

# Supplementary material for “Continuous-action planning for discounted infinite-horizon nonlinear optimal control with Lipschitz values”

## List of main notations

$x, X, u, U$	state, state space, action, action space
$f, \mathbf{u}$	dynamics, sequence of actions
$\gamma, r, \rho, v$	discount factor, reward, reward fcn., value
$L_f, L_\rho, L_v$	Lipschitz constants of respective fcn.
$\mathcal{U}$	box in the space of action sequences
$i, k; i^\dagger, k^\dagger$	box and dimension indices; selected indices
$K$	number of discretized box dimensions
$\mu, d$	action interval, interval length
$n$	computation budget
$M$	number of subintervals for splitting
$\mathcal{T}, \mathcal{T}^*, \mathcal{L}$	tree, near-optimal tree, set of leaves
$h, s$	depth in tree, number of splits
$b(i), \delta(i)$	b-value, diameter of box $i$
$m$	branching factor of near-optimal tree
$h_{\max}(n)$	maximum depth function
$\tau, c, C$	constants
$O(\cdot), \tilde{O}(\cdot)$	bounded by $\cdot$ up to const., log. terms
$\lceil \cdot \rceil$	ceiling (smallest integer still larger than $\cdot$ )
$\text{diag}[\cdot]$	diagonal matrix with $\cdot$ on diagonal

## A Proofs

*Proof of Lemma 3:* We will prove the inequality from the theorem for any two sequences  $\mathbf{u}_\infty$  and  $\mathbf{u}'_\infty$ , which directly implies it for the particular case  $\mathbf{u}'_\infty = \mathbf{u}_\infty^*$  from (3). Denote by  $x_k, x'_k, r_k, r'_k$  for  $k \geq 0$  the state and reward trajectories generated by the two sequences, with  $x'_0 = x_0$ . Then, by induction:

$$\|x_k - x'_k\| \leq \sum_{j=0}^{k-1} L_f^{k-j} |u_j - u'_j| \quad (\text{A.1})$$

Indeed, at  $k = 1$ , we have:

$$\|x_1 - x'_1\| \leq L_f(\|x_0 - x'_0\| + |u_0 - u'_0|) = L_f |u_0 - u'_0|$$

and assuming the relation holds at  $k - 1$ , we get:

$$\begin{aligned} \|x_k - x'_k\| &\leq L_f(\|x_{k-1} - x'_{k-1}\| + |u_{k-1} - u'_{k-1}|) \\ &\leq L_f \sum_{j=0}^{k-2} L_f^{k-1-j} |u_j - u'_j| + L_f |u_{k-1} - u'_{k-1}| \end{aligned}$$

equivalent to (A.1).

Then:

$$|v(\mathbf{u}_\infty) - v(\mathbf{u}'_\infty)| \leq \sum_{k=0}^{\infty} \gamma^k |r_k - r'_k|$$

$$\begin{aligned} &\leq \sum_{k=0}^{\infty} \gamma^k L_\rho(\|x_k - x'_k\| + |u_k - u'_k|) \\ &\leq L_\rho \sum_{k=0}^{\infty} \gamma^k \sum_{j=0}^k L_f^{k-j} |u_j - u'_j| \\ &= L_\rho \sum_{k=0}^{\infty} |u_k - u'_k| \sum_{j=0}^{\infty} \gamma^{k+j} L_f^j \\ &= \frac{L_\rho}{1 - \gamma L_f} \sum_{k=0}^{\infty} \gamma^k |u_k - u'_k| \end{aligned}$$

Here, we used the Lipschitz continuity of  $\rho$ , and then applied (A.1). The three equalities simply rewrite the right hand side, isolating the contribution of each  $|u_k - u'_k|$ ; the middle equality swaps indices  $k$  and  $j$ , and can be verified by writing out explicitly the summations. The last step holds because  $\gamma L_f < 1$ . Thus the inequality is proven with  $L_v = \frac{L_\rho}{1 - \gamma L_f}$ .  $\square$

