Aiding reinforcement learning for set point control

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Abstract:
While reinforcement learning has made great improvements, state-of-the-art algorithms can still struggle with seemingly simple set-point feedback control problems. One reason for this is that the learned controller may not be able to excite the system dynamics well enough initially, and therefore it can take a long time to get data that is informative enough to learn for good control. The paper contributes by augmentation of reinforcement learning with a simple guiding feedback controller, for example, a proportional controller. The key advantage in set point control is a much improved excitation that improves the convergence properties of the reinforcement learning controller significantly. This can be very important in real-world control where quick and accurate convergence is needed. The proposed method is evaluated with simulation and on a real-world double tank process with promising results.

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1. INTRODUCTION

During the last decade, reinforcement learning (RL) has made significant improvements, resulting in for example computers playing GO (Silver et al., 2016), Atari games (Mnih et al., 2015) and even realistic driving games (Wurman et al., 2022), performing beyond human-level. This has also led to an increased interest in applying RL to nonlinear control problems. In this paper the focus will be on set point control. In this case (model-free) RL-methods can be seen as (direct) nonlinear adaptive control methods (Krstić et al., 1995; Åström and Wittenmark, 2013), and the same effects that limit adaptive control are likely to affect RL. In this paper it will indeed be seen that even for the relatively simple problem of level control in a cascaded double tank process, state of the art RL-methods may require long times to learn, sometimes they even fail completely. While there are several reasons why RL-methods struggle, this paper argues that one major reason is that they initially provide limited excitation of different amplitudes, and it is shown by experiments that this problem can be mitigated by the introduction of a simple guiding feedback controller.

In system identification and adaptive control it is well-known that in order to learn how to control a system, the data collected must excite the system dynamics. In RL this is called exploration. There is a vast literature on exploration in RL, cf. (Jin et al., 2020; Tang et al., 2017; Nair et al., 2018), but the practical state of the art algorithms for deep RL often just add white probing noise to the input, either explicitly (Fujimoto et al., 2018; Silver et al., 2014) or implicitly via a stochastic control policy (Schulman et al., 2017; Haarnoja et al., 2018). While this is an efficient way to excite different frequencies, it does not by itself ensure that the system gets excited in amplitude, even though this is important for nonlinear systems, cf. (Wigren, 1993).

In adaptive set-point control of nonlinear systems, the amplitude excitation is crucial, since the controller should learn how to handle different reference levels. This control objective is often called multi-goal in RL (Plappert et al., 2018). One problem for RL in such a setting is that it begins the learning without any prior knowledge. Hence, initially the RL-controller uses more or less white noise as input. The data collected in this way will typically not excite amplitudes sufficiently in the whole range of the control objective, therefore it can take a long time for the RL controller to learn even how to move towards the reference level. There is also a risk that the controller ends up in a saturated state, where the white probing noise has no effect on the output, which again leads to insufficient excitation. However, the problem of moving in the general direction of the reference signal is handled by feedback control, and it is often sufficient to use a roughly tuned proportional (P) controller to achieve the purpose.

This paper thus contributes by augmentation with a prior guiding feedback controller to any standard RL method. This controller ensures that the process react to commanded set point changes from the start, thereby providing the amplitude excitation needed for the RL-method to learn a good control policy. The paper argues that a simple P-controller is often sufficient, as illustrated by simulations and experiments on a real-world process.
other words, a simple feedback controller can ensure that the output will change when the set point changes, thus giving a more efficient exploration of different amplitudes. Note that the cascaded tank process used in the paper could be controlled with PID control. However, the scope of the paper is not to advocate RL for set-point control for mildly nonlinear processes, it is rather to demonstrate that set-point controlling RL methods need improvements also for such mildly nonlinear processes, to perform reasonably well. The proposed enhancements of the paper are therefore believed to become critical when RL is applied to set point control of severely nonlinear systems.

While the proposed guiding feedback controller can be combined with any RL-method, the PPO-method by Schulman et al. (2017) is used in this paper. One reason for this is that PPO is constructed so that each adaptiveupdate of the control policy is limited in size, and therefore the risk that the training process immediately forgets about the prior controller is reduced.

There are prior work with similar ideas. In (Silver et al., 2018) and (Johannink et al., 2019), prior controllers in the form of ad-hoc algorithms or model-based predictive control in a fixed-goal/set point setting were used. In this paper the focus is on the excitation of amplitudes, and it is argued that even simpler strategies can improve RL-methods substantially. It can also be noted that in these prior works off-policy RL-methods are used, and the performance of the adaptive controller tends to first degrade compared to the prior controller before it starts to improve again. In this paper the experiments indicate that when the prior controller instead is combined with PPO, the performance tends to improve from the first update of the control policy.

