mdp_CTL_BR Artifacts Abstract

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***Please note that the artifacts were presented in MATLAB code, therefore, MATLAB will be needed for reproducing these artifacts.**
This document is submitted along with the artifact for the evaluation of the algorithm presented in the paper *"CTL Model Checking of Markov Decision Processes over the Distribution Space"*
The paper presented two examples to examine the algorithm.

1. We restated the first example:

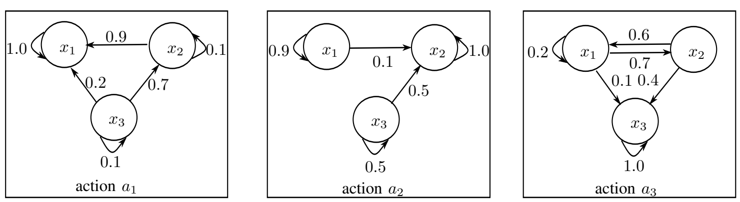

Figure 1: Graphical representation of the MDP in Example 1.

Consider the MDP with $\mathbb{X} = \{x_1, x_2, x_3\}, \mathbb{U} = \{a_1, a_2, a_3\}$, and the corresponding transition probability matrices displayed in Fig. 1. In order to define the MDP-induced transition system MTS, let us introduce two sets of state distributions, as shown in blue and red in Fig. **??**. The set in red is $\{\pi \in \mathcal{P}(\mathbb{X}) \mid \|\pi - [1/3\ 1/3\ 1/3]\|_\infty \leq 0.1\}$ and the set in blue is $\{\pi \in \mathcal{P}(\mathbb{X}) \mid \|\pi - [0.1\ 0.2\ 0.7]\|_\infty \leq 0.05\}$. The label function L_d maps the distributions in the blue region to the atomic proposition a and the distributions in the red region to b. Let us consider two distribution-specified CTL formulae as $\Phi_1 = \exists(\neg a \mathsf{U} b)$ and $\Phi_2 = \forall(\bigcirc \neg a)$, to be verified.

By running the *main.m* in the 3statesMDP-Example1 folder, the result can be reproduced.

2. For the second example:

UAV case study shown in Fig. 2, the UAV moves in a 5×5 grid world and has five possible actions $\{$*up, down, left, right, stay*$\}$. Due to environmental uncertainties (e.g., wind), we assume that the first four actions will

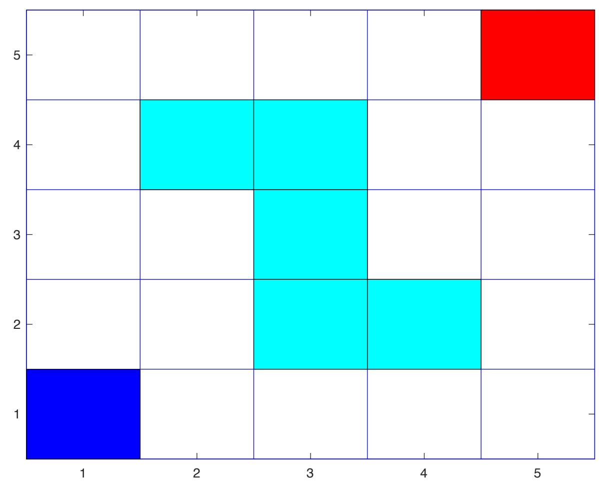

Figure 2: Case Study - UAV Motion Planning

drive the state to the desired next configuration with probability $1-\alpha$, and to to other neighboring states with likelihood $\frac{\alpha}{N_{neigh}}$, where N_{neigh} is the number of available/feasible neighboring states (not including the desired state). We say that a state (x_1, y_1) is a neighboring state of a state (x_1, y_1) if $\max\{|x_1 - x_2|, |y_1 - y2|\} \leq 1$. The cyan regions are obstacles and we assume that the corresponding states are absorbing states, that is, these states are invariant under all actions. Denote by Obs the set of obstacle states. The red grid $(5, 5)$ is the target state, denoted by Target. The initial state is the blue square at $(1, 1)$. We consider the following path planning problem: to find a feasible policy such that, starting from the initial state, the UAV reaches the target set, whilst avoiding the obstacle states, with a desired probability (assumed to be given).

(a) We consider two scenarios. In the first one, the parameter α is set to be 0, that is, each action drives the current state to the specified direction with probability 1 - the model's dynamics are deterministic. The probability levels β and p are set to be 0 and 0.8, respectively.

We ran the file *uav_determin.m* in UAV-Case Study to validate this scenario.

(b) In the second scenario, the parameter α is set to be 0.05 so that there exist possible transitions to other neighboring states under the first four actions.

We ran the file *uav_noisy.m* in UAV-Case Study to validate this scenario.