

EECI-IGSC Course Networked Model Predictive Control for Multi-Vehicle Decision-Making

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Part 3

Control Engineering and Optimization

Course contents

- Dynamic vehicle models
- Control and optimization
- Network and distribution
- Software architectures and testing concepts



CPM Lab architecture



Networked Model Predictive Control for Multi-Vehicle Decision-Making Part 3: Control Engineering and Optimization | Dr.-Ing. Bassam Alrifaee

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CPM Lab architecture





Literature

- J. Maciejowski. Predictive Control with Constraints. Prentice Hall, 2002.
- S. Boyd and L. Vandenberghe. Convex Optimization. Cambridge University Press, 2004.
- R.C. Dorf and R.H. Bishop. Modern Control Systems. Prentice-Hall, 2008.



Further literature (1)

F. Borrelli, A. Bemporad, and M. Morari. Predictive control for linear and hybrid systems. Cambridge University Press, 2017.

Many



Further literature (2)

- B. Alrifaee. Networked Model Predictive Control for Vehicle Collision Avoidance. PhD thesis, RWTH Aachen University, 2017.
- B. Alrifaee, J. Maczijewski, and D. Abel. Sequential Convex Programming MPC for Dynamic Vehicle Collision Avoidance. In IEEE Conference on Control Technology and Applications (CCTA), 2017.
- B. Alrifaee, M. G. Mamaghani, and D. Abel. Centralized Non-Convex Model Predictive Control for Cooperative Collision Avoidance of Networked Vehicles. In IEEE International Symposium on Intelligent Control (ISIC), 2014.
- B. Alrifaee, K. Kostyszyn, and D. Abel. Model Predictive Control for Collision Avoidance of Networked Vehicles Using Lagrangian Relaxation. In IFAC Symposium on Control in Transportation Systems (CTS), 2016.
- B. Alrifaee and J. Maczijewski. Real-time Trajectory Optimization for Autonomous Vehicle Racing using Sequential Linearization. In IEEE Intelligent Vehicles Symposium (IV), 2018.
- B. Alrifaee. MATLAB Simulation of Networked Model Predictive Control for Vehicle Collision Avoidance, 2017. Available: <u>https://doi.org/10.5281/zenodo.1252992</u>





Reading

- B. Alrifaee. Networked Model Predictive Control for Vehicle Collision Avoidance. PhD thesis, RWTH Aachen University, 2017.
 - Section 2.3, pages 8-14
 - Section 4.5.1.1, pages 100-101
- J. Maciejowski. Predictive Control with Constraints. Prentice Hall, 2002. [optional]
 - Section 2.6.1, pages 53-56
 - Sections 2.6.2 and 2.6.3, pages 56-61 [optional]
 - Section 3.1.1, pages 74-77
 - Section 3.2.1, pages 81-84
 - Section 3.4, pages 97-99



Pedestrian walking

- Task
 - Follow the line
 - Act as little as possible
 - Consider physical and logical limits
- Sense
 - Use sensing organs
 - Build an environment model
- Plan
 - Use discrete model to anticipate your free movement for 5 steps
 - Consider your physical (body) limits
 - Consider physical and logical limits of your
 - Action
 - Position
 - Orientation
 - Plan your actions for 2 steps
- Act
 - Move one step using some muscles of your body





classical control (PID)













schach-tipps.de, euroschach.de





- 1. Bd3
- 2. Qc2





schach-tipps.de, euroschach.de



Further examples

- Automotive systems
- Aeronautic industry
 - See SpaceX landing
- Smart electricity grids
- Drinking water networks
- Financial engineering









Alrifaee, Networked Model Predictive Control for Vehicle Collision Avoidance, 2017



$$J^{\star} = \min_{\Delta \mathbf{u}(\cdot)} \sum_{k=1}^{H_p - 1} l_x(\mathbf{x}(t+k), \mathbf{r}(t+k)) + l_{x_{H_p}}(\mathbf{x}(t+H_p), \mathbf{r}(t+H_p)) + \sum_{k=0}^{H_u - 1} l_u(\Delta \mathbf{u}(t+k))$$

subject to: $\mathbf{x}(t+1+k) = f(\mathbf{x}(t+k), \mathbf{u}(t+k)), \ k = 0, \dots, H_p - 1$ $\mathbf{x}(t+k) \in \mathcal{X}, \ k = 1, \dots, H_p - 1$ $\mathbf{x}(t+H_p) \in \mathcal{X}_{H_p}$ $\mathbf{u}(t+k) \in \mathcal{U}, \ k = 0, \dots, H_u - 1$ $\Delta \mathbf{u}(t+k) \in \Delta \mathcal{U}, \ k = 0, \dots, H_u - 1$ where

$$\Delta \mathbf{u}(t+k) = \mathbf{u}(t+k) - \mathbf{u}(t+k-1), \ k = 0, \dots, H_u - 1$$