The paper is organized with the problem statement in Section 2, followed by a brief review of RL combined with a discussion on the exploration/excitation problem in Section 3. The proposed method is given in Section 4, and is experimentally evaluated in Section 5 and 6. Finally conclusions are found in Section 7.

2. PROBLEM STATEMENT

Consider a discrete-time nonlinear state space model

\[
x_{t+1} = f(x_t, u_t, w_t) \\
y_t = h(x_t)
\]

where \( f \) and \( h \) are unknown functions, \( x_t \in \mathbb{R}^{n_x} \) is the current state of the system, \( u_t \in \mathbb{R}^{n_u} \) is the input, \( y_t \in \mathbb{R}^{n_y} \) is the output, \( w_t \in \mathbb{R}^{n_w} \) is the system noise, and \( t \) is the time step.

The problem considered in the paper is to use RL to train a state feedback set point control policy,

\[
u(t) = g(x_t, y_t^{\text{ref}})
\]

to make the output \( y_t \) track a reference level \( y_t^{\text{ref}} \). In order to allow for varying set points, the framework of multi-goal RL will be utilized.

3. MULTI-GOAL REINFORCEMENT LEARNING

In multi-goal RL, the aim is to find a goal-conditioned policy that maximizes the discounted future return

\[
G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1},
\]

where \( \gamma \) is a discount factor, and \( r_t = R(x_t, u_t, y_t^{\text{ref}}) \) is a scalar reward (negative cost). In the standard RL-setting, the reward is typically determined by the state \( x_t \) and the input \( u_t \) alone. This would however restrict the controller to handle a fixed set point, so here \( y_t^{\text{ref}} \) is included to allow for arbitrary and varying set points. This setting is sometimes called multi-goal RL (Plappert et al., 2018), where the set points \( y_t^{\text{ref}} \) are the goals.

In model-free RL the policy is trained without explicitly identifying the system dynamics of (1), and it is thus related to direct adaptive control (Åström and Wittenmark, 2013). During training new samples are collected while the current control policy is running on the system, i.e. in closed-loop. This data is then used in order to improve the policy.

3.1 Exploration

In system identification and adaptive control, it is well known that the system dynamics must be excited. Two common ways to achieve such exploration are to either use a deterministic control policy and add random probing noise or to directly train a stochastic policy where the variance gives excitation of different frequencies.

In this paper a stochastic policy will be utilized during training. That is, the policy can be seen as a distribution \( \pi_\theta(u_t|x_t, y_t^{\text{ref}}) \), where \( \theta \) is the parameter vector to be trained. For example, the input \( u_t \) can be drawn from a Gaussian distribution with mean \( \theta(x_t, y_t^{\text{ref}}) \) and standard deviation \( \sigma_\theta \). Alternatively, it can be seen as a deterministic control policy with added probing noise,

\[
u_t = \theta(x_t, y_t^{\text{ref}}) + \varepsilon_\theta
\]

where \( \varepsilon_\theta \) is zero mean probing noise with standard deviation \( \sigma_\theta \). Note that since the standard deviation depends on \( \theta \), it can be adjusted adaptively during training. This is somewhat related to the dual control problem in optimal control (Åström, 1970; Florentin, 1962).

While well-chosen zero mean probing noise \( \varepsilon_\theta \) can ensure good excitation of different frequencies, the excitation of different amplitudes is also important in training set point controllers for nonlinear systems. In closed-loop system identification, this can be achieved by regularly changing the set point \( y_t^{\text{ref}} \) to random levels. However, in RL the problem is that initially the mean \( \theta(x_t, y_t^{\text{ref}}) \) is typically a random control policy, so it will not necessarily react to changes in the set point, and therefore the collected data does initially not excite different amplitudes sufficiently. In Section 4 a method to overcome this problem is presented.

