frequently require a prohibitive amount of experience to learn good-quality policies. Second, it is difficult to specify different walking styles using current RL-based quadruped locomotion methods. This research is motivated by the above-mentioned two limitations.

In this paper, we apply RL to the problem of quadruped locomotion, while addressing the issues of learning efficiency and quadruped locomotion style specification. The issues are mitigated through the use of Reward Machines (RMs) [11]. RMs allow for task specification via a human-designed automaton over Linear Temporal Logic (LTL) formulas, which makes it easy to specify diverse locomotion behaviors. Also, RM algorithms have been developed for exploiting the provided human knowledge to improve the learning efficiency [11, 22, 18].

We ran experiments in simulation, where we trained a Minitaur quadruped robot to walk in three different styles. We demonstrate that one can easily define the walking styles. We have compared our approach to a non-RM baseline that is unable to reuse interaction experience. Results showed that our RM-based approach substantially improved learning efficiency for all walking styles.

II. RELATED WORK

Traditional approaches to legged locomotion consider using optimization methods in the presence of a dynamics model, and in some cases expert demonstrations as well [16, 13]. While proven effective in many settings, we do not have access to a dynamics model in many real-world scenarios.

There are also numerous works on application of RL for robot locomotion [21, 8, 17, 6, 5, 15]. Approaches of this type often lead to robust locomotion gaits, some of which can transfer to real robots. However, these approaches require extensive experience to train, and usually cannot leverage human knowledge (in the form of LTL or others) in the learning process. Additionally, these works do not consider non-Markovian reward functions, which allow us to express a greater diversity of locomotion behaviors.

Human knowledge has been leveraged via RL in a variety of ways [25]. In policy shaping, a human can provide feedback labels to the agent on whether the action it took was optimal [4]. In some reward shaping approaches, a human’s internal reward function, along with the environment’s reward function can both be leveraged [14, 1]. In imitation learning, policies can be learned directly via expert demonstrations [10]. There are recent methods for knowledge-based RL for real robots, e.g., [9, 12], but there is no evidence that those methods...
are effective on complex tasks such as robot locomotion [26]. In our work, we only need human knowledge in the form of LTL for task specifications.

Since the introduction of reward machines, there have been various new research directions such as learning the RM structure [24] [19], RM for partially observable environments [22], and RM for multi-agent settings [18] to name a few. As far as we know, this is the first work to apply RMs to legged locomotion – a long-standing challenge in robotics.

III. Our Approach

In this section, we present our RM-based RL approach for learning quadruped locomotion policies.

A. RL for Quadruped Locomotion

In RL, environments are modeled as an MDP in the form of $M = (S, A, T, R, \gamma)$. $S$ refers to the state space, which in our domain contains robot features including motor angles, velocities, and torques, as well as the orientation of the base of the quadruped. $A$ is the set of actions the agent can take, which we consider as target joint angles. $T : S \times A \times S \rightarrow [0, 1]$ is the transition function which outputs the probability of reaching state $s'$ given state $s$ and action $a$. $T$ is unknown to our quadruped agent, as we assume no knowledge of a dynamics model. $R : S \times A \times S \rightarrow \mathbb{R}$ is the reward received by taking action $a$ from state $s$ and ending up in state $s'$. We use the quadruped walking reward as defined by [21]:

$$R_{walk}(s) = \Delta x - |\Delta y| - E(s)$$

where $E(s) = w_c \Delta t ||\tau \cdot v||$. $\Delta x$ and $\Delta y$ refer to the change in base position over $t$ time steps. $E(s)$ is a measure of energy usage, where $\tau$ is a vector of motor torque’s per joint, and $v$ is a vector of joint velocities. $\Delta t$ refers to the number of simulation time steps, and $w_c$ is a constant which we set to 0.005 in experiments. $\gamma$ is the discount factor, which determines how valuable future reward should be considered in comparison to immediate reward.

The goal in RL is to find a policy $\pi : S \rightarrow A$ that selects actions that maximizes expected future discounted reward, given a state. Importantly, the RL agent does not have any knowledge about the transition or reward functions, and thus can only learn through trial and error experiences in the environment. Policy optimization and dynamic programming are two types of commonly used approaches for RL.

B. RM for Quadruped Locomotion

An RM is defined as the tuple $(U, u_0, F, \delta_u, \delta_r)$ [11], where $U$ is the set of automaton states, $u_0$ is the start state, $F$ is the set of accepting states, $\delta_u : U \times 2^P \rightarrow U \cup F$ is the automaton transition function, and $\delta_r : U \times 2^P \rightarrow [S \times A \times S \rightarrow \mathbb{R}]$ is the reward function associated with each automaton transition. The set $P$ contains propositional symbols, which refer to high-level events from the environment that the agent can detect.

In our domain, we consider $P = \{P_{FL}, P_{FR}, P_{RL}, P_{RR}\}$, where $p \in P$ is a Boolean variable. These indicate whether the front-left (FL), front-right (FR), rear-left (RL), and rear-right (RR) feet are in the air respectively. Note that for any $p \in P$ to be true ($L(s) = p$), the roll and pitch angles of the body must be $< 0.1$ radians, to ensure the body is not significantly tilted. The labeling function $L : S \rightarrow 2^P$ maps states from an MDP to truth values of propositional symbols. Thus, our labeling function determines which feet are in the air, based on the quadruped joint angles from the state space.