Result

$$\Delta \mathbf{u}^{\star}(\cdot) = \begin{pmatrix} \Delta \mathbf{u}^{\star}(t) & \dots & \Delta \mathbf{u}^{\star}(t + H_p - 1) \end{pmatrix}^T$$

$$\mathbf{u}^{\star}(t) = \mathbf{u}(t-1) + \Delta \mathbf{u}^{\star}(t), \text{ during } [t, t+1)$$

 $J^{\star} = \min_{\Delta \mathbf{u}(\cdot)} \sum_{k=1}^{H_p - 1} l_x(\mathbf{x}(t+k), \mathbf{r}(t+k)) + l_{x_{H_p}}(\mathbf{x}(t+H_p), \mathbf{r}(t+H_p)) + \sum_{k=0}^{H_u - 1} l_u(\Delta \mathbf{u}(t+k))$

subject to:

$$\mathbf{x}(t+1+k) = f(\mathbf{x}(t+k), \mathbf{u}(t+k)), \ k = 0, \dots, H_p - 1$$

$$\mathbf{x}(t+k) \in \mathcal{X}, \ k = 1, \dots, H_p - 1$$

$$\mathbf{x}(t+H_p) \in \mathcal{X}_{H_p}$$

$$\mathbf{u}(t+k) \in \mathcal{U}, \ k = 0, \dots, H_u - 1$$

$$\Delta \mathbf{u}(t+k) \in \Delta \mathcal{U}, \ k = 0, \dots, H_u - 1$$
where

$$\Delta \mathbf{u}(t+k) = \mathbf{u}(t+k) - \mathbf{u}(t+k-1), \ k = 0, \dots, H_u - 1$$





$$J^{\star} = \min_{\Delta \mathbf{u}(\cdot)} \sum_{k=1}^{H_p - 1} l_x(\mathbf{x}(t+k), \mathbf{r}(t+k)) + l_{x_{H_p}}(\mathbf{x}(t+H_p), \mathbf{r}(t+H_p)) + \sum_{k=0}^{H_u - 1} l_u(\Delta \mathbf{u}(t+k))$$

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Pedestrian walking as MPC

Pedestrian walking		MPC		
Task	Follow the line	Reference	1	Obiostivo fuestio
	Act as little as possible	Control input	5	Objective function
	Consider physical and logical limits	Constraints		
Plan	Use discrete model to anticipate your free movement for 5 steps	Predict, prediction horizon	_	
	Consider your physical (body) limits	Model as a constraint		
	 Consider physical and logical limits of your Action Position Orientation 	Inputs' and states' constraints		
	Plan your actions for 2 steps	Control horizon		



Sequential convex programming

Reading

- B. Alrifaee. Networked Model Predictive Control for Vehicle Collision Avoidance. PhD thesis, RWTH Aachen University, 2017.
 - Section 4.5, the introduction part, pages 99-100
 - Section 4.5.3, pages 110-119

Sequential convex programming – concept

"Solves" non-convex optimization problems

Idea

- Convexify non-convex parts of the objective function and constraints using convex approximations and preserve their convex parts
- Solve convex problem
 - Global solution
 - Computationally efficient
- New approximation around optimal solution
- Repeat until convergence



Sequential convex programming





Alrifaee, Networked Model Predictive Control for Vehicle Collision Avoidance, 2017



Sequential convex programming

Application to "solve" non-convex QCQPs

QCQP (Quadratic Constrained Quadratic Program)

$$\min_{\mathbf{x}} \quad \mathbf{x}^T \mathbf{P}_0 \mathbf{x} + \mathbf{q}_0^T \mathbf{e} + r_0$$

subject to:
$$\mathbf{x}^T \mathbf{P}_i \mathbf{x} + \mathbf{q}_i^T \mathbf{e} + r_i \le 0, \ i = 1, \dots, m$$

\triangleright **P**_{*i*} is symmetric but not positive semi-definite

• In the vehicle example, the collision avoidance constraints are concave functions