3.2 Universal value functions

An important concept in RL is the state-value function, which is the expected value of \( G_t \) in (4). This shows how rewarding the current state is in terms of expected future returns. In order to handle the multiple-goal setting, the value function can be extended to the universal value function (Schaul et al., 2015), which depends not just on the state, but also the set point \( y_t^{\text{ref}} \), and is defined as
\[ V_{\sigma}(x_t, y_t^{ref}) = E_{\sigma}[G_{t} | x_t, y_j^{ref}], \quad (6) \]

where \( E[\cdot] \) denotes the expected value while using policy \( \pi \) and \( t \) is any time step. Similarly, the so called Q-value function, estimating the value of a state-input pair, is defined as

\[ Q_{\sigma}(x_t, u_t, y_t^{ref}) = E_{\sigma}[G_{t} | x_t, u_t, y_t^{ref}], \quad (7) \]

which indicates the expected value starting from the state \( x_t \) with input \( u_t \), and after that following the policy \( \pi \). When improving the policy, it is relevant to know how much better a specific input is in terms of a certain state as compared to the input given by the current policy. The advantage function is defined as

\[ A_{\sigma}(x_t, u_t, y_t^{ref}) = Q_{\sigma}(x_t, u_t, y_t^{ref}) - V_{\sigma}(x_t, y_t^{ref}), \quad (8) \]

and it corresponds to how much better the input \( u_t \) is than taking an input \( u \) from the policy distribution \( \pi \). The value functions \( V_{\sigma} \), \( Q_{\sigma} \) and \( A_{\sigma} \) can be estimated, for example, using Monte Carlo methods or Temporal-Difference Learning algorithms (Sutton and Barto, 2018). There are several choices for the advantage estimator. The estimator used in this paper is the generalized advantage estimator (Schulman et al., 2016) to reduce the variance.

### 3.3 Policy Gradient Methods

Policy Gradient (PG) algorithms are a class of model-free RL algorithms that directly optimize the policy \( \pi_\theta \) with respect to \( \theta \), with the goal of finding a policy that maximizes \( J(\theta) = V_{\pi_\theta}(x_t, y_t^{ref}) \). According to the policy gradient theorem with advantage functions (Sutton and Barto, 2018), the gradient can be computed as

\[ \nabla J(\theta) = E_{\pi_\theta}(A_{\pi_\theta}(x_t, u_t, y_t^{ref}) \nabla \log \pi_\theta(u_t | x_t, y_t^{ref})) , \quad (9) \]

where \( E_{\pi_\theta}[\cdot] \) indicates the expectation over the state-input pairs distribution under the policy \( \pi_\theta \). Thus, a commonly used gradient estimator has the form,

\[ \hat{g} = \hat{E}_{\pi_\theta} \left[ \hat{A}_{\pi_\theta}(x_t, u_t, y_t^{ref}) \nabla \log \pi_\theta(u_t | x_t, y_t^{ref}) \right] , \quad (10) \]

where \( \hat{E}_{\pi_\theta}[\cdot] \) denotes the empirical average over a batch of samples and \( \hat{A} \) is an estimator of the advantage function. In implementations, the gradient can be automatically computed by automatic differentiation software, e.g., PyTorch (Paszke et al., 2019), through constructing a surrogate objective function,

\[ J^{PG}(\theta) = \hat{E}_{\pi_\theta} \left[ \hat{A}_{\pi_\theta}(x_t, u_t, y_t^{ref}) \log \pi_\theta(u_t | x_t, y_t^{ref}) \right] , \quad (11) \]

whose gradient is the gradient estimator \( \hat{g} \). One of the most popular PG-algorithms is the PPO-algorithm (Schulman et al., 2017), which clip the criterion (11) to limit the step of the policy update. In should be noticed that, in the paper, unlike in PPO, the stochastic policy is only used during the training process.

### 4. PROPOSED METHOD

In standard RL, it is typical to start the training from an initial random control policy. This means that initially the controller does not react in a systematic way to changes in the set point, and therefore the collected data may not not excite the system well in amplitude, even if random set points are used.

However, even with limited knowledge about the system it is often possible to design a controller that at least will

![Fig. 1. Block diagram of the closed loop system using the proposed method.](image-url)
Algorithm 1 Residual Multi-goal Reinforcement Learning

\textbf{Input:} Policy \( \pi_\theta \), prior controller \( g^o \), goal space \( \mathcal{G} \)

1: \textbf{for} iteration=1, 2, \ldots \textbf{do}
2: \hspace{1em} Start collecting data with \( M \) different goals
3: \textbf{for} \( m = 1, 2, \ldots, M \) \textbf{do}
4: \hspace{2em} Sample \( y^m_{\text{ref}} \) from \( \mathcal{G} \) uniformly
5: \hspace{2em} Sample initial state of dynamic system \( x_0 \) (for real-world systems, just start from whatever state the system is in)
6: \hspace{2em} \textbf{for} \( t = 0 \ldots T - 1 \) \textbf{do}
7: \hspace{3em} Get prior input \( u^o_t = g^o(x_t, y^m_{\text{ref}}) \)
8: \hspace{3em} Sample input from policy distribution \( \pi_\theta \) by \( \delta^u_t \sim \mathcal{N}(0, \sigma(\mathcal{G})) \)
9: \hspace{3em} Apply the input \( u_t = u^o_t + \delta^u_t \)
10: \hspace{3em} Get next state \( x_t \) from dynamics and reward signal \( r_t \) from reward function
11: \hspace{2em} Store \( (x_t, y^m_{\text{ref}}, u_t, x_{t+1}, r_t) \)
12: \textbf{end for}
13: \textbf{end for}
14: Optimize \( \theta \) using RL algorithm, e.g., PPO.
15: \textbf{end for}