We construct a two-state automaton to encourage quadruped locomotion, which can be seen in Figure [1]. In this automaton, we want to synchronize lifting the FL leg with the RR leg, and the FR leg with the RL leg. LTL formula $P_{FL} \land P_{RR} \land \neg P_{FR} \land \neg P_{RL}$ evaluates to true only when both the FL and RR feet are in the air simultaneously, while $P_{FR} \land P_{RL} \land \neg P_{FL} \land \neg P_{RR}$ evaluates to true only when both the FR and RL feet are in the air simultaneously.

More precisely, we have $U = \{q_0, q_1\}$, $u_0 = q_0$, and $F = \emptyset$. The two states correspond to which combination of feet were previously in the air. If the agent is in state $q_1$, then $P_{FL} \land P_{RR} \land \neg P_{FR} \land \neg P_{RL}$ must have been evaluated as true at some point earlier. We leave $F$ empty, as this locomotion task has an infinite horizon. We present $\delta_u$ below, which defines all automaton transitions:

$$\delta_u(q_0, \neg(P_{FL} \land P_{RR} \land \neg P_{FR} \land \neg P_{RL})) = q_0$$
$$\delta_u(q_0, P_{FL} \land P_{RR} \land \neg P_{FR} \land \neg P_{RL}) = q_1$$
$$\delta_u(q_1, \neg(P_{FR} \land P_{RL} \land \neg P_{FL} \land \neg P_{RR})) = q_1$$
$$\delta_u(q_1, P_{FR} \land P_{RL} \land \neg P_{FL} \land \neg P_{RR}) = q_0$$

Note that when we do not change to the desired “pose”, or desired combination of feet in the air, we have self-loops to remain in the current automaton state. Lastly, we present $\delta_r$, which defines the reward functions associated with each automaton transition:

$$\delta_r(q_0, \neg(P_{FL} \land P_{RR} \land \neg P_{FR} \land \neg P_{RL})) = R_{walk}(s, \cdot)$$
$$\delta_r(q_0, P_{FL} \land P_{RR} \land \neg P_{FR} \land \neg P_{RL}) = R_{walk}(s, \cdot)$$
$$\delta_r(q_1, \neg(P_{FR} \land P_{RL} \land \neg P_{FL} \land \neg P_{RR})) = R_{walk}(s, \cdot)$$
$$\delta_r(q_1, P_{FR} \land P_{RL} \land \neg P_{FL} \land \neg P_{RR}) = R_{switchPoseBonus}(s, b)$$

For each environment step the agent takes, the agent evaluates which automaton state transition to take via $\delta_u$, and receives reward via $\delta_r$. In our domain, $\delta_r$ will return the reward computed by $R_{walk}$, except when we complete a sequence of two poses. Then, $\delta_r$ returns the reward computed by $R_{switchPoseBonus}$:

$$R_{switchPoseBonus}(s, b) = b \cdot \tanh(\Delta x \cdot 10) - b \cdot \tanh(|\Delta y| \cdot 10)$$

We add this bonus reward in order to encourage the sequence of poses specified by the LTL formulas. Note that the bonus reward defined by $R_{switchPoseBonus}$ is scaled based on how far we are moving in the x direction, and penalized by moving in the y direction. We use the tanh function, because it will squeeze the x and y distances we travel in the range (-1, 1), which can appropriately scale the proportion of bonus
C. Specification of Diverse Quadruped Behaviors

Via RMs, we specify three different quadruped locomotion styles: Diagonal, Gallop, and Dog, where the Diagonal style corresponds to what is described in Section III-B. For the Gallop style, we synchronize lifting the FL leg with the FR leg, and the RR leg with the RL leg.

To construct an RM to encourage the Gallop locomotion style, we simply replace \( P_{FL} \land P_{RR} \land \neg P_{FR} \land \neg P_{RL} \) from Equations 1, 2, 5 and 6 with \( P_{FL} \land P_{FR} \land \neg P_{RR} \land \neg P_{RL} \), and replace \( P_{FR} \land P_{RL} \land \neg P_{FL} \land \neg P_{RR} \) from Equations 3, 4, 7 and 8 with \( P_{RR} \land P_{RL} \land \neg P_{FR} \land \neg P_{FL} \).

For the Dog style, we synchronize lifting the FL leg with the RL leg, and the FR leg with the RR leg. Accordingly, we just need to replace \( P_{FL} \land P_{RR} \land \neg P_{FR} \land \neg P_{RL} \) from Equations 1, 2, 5 and 6 with \( P_{FL} \land P_{RL} \land \neg P_{FR} \land \neg P_{RR} \), and replace \( P_{FR} \land P_{RL} \land \neg P_{FL} \land \neg P_{RL} \) from Equations 3, 4, 7 and 8 with \( P_{FR} \land P_{RR} \land \neg P_{FL} \land \neg P_{RL} \).

