# Monte Carlo Tree Search with Reinforcement Learning for Motion Planning

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ITSC, September 2020

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- Problem description
- 2 Problem formulation
- Algorithms
- 4 Results
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## Motion Planning

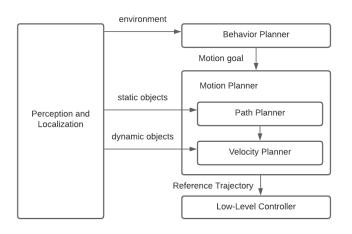


Figure 1: Decision Making and Planning

## Two-Steps Path-Velocity Decomposition

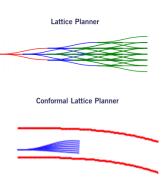


Figure 2: Path Planner

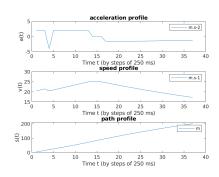


Figure 3: Velocity Planner

#### Avoiding multiple dynamic obstacles

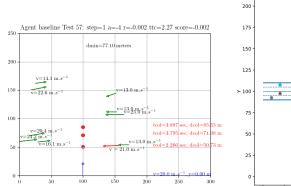


Figure 4: First Benchmark Setup

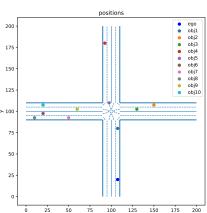


Figure 5: Multi-lanes Crossing

## Motion Planning Challenges

#### Dynamic Obstacles Avoidance

- Combinatorial explosion:
  - Usually 1 single dynamic obstacle is considered
  - We will consider up to 10 dynamic obstacles
- Non convex collision avoidance problem:
  - Proceed OR yield the way
  - OR constraints typically handled via Mixed Integer Programming

#### Real Time constraints

- Plan in less than 40 ms
- Plan a velocity profile for multiple (> 6) candidate paths

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## Complexity Reduction via S-T projection

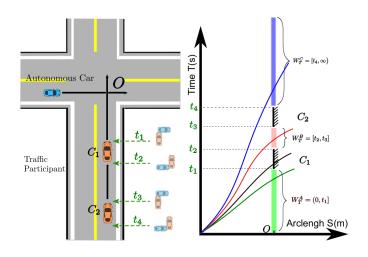


Figure 6: S-T projection [ZCW<sup>+</sup>18]

## Uncertainty Handling in S-T graphs

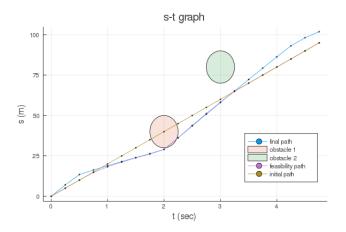


Figure 7: S-T graph

## Search Model: for A\*, MCTS and DQN algorithms

- States:  $S = \left\{ \frac{s}{s_{max}}, \frac{\dot{s}}{\dot{s}_{max}}, t \right\}$
- Desired Terminal State:  $\left(\frac{s_f}{s_{max}}, \frac{\dot{s_f}}{\dot{s}_{max}}\right)$
- Undesired Terminal States:

$$\mathcal{S} \cap \mathcal{C} = \left\{ \left( \frac{s_i}{s_{max}}, t_i \right) \right\}_{i=1..n}$$

- Actions:  $A = [-4, -2, -1, 0, 1, 2] \text{ ms}^{-2}$
- Transitions:

$$\begin{bmatrix} s \\ \dot{s} \end{bmatrix}_{t+1} = A_d \begin{bmatrix} s \\ \dot{s} \end{bmatrix}_t + B_d \begin{bmatrix} \ddot{s} \end{bmatrix}_t \text{ with } A_d = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}, B_d = \begin{bmatrix} \frac{\Delta t^2}{2} \\ \Delta t \end{bmatrix}$$

Reward or cost model:

$$R(s,a) = -0.001 - 1 imes 1$$
 [distance(ego, obj)  $\leq d_{
m col}$ ]  $-0.002 imes 1$  [ $a \leq -4$ ]

## MPC Model: for MPC algorithms

$$\min_{u_0,...,u_{T-1}} (x_T - x_{\text{ref}})^{\mathsf{T}} Q_T (x_T - x_{\text{ref}}) + \sum_{k=0}^{T-1} (x_k - x_{\text{ref}})^{\mathsf{T}} Q (x_k - x_{\text{ref}}) + u_k^{\mathsf{T}} R u_k$$

subject to 
$$\begin{cases} x_{k, \min} \leq x_k \leq x_{k, \max} \\ u_{k, \min} \leq u_k \leq u_{k, \max} \\ x_{k+1} = A_d x_k + B_d u_k \\ x_0 = x_{\text{init}} \\ \forall \left(t_{\text{col}}, s_{\text{col}}\right)_{i \in [1, 10]} \qquad \times_{t_{\text{col}}^{(i)}} [1] < s_{\text{col}}^{(i)} - \Delta_{\text{safety}} \text{ or } x_{t_{\text{col}}^{(i)}} [1] > s_{\text{col}}^{(i)} + \Delta_{\text{safety}} \end{cases}$$

$$\begin{bmatrix} s \\ \dot{s} \end{bmatrix}_{k+1} = A_d \begin{bmatrix} s \\ \dot{s} \end{bmatrix}_k + B_d \begin{bmatrix} \ddot{s} \end{bmatrix}_k \text{ with } A_d = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}, B_d = \begin{bmatrix} \frac{\Delta t^2}{2} \\ \Delta t \end{bmatrix}$$