5. EXPERIMENTS

The above ideas were evaluated on a cascaded double tank system, both in simulation and in real-world. The reward function is the negative value of the absolute distance to the reference signal and the reference signal is generated randomly at the beginning of the episode. As for the evaluation, due to the random set points for each episode, Monte Carlo simulations are performed with 100 runs to compute the expected performance. A modified version of Stable-Baselines3 (Raffin et al., 2019) was used for the implementation.

Water Level Control with Simulation The water tank system consists of two identical tanks mounted on top of each other. As depicted in Fig. 2, the water flows into the upper tank with the flow controlled by an electrical pump. There is a small hole in the bottom of each tank, so the water can flow from the upper tank to the lower tank and from the lower tank to the container below the tank system. The input signal \( u_t \) is the voltage applied to the pump and the goal is to keep the water at a certain level in the second tank.

Below the notation that \( x(t) \) is the signal at continuous time \( t \), while \( x_t \) is the signal at the \( t \)th discrete time-step is used, and for the example the sampling period is set to 2 seconds.

The state of the system contains the water levels of the two tanks,
\[
x(t) = [x_1(t) \ x_2(t)]^T
\]
and the output is
\[
y(t) = x_2(t) \tag{15}
\]
A standard model (Wigren and Schoukens, 2013) for this system is given by
\[
x_1(t) = \frac{a_1}{A_1} \sqrt{2g x_1(t)} + \frac{K_{\text{pump}}}{A_1} V_p(t),
\]
\[
x_2(t) = \frac{a_1}{A_2} \sqrt{2g x_1(t)} - \frac{a_2}{A_2} \sqrt{2g x_2(t)} \tag{16}
\]

Fig. 2. The water tank process.

where \( K_{\text{pump}} \) is the pump constant, \( V_p \) is the voltage, \( a_1 \) and \( a_2 \) are the areas of the holes, \( A_1 \) and \( A_2 \) are the areas of the cross sections of the tanks.

The values of the parameters of the model are the measured parameters from the real-world water tank with the ratio of the area of holes and the area of the cross sections of the tank being \( a/A = 0.0019 \), and the range of input voltage from the pump being [0, 10] V. The pump constant is 0.12 cm/Vs. The initial levels of the two tanks and the reference signal are generated uniformly between 0 and 10 cm at the beginning of each episode, which by itself gives some extra amplitude excitation. The reference signal was changed every 400 s. The prior policy for this task is a discrete-time proportional controller,
\[
u^o_t = g^o(x_t, y^m_{\text{ref}}) = -K_p(y^m_{\text{ref}} - y_t) + u_0 \tag{17}
\]
with \( K_p = 2 \) and \( u_0 = 5 \). Note that this is not a well-tuned P controller. The purpose of these experiments is not to compare the use of a P controller with RL methods, the purpose is instead to show the the inclusion of a roughly tuned prior P controller can improve standard RL methods substantially.

Real-world Water Tank Level Control The setup for the real water tank is the same as for the simulated one, with a sampling period of 2 seconds and a prior P-controller. However, the system is a bit different since the real tank can overflow. In addition, when the upper tank overflows, parts of the water enter the lower tank, and the rest flows to the container. This is not taken into account in simulations. Also, instead of using measured water levels as output, the sensors give noisy voltage measurements instead of the true water levels in each tank. The voltages of the sensors are proportional to the water levels.