We find it necessary to have non-Markovian reward functions in order to be able to specify a diverse set of quadruped locomotion styles. This highlights the importance of using RMs, as they are designed to express non-Markovian reward functions. The resulting reward function that encourages Diagonal locomotion style without the use of RMs is defined in Equation (9). This function can also specify different locomotion styles by replacing LTL formulas. While this shows we can also specify diverse locomotion styles without RMs, the RM is necessary to be able to efficiently learn from such specifications.

IV. Experiments

We use a PyBullet\[3\] Minitaur environment, called \texttt{MinitaurBulletEnv-v0}\[4\], where a Minitaur robot with 8 joints is being simulated. This environment considers locomotion at the joint level. The simulator converts target joint angles from the action space to torque values before executing the action. We set \( \gamma = 0.99, b = 10000 \), and replace the reward function defined by the PyBullet environment with an RM for each of the walking styles.

As a baseline, we run Soft Actor Critic (SAC)\[7\] on the Minitaur environment, with \( R_{\text{NonMarkovWalk}} \) as the reward function. The RM approach also runs SAC, but differs from the baseline in that it uses the RM defined in figure 1 to construct a cross-product MDP. Although the baseline and RM approaches have different state spaces, the reward function is the same with respect to quadruped behavior. Both approaches get the same step-wise rewards defined by \( R_{\text{walk}} \) and the same pose switching bonuses defined by \( R_{\text{SwitchPoseBonus}} \). With respect to the state space of the baseline, this reward function is non-Markovian, and needs a history of states to be computed, as seen in \( R_{\text{NonMarkovWalk}} \). This same reward function is Markovian with respect to the cross-product state space the RM approach uses, as the current automaton state is considered in its state space.

Another difference with the RM approach is the use of the CRM algorithm, which exploits the RM to learn from counterfactual examples. For example, if \( P_{FR} \land P_{RL} \land \neg P_{FL} \land \neg P_{RR} \) evaluates to true, even if the agent is in state \( q_0 \), we still evaluate \( R_{\text{SwitchPoseBonus}}(s, 10000) \) and add a sample with this “fake” reward to the replay buffer, despite the agent not seeing the state before.
\[
R_{\text{NonMarkovWalk}}(s_t) = \begin{cases} 
R_{\text{SwitchPoseBonus}}(s_t, 10000) \\
R_{\text{walk}}(s_t)
\end{cases}
\]

\[
L(s_t) = P_{FR} \land P_{RL} \land \neg P_{FL} \land \neg P_{RR}, \\
L(s_i) = P_{FL} \land P_{RR} \land \neg P_{FR} \land \neg P_{RL}, \\
L(s_j) \neq P_{FR} \land P_{RL} \land \neg P_{FL} \land \neg P_{RR}, \quad \forall j \in \mathbb{N} > i, j < t \quad (9)
\]

\[\text{Fig. 2: Reward curves for } \text{Diagonal, Gallop, and Dog locomotion styles. The RM approach more efficiently learns locomotion across all styles.}\]

\[\text{Fig. 3: Top row is } \text{Diagonal locomotion style. Middle row is Gallop locomotion style. Bottom row is Dog locomotion style. First column is time step zero, middle column is time step one, last column is time step two. Red circles indicate points of foot contact.}\]

We hypothesize the RM approach was able to learn locomotion behaviors for all styles more efficiently due to the fact that the RM approach can more easily learn to achieve the bonus reward when transitioning from \(q_1\) to \(q_0\), as the CRM algorithm learns from samples where \(P_{FR} \land P_{RL} \land \neg P_{FL} \land \neg P_{RR}\) is true but the agent is in state \(q_0\). The reward is harder to find for the baseline, as its state space does not encode the current automaton state, and can only learn from the bonus when the agent actually receives it. This is reflected in the reward curves, where particularly in the beginning training episodes, the baseline consistently takes longer to learn anything.

Additionally, SAC expects to be learning from a Markovian reward function, as the policy takes an action given a single state. This is an issue for the baseline, but not for RM, as the baseline reward function is non-Markovian with respect to its state space, while the reward is Markovian with respect to the RM’s state space.

\[\text{V. CONCLUSION AND FUTURE WORK}\]

We specify various quadruped locomotion styles via an automaton over simple LTL formulas. We use RM to efficiently learn and specify these diverse walking gaits in experiments simulating a Minitaur robot. Our results indicate that RMs are useful in learning such locomotion behaviors when compared to a baseline.

In the future, we will test the learned locomotion policies on a real quadruped robot. It is very likely that the learned policies will suggest motions that violate the robot’s kinematic constraints. In that case, we will iterate over adding more constraints.

\[
L(s_t) = P_{FR} \land P_{RL} \land \neg P_{FL} \land \neg P_{RR}, \\
L(s_i) = P_{FL} \land P_{RR} \land \neg P_{FR} \land \neg P_{RL}, \\
L(s_j) \neq P_{FR} \land P_{RL} \land \neg P_{FL} \land \neg P_{RR}, \quad \forall j \in \mathbb{N} > i, j < t \quad (9)
\]
constraints to the PyBullet environment and testing the learned policies in the real world.

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