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  - v1: focus on 1 single dynamic obstacle (with smallest TTC)
  - v2: emergency braking, same as v1 with maximum braking
  - v3: constant speed, no braking

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  - A\*
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- MCTS-NNET: MCTS with a Neural Network heuristic (paper)
- MPC: Model Predictive Control based
  - default: with dynamic obstacles avoidance pre-convexification
  - latest: with Mixed Integer Programming and Elastic Model (new)

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## Average Tests Results

Table 1: Results with multiple crossing-points tests

Mean over 89 Tests	Success	Runtime	Hardbrakes	Steps	Collision Speed
Baseline v1	43%	40 μs	0	43	13.04 m.s <sup>-1</sup>
Baseline v2	72%	40 μs	10.57	53	7.38 m.s $^{-1}$
MCTS	85%	3 ms	4.43	42	14.77 m.s <sup>-1</sup>
DDQN	84%	300 μs	5.15	62	$17.13 \; \mathrm{m.s^{-1}}$
MPC	82%	18 ms	6.22	47	8.72 m.s $^{-1}$
MCTS-NNET v1	98%	4 ms	4.79	62	19.04 m.s <sup>-1</sup>
MCTS-NNET v2	96%	4 ms	4.89	48	18.40 m.s <sup>-1</sup>
Oracle (A* search)	100%	6 sec	1.52	40	-

#### Distribution of Tests Results

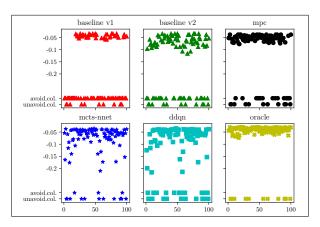


Figure 8: Scores (higher is better) for Multiple Crossing-Points Tests

## Runtime vs Accuracy

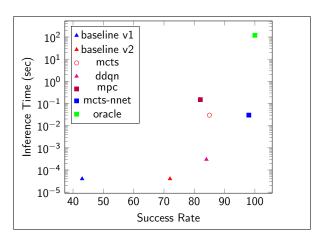


Figure 9: Runtime vs Accuracy (Multiple Crossing-Points Tests)

#### Latest MPC Improvements (not in the paper)

Mean	Success	Runtime	HardBrakes	Steps	Collision Speed
Baseline (Constant Speed)	23%	$< 1 \mu$ s	0.0	40.0	20.0 m.s <sup>-1</sup>
MPC	82%	18 ms	3.09	39.5	$18.5 \; {\rm m.s^{-1}}$
MPC_MIP	100%	22 ms	0.19	53.8	$18.7 \; {\rm m.s^{-1}}$
MPC_SIMPLEX	100%	6 ms	4.72	43.48	$18.8 \; {\rm m.s^{-1}}$
Oracle (Dynamic Programming)	100%	22.3 sec	0.48	33.1	$15.5 \; {\rm m.s^{-1}}$

Table 2: With Elastic Model and Big-M reformulation of disjunctive constraints

$$\begin{aligned} & & & \min_{x} & & \mathsf{Quadratic}\left(x\right) + y \\ \mathsf{s.t.} & & a^Tx \leq b + \mathsf{y} \text{ (safety distance constraint)} \\ & & & \mathsf{elastic slack variable: } y \in \mathbb{R} \end{aligned}$$

mpc-mip project (slightly different tests vs paper tests)

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#### Conclusion

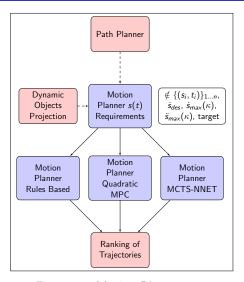


Figure 10: Motion Planner

## Key Ideas and Improvements

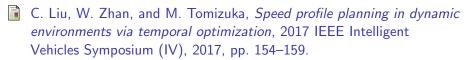
#### MCTS improvements (paper)

- Faster search with a Neural Network heuristic
- Deep Learning (DL) to learn a faster version of an accurate model
- We do not depend on collected data for training
- DL to reduce computational load, not to make final decision
- Increase MCTS exploration when NNET heuristic confidence is low

#### MPC improvements for Collision Avoidance in Real-Time (new)

- Mixed Integer Programming to handle disjunctive constraints
- Use an Elastic Collision Avoidance Model
- Linearization to enable optimization with a faster Simplex algorithm
- Take advantage of Hessian matrix structure (sparse, bands) to speed up quadratic MPC optimization (to do)

#### References I



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