5.1 Policy Network and Training Details

For consistency, the same actor-critic architecture is used for PPO agents with or without a prior controller. The network for the residual policy consists of three fully connected layers of 128 units each with a tangent function as a nonlinear activation function except for the last layer. In all tasks, the inputs are normalized to lie between -1 and
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5. EXPERIMENTS
15: Optimize
9: Sample initial state of dynamic system
8: Sample input from policy distribution
7: Store (x_t, r_t) = (x_t, V_t)
6: Start collecting data with (x_t, r_t)
5: For each update, the training samples contain M = 5 different reference signals. The hyperparameters of the PPO algorithm are tuned following the recent study on Deep RL reproducibility by Andrychowicz et al. (2021), with GAE parameter λ = 0.97, discount factor γ = 0.99, clipping parameter ϵ = 0.2 and coefficients in complete objective c_1 = 1.0, c_2 = 0.02.
4: The agents are evaluated 10 times, with seeds from 1 to 10. Unlike in (Silver et al., 2018), where the value function estimator is trained alone for a "burn in" period while leaving the policy fixed, the value function estimator starts from scratch.
3: In this section, the results for PPO are compared with ResidualPPO, where PPO is augmented with a prior P-controller as proposed in Section 4. All empirical results are presented with mean and standard deviation across 10 random seeds. It is again noted that the cascaded tank process can be well controlled e.g. with PID control. Thus, it is stressed that the purpose here is to demonstrate the need for aiding control when RL is used.
2: Water Level Control with Simulation
1: Both PPO and ResidualPPO achieve the ability to deal with varying level control, but ResidualPPO requires fewer training samples and shows a smaller training variance. As shown in Fig. 3a, the PPO algorithm needs 20000 to 25000 samples to reach the P-controller’s performance, which is the initial performance of the ResidualPPO.
Note that although the value function approximator is initialized with poor performance with no pre-train period, there is no drop in performance of the ResidualPPO during training unlike in (Silver et al., 2018). One explanation may be that the PPO is an on-policy algorithm and the agent is trained using 5 different reference levels for each update. Also, as mentioned in Section 4.1, the clipped surrogate objective in PPO avoids the large step between a new policy and the old one. It can be seen that from Fig. 3b that both PPO and PPO with a P-controller perform well reaching the reference levels, [2, 6, 9, 4, 1]. It may be noted that ResidualPPO has a small overshoot, but this actually results in a slightly higher reward than for the PPO.

6.2 Real-world Water Tank Level Control

As shown in Fig 3, ResidualPPO and PPO with different training samples are tested to track different reference levels in the second tank. The ResidualPPO improves the performance, and with more training samples it is able to track various reference signals at a smaller cost. By contrast, PPO without any prior controller fails this task when using 15000 training samples.

It can be noted that PPO seems to find a policy that always maximizes the input after the first 5000 samples. From this controller, the new data that is collected is noninformative regarding the exciting system dynamics. Even though white probing noise is added during training, it is in a saturated state of the system, so the output will not change significantly. The residual version however will get data that excites different amplitudes immediately, and can thus learn a better policy faster.

7. DISCUSSION AND CONCLUSION

The paper argues that when RL-methods are applied to set point control problems, the inclusion of a conventional feedback controller can improve the learning of a control policy. The numerical experiment also shows that with the prior policy the RL-method requires fewer training samples and gives a more stable training performance than the standard RL-method. One reason is that the prior policy gives better amplitude excitation for changing set points, and thus more relevant training data.

When applied to real world data the aiding controller enables the RL controller to converge to a well performing closed loop system, while un-aided RL controller gets stuck in a saturated state.

Interesting topics for further research include stability analysis of control loops employing the proposed methods. The basic idea can also be expanded in several directions, deriving other adaptation schemes. It would also be interesting to compare the performance of the proposed RL method, to classical nonlinear control schemes, from nonlinear optimal control or the geometric field of nonlinear control.

REFERENCES


Interesting to compare the performance of the proposed RL algorithm with deriving other adaptation schemes. It would also be interesting to analyze of control loops employing the proposed methods. The policy gives better amplitude excitation for changing set points, and thus more relevant training data.

The paper argues that when RL-methods are applied to set point control problems, the inclusion of a conventional feedback controller can improve the learning of control loops. A conventional controller can thus learn a better policy faster.

Even though white probing noise is added during training, it is in a saturated state of the system, so the output will not be meaningful. From this controller, the new data that is collected is used to update the policy.

As shown in Fig 3, ResidualPPO improves the performance over PPO. ResidualPPO has a small overshoot, but this actually helps in learning. Note that although the value function approximator is initialized with poor performance with no pre-train period, it may be that the PPO is an on-policy algorithm and the surrogate objective in PPO avoids the large step between a pre-trained policy and the new policy.

The ResidualPPO improves the performance of the system. It may be noted that ResidualPPO has a small overshoot, but this actually helps in learning. By initializing with poor performance with no pre-train period, it may be that the PPO is an on-policy algorithm and the surrogate objective in PPO avoids the large step between a pre-trained policy and the new policy.

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