*Proof of Theorem 6:* Our goal is to find an upper bound for the diameter of an arbitrary box  $i$  at some depth  $h$ . Since we deal with this single box, we will omit its index  $i$  for most of the derivation. Indeed, due to dimension selection (7), all the boxes at a given depth have the same shape. Recall function  $s(k)$ , the number of splits per dimension  $k$ , which is clearly decreasing, see Fig. A.1 for an example. In addition  $s$  decreases in steps of at most 1. To see this, consider  $k$  like in the figure, the first dimension in a constant- $s$  range, which will always be preferred to later dimensions in the same range. To increase the gap to 2, dimension  $k - 1$  must be expanded before  $k$ , which means  $\gamma^{k-1} M^{-(s(k)+1)} \geq \gamma^k M^{-s(k)}$ , or  $M \leq 1/\gamma$ . This contradicts Assumption 5(ii).

Denote now the lengths of the ranges in  $s$  by  $\tau_0, \tau_1, \dots, \tau_N$  where  $N$  is the last, infinitely long range where  $s = 0$ . Let  $j$  be the index of the range starting with  $k$ . By direct computation like above, we find that if node  $k$  is expanded:

$$\tau_j \geq \frac{\log M}{\log 1/\gamma}, \quad \tau_{j-1} < \frac{\log M}{\log 1/\gamma} \text{ if } j \geq 1 \quad (\text{A.2})$$

Recall that  $\tau = \left\lceil \frac{\log M}{\log 1/\gamma} \right\rceil \geq 2$ , so (A.2) implies  $\tau_j \geq \tau, \tau_{j-1} < \tau - 1$ . Keeping in mind that  $s$  (and so  $N, \tau_j$ ) depend on  $h$ , we prove by induction that at any depth  $h$ , we have:

$$\begin{cases} \tau_0 \leq \tau \\ \tau_j \in \{\tau - 1, \tau\} & \text{for } 1 \leq j < N \\ \tau_N = \infty \end{cases} \quad (\text{A.3})$$



$b(i_t) \geq b(j) \geq v^*$ . Further,  $v(i_t) + \delta_h \geq b(i_t)$ , where  $h$  is the depth of  $i_t$ , and therefore finally  $i_t \in \mathcal{T}^*$ .

For the second part, among the descendants of  $i_t$  there exists a leaf  $j$  on the final tree so that  $v(j) \geq v(i_t)$ , due to Assumption 5(i). Since  $\hat{\mathbf{u}}$  maximizes the value among the leaves,  $v(\hat{\mathbf{u}}) \geq v(j) \geq v(i_t)$ . Combining this with  $b(i_t) \geq v^*$  from the first part, we get  $v^* - v(\hat{\mathbf{u}}) \leq b(i_t) - v(i_t) = \delta(i_t)$ . Since this holds at any iteration, the bound  $\delta_{\min} = \min_t \delta(i_t)$  follows.  $\square$

*Proof of Theorem 9:* For a given budget  $n$  the branching factor is used to infer a lower bound on the depth reached by OPC. For  $m > 1$ , take the smallest depth  $h$  so that  $Cm^{h+1}Mh \geq n$ . The left-hand side is chosen since there are less than  $Cm^{h+1}$  nodes in the explored tree up to depth  $h$ , and each of them takes at most  $Mh$  computation to expand, see Fig. A.3. Therefore, we are sure

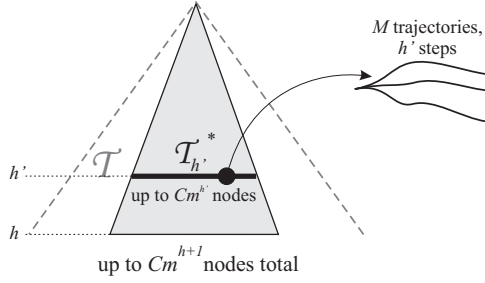


Fig. A.3. To reach depth  $h$ , at most  $Cm^{h'}$  nodes must be expanded on  $\mathcal{T}_{h'}^*$  at depths  $h' \leq h$ , for a total of  $Cm^{h+1}$ . Each of these expansions requires, at worst, simulating  $M$  trajectories with  $h'$  steps.

that at least a node at depth  $h_{\min} = h - 1$  has been expanded, and by solving the inequality we get after some computation:

$$h_{\min} \geq \frac{\log n}{\log m} - \frac{\log \log(n\alpha)^\beta}{\log m}$$

for  $\alpha, \beta > 0$  and sufficiently large  $n$ . Replacing this in the formula for  $\delta_{h_{\min}}$ , we obtain:

$$\begin{aligned} \delta_{\min} &\leq \delta_{h_{\min}} = \tilde{O} \left( \gamma \sqrt{2 \frac{\tau-1}{\tau^2} \left[ \frac{\log n}{\log m} - \frac{\log \log(n\alpha)^\beta}{\log m} \right]} \right) \\ &= \tilde{O} \left( \gamma \sqrt{\frac{2(\tau-1) \log n}{\tau^2 \log m}} \cdot \left( \frac{1}{\gamma} \right)^\wedge \sqrt{2 \frac{\tau-1}{\tau^2} \frac{\log \log(n\alpha)^\beta}{\log m}} \right) \\ &= \tilde{O} \left( \gamma \sqrt{\frac{2(\tau-1) \log n}{\tau^2 \log m}} \cdot \left( \frac{1}{\gamma} \right)^\wedge \left( 2 \frac{\tau-1}{\tau^2} \frac{\log \log(n\alpha)^\beta}{\log m} \right) \right) \end{aligned}$$

$$\begin{aligned} &= \tilde{O} \left( \gamma \sqrt{\frac{2(\tau-1) \log n}{\tau^2 \log m}} \cdot [\log(n\alpha)]^{\beta'} \right) \\ &= \tilde{O} \left( \gamma \sqrt{\frac{2(\tau-1) \log n}{\tau^2 \log m}} \right) \end{aligned}$$

where  $\beta' > 0$  is a constant and we temporarily use notation  $z^\wedge y = z^y$  for readability. In the second step, the square root can be split in this way for sufficiently large  $n$ ; then we show that the second term enters in fact the logarithmic, negligible part of the expression.

When  $m = 1$ , take the smallest  $h$  so that  $Ch^2M \geq n$ . Since at most  $C$  nodes must be expanded at each depth, this guarantees that some node was expanded at depth  $h_{\min} \geq \sqrt{n/MC} - 1$ . Replacing this in the diameter formula leads to the desired result.

Note that we did not make explicit the term  $\sqrt{2h_{\min}(\tau-1)}$  in the diameter bounds. However, trivial upper bounds for  $h_{\min}$  are on the order of  $\log n$  in the first case (since a tree with branching factor greater than 1 must asymptotically be explored, larger depths than this cannot be reached), and  $n$  in the second case. Both of these remain in the logarithmic part of the bound.  $\square$

*Proof of Lemma 10:* Consider one top-level loop of SOPC in Alg. 2, and denote the number of elapsed such loops by  $\ell$ . The major part of the proof will be to show by induction that, for any  $h \leq h_{\max}(n)$ , if  $\ell \geq C \sum_{h'=0}^h m^{h'}$ , then at least a box (tree node) containing an optimal sequence at  $h$  has been expanded.

For the base case, if  $\ell \geq Cm^0 \geq 1$ , then the root has been expanded, and it contains the optimal solution by definition. Take now an arbitrary  $h < h_{\max}(n)$ , and define  $\ell_h$  to be the loop where the first node  $i_h^*$  at  $h$  that contains an optimal solution was expanded. By the induction hypothesis,  $\ell_h \leq C \sum_{h'=0}^h m^{h'}$ . Node  $i_h^*$  has itself some child  $i_{h+1}$  that contains an optimal solution. (Note that another optimal node  $i_{h+1}^*$  may be expanded before this particular child; we will be interested in  $i_{h+1}^*$  below.) Consider now any iteration  $\ell_h + \ell'$  where some other node  $i'_{h+1}$ , different from  $i_{h+1}$ , is expanded at depth  $h+1$ . Then it must be that:

$$v(i'_{h+1}) \geq v(i_{h+1}) \geq v^* - \delta(i_{h+1}) \geq v^* - \delta_{h+1}$$

where the middle inequality holds because  $i_{h+1}$  contains an optimal solution. But then  $i'_{h+1} \in \mathcal{T}_{h+1}^*$ , and since there are at most  $Cm^{h+1}$  nodes in this set, including  $i_{h+1}$  which was not yet expanded, it means at most  $Cm^{h+1} - 1$  loops can pass before  $i_{h+1}$  must be expanded. Thus the loop  $\ell_{h+1}$  where  $i_{h+1}^*$  is expanded is, at worst,  $\ell_h + Cm^{h+1} \leq C \sum_{h'=0}^{h+1} m^{h'}$ , and the induction is proven.

Observe next that each loop  $\ell$  expands at most  $h_{\max}(n)$  nodes, where each node expansion takes at most

$Mh_{\max}(n)$  model calls. Then, by combining this with the bound on  $\ell$  obtained above, the algorithm is sure to expand an optimal node at  $h(n)$  when this is smaller than  $h_{\max}(n)$  – or, when  $h(n) > h_{\max}(n)$ , it expands an optimal node at  $h_{\max}(n)$ . Thus finally it expands some optimal node  $i_h^*$  at  $\underline{h}$ , and therefore the solution returned by SOPC satisfies:

$$v(i^*) \geq v(i_h^*) \geq v^* - \delta_{\underline{h}}$$

i.e. it is  $\delta_{\underline{h}}$ -optimal.

Note that here we streamlined the proof of the SOO depth bound from [18] so as to take advantage of the fact that, unlike SOO, SOPC always expands a full path down to  $h_{\max}(n)$ .  $\square$

*Proof of Theorem 11:* Consider first  $m > 1$ . Since  $h(n)$  is the smallest for which (8) holds, we have:

$$n > CMh_{\max}^2(n) \sum_{h'=0}^{h(n)-1} m^{h'} = CMh_{\max}^2(n) \frac{m^{h(n)} - 1}{m - 1}$$

Therefore:

$$h(n) < \frac{1}{\log m} \log \left[ \frac{n(m-1)}{CMh_{\max}^2(n)} + 1 \right] < c_3 \log n^{1-2\varepsilon}$$

for some constant  $c_3 > 0$ , where  $h_{\max}(n) = n^\varepsilon$  was used. Thus  $h(n)$  is logarithmic in  $n$  and, for large  $n$ , smaller than  $h_{\max}(n)$  since the latter is a power of  $n$ . Thus, for large  $n$ ,  $\underline{h} = h(n)$  in Lemma 10.

Similarly solving (8) for a lower bound on  $h(n)$ , we get:

$$\begin{aligned} h(n) &\geq \frac{1}{\log m} \log \left[ \frac{n(m-1)}{CMh_{\max}^2(n)} \right] - 1 \\ &= \frac{1}{\log m} \left[ \log n^{1-2\varepsilon} - \log \frac{eCM}{m-1} \right] \end{aligned}$$

and plugging this into  $\delta_{h(n)}$ :

$$\begin{aligned} \delta_{h(n)} &= \tilde{O} \left( \gamma \sqrt{2 \frac{\tau-1}{\tau^2 \log m} \left[ \log n^{1-2\varepsilon} - \log \frac{eCM}{m-1} \right]} \right) \\ &= \tilde{O} \left( \gamma \sqrt{\frac{2(\tau-1)(1-2\varepsilon) \log n}{\tau^2 \log m}} \right) \end{aligned}$$

where the elimination of the subtracted term holds due to  $n$  being large. By Lemma 10 this is also the near-optimality of the algorithm.

When  $m = 1$ , (8) becomes simply  $CMh_{\max}(n)(h(n) + 1) \geq n$ , leading via  $h_{\max}(n) = n^{1/3}$  to  $h(n) \geq \frac{\sqrt[3]{n}}{CM} - 1$ . Therefore

$$\underline{h} = \min \left\{ \frac{\sqrt[3]{n}}{CM} - 1, \sqrt[3]{n} \right\} \geq \sqrt[3]{n} \min \left\{ \frac{1}{CM}, 1 \right\} - 1$$

and finally:

$$\begin{aligned} \delta_{\underline{h}} &= \tilde{O} \left( \gamma \sqrt{2 \frac{\tau-1}{\tau^2} \left[ \sqrt[3]{n} \min \left\{ \frac{1}{CM}, 1 \right\} - 1 \right]} \right) \\ &= \tilde{O} \left( \gamma \left( n^{1/6} \sqrt{2 \frac{\tau-1}{\tau^2} \min \left\{ \frac{1}{CM}, 1 \right\}} \right) \right) \end{aligned}$$

which is the desired result.  $\square$

## B Execution time of planning algorithms

Fig. B.1 shows the execution time of the planning algorithms evaluated in Sec. 5 of the main paper. These results confirm the expectation that the budget  $n$  is the most important factor: the execution time is very close to linear in  $n$ , with minor differences between the algorithms due to their varying overhead of e.g. searching the tree in different ways. SOPC is the fastest.

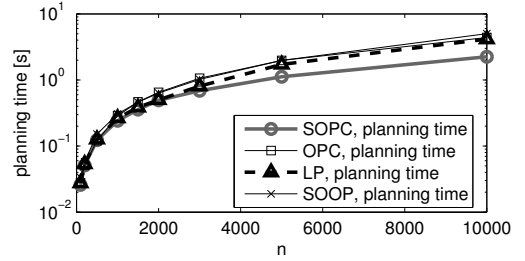


Fig. B.1. Runtime of one call to the planner, averaged over the 50 steps in the trajectory.

## C Extension of SOPC to multiple actions

Although our analysis does not cover it, we briefly illustrate an extension of SOPC to 2 control actions. Here, each time step  $k$  is associated with 2 intervals rather than just 1. The idea is simple: boxes and steps  $k$  are selected for expansion using the same rules as in SOPC, but when a box must be expanded along step  $k$ , we split both intervals into  $M$  pieces, leading to  $M^2 = 9$  child boxes. More refined rules could be given that avoid this direct exponential growth with the number of inputs.

To evaluate this extension, we use the rotational pendulum system from Sec. 5 of the main paper, but a second motor is added to the vertical joint of the pendulum. This motor has the same viscous damping and torque constant as the first one, but its model is simplified in that the torque is linearly related to the voltage  $u_2 \in [-9, 9]$  V, rather than dynamically like for the first motor. The unnormalized reward function is  $-x^\top \text{diag}[0.5, 0.05, 1, 0.05]x - u^\top \text{diag}[0.2, 0.2]u$ . The C++ implementation of SOPC is used with a budget  $n = 5 \cdot 10^5$  and  $\varepsilon = 0.33$  in  $h_{\max}$ . The resulting trajectory from the pointing-down state is shown in Fig. C.1. The angles are approximately stabilized, although with worse performance and larger input adjustments than

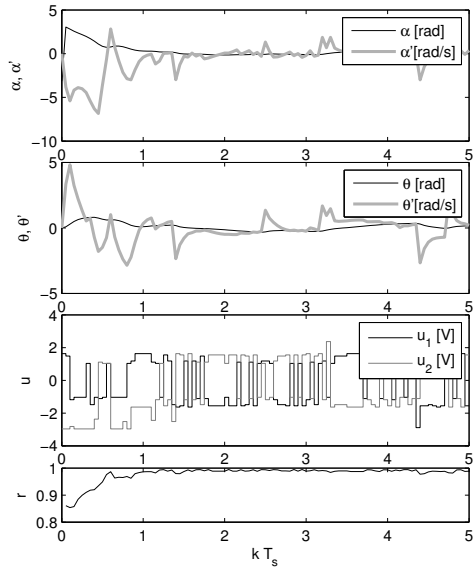


Fig. C.1. Two-input trajectory.

in the single-input case, since this simple extension has exponential complexity in the number of actions (and we increased the budget less than quadratically).