Sequential convex programming – concept

"Solves" non-convex optimization problems

Idea

- Convexify non-convex parts of the objective function and constraints using convex approximations and preserve their convex parts
- Solve convex problem
 - Global solution
 - Computationally efficient
- New approximation around optimal solution
- Repeat until convergence



Algorithm 1 SCP algorithm to "solve" the non-convex QCQP $% \mathcal{A}$

Input: The non-convex QCQP

Output: Solution vector $\mathbf{x} \in \mathbb{R}^n$

- 1: c := 1 {Iteration counter}
- 2: Determine starting point \mathbf{x}_c
- 3: Compute the objective value of the non-convex program J_c using \mathbf{x}_c
- 4: Form a convex approximation of the non-convex parts of the inequality constraints using \mathbf{x}_c
- 5: Compute the optimal solution \mathbf{x}_{c+1} of the resulting convex program
- 6: Compute the objective value of the non-convex program J_{c+1} using \mathbf{x}_{c+1}
- 7: if $J_c J_{c+1} \leq \epsilon$ then
- 8: return \mathbf{x}_{c+1}
- 9: **end if**
- 10: c := c + 1
- 11: **go to** 4



Starting point

- Use time-shifted solution from previous time step of MPC
- No feasible solution
 - May be bad local minimum
 - Try other starting points

Algorithm 1 SCP algorithm to "solve" the non-convex QCQP						
Input: The non-convex QCQP						
Output: Solution vector $\mathbf{x} \in \mathbb{R}^n$						
1: $c:=1$ ·	{Iteration counter}					
2: Determ	ine starting point \mathbf{x}_c					
3: Compu	te the objective value of the non-convex program J_c using \mathbf{x}_c					
4: Form a	convex approximation of the non-convex parts of the inequality constraints using \mathbf{x}_c					
5: Compu	te the optimal solution \mathbf{x}_{c+1} of the resulting convex program					
6: Compu	te the objective value of the non-convex program J_{c+1} using \mathbf{x}_{c+1}					
7: if J_c –	$J_{c+1} \leq \epsilon$ then					
8: retu	$\mathbf{rn} \ \mathbf{x}_{c+1}$					
9: end if						
10: $c := c$ -	+1					
11: go to	4					



Convex approximation (local)

- Linearization of quadratic constraints around x_c
 - Best convex approximation of a concave function is its affine approximation*
 - Affine function lies above the concave function at all points, i.e., the affine function is globally upper bound on the concave function
 - Resulting program is a restriction of the original one

Convex approximation (local)

- Linearization of quadratic constraints around \mathbf{x}_c
 - Best convex approximation of a concave function is its affine approximation*
 - Affine function lies above the concave function at all points, i.e., the affine function is globally upper bound on the concave function
 - Resulting program is a restriction of the original one

Alrifaee, Networked Model Predictive Control for Vehicle Collision Avoidance, 2017 * D. Zwick. Best Approximation by Convex Functions. The American Mathematical Monthly, 94(6):528–534, 1987. Link



Solve convex sub-problem

- Fast
- Iterating around the new solution produces solutions with lower objective values, because convex; and therefore, of original program

Ale	Algorithm 1 SCP algorithm to "solve" the non-convex OCOP				
Inţ	but: The non-convex QCQP				
Ou	tput: Solution vector $\mathbf{x} \in \mathbb{R}^n$				
1:	$c := 1$ {Iteration counter}				
2:	Determine starting point \mathbf{x}_c				
3:	Compute the objective value of the non-convex program J_c using \mathbf{x}_c				
4:	Form a convex approximation of the non-convex parts of the inequality constraints using \mathbf{x}_c				
5:	Compute the optimal solution \mathbf{x}_{c+1} of the resulting convex program				
6:	Compute the objective value of the non-convex program J_{c+1} using \mathbf{x}_{c+1}				
7:	$\mathbf{if} J_c - J_{c+1} \leq \epsilon \mathbf{then}$				
8:	$\mathbf{return} \ \mathbf{x}_{c+1}$				
9:	end if				
10:	c := c + 1				
11:	go to 4				



Progress evaluation

Decreases in objective value of original problem indicates progress

Algorithm 1 SCP algorithm to "solve" the non-convex QCQP					
Input: The non-convex QCQP					
Output: Solution vector $\mathbf{x} \in \mathbb{R}^n$					
1: $c := 1$ {Iteration counter}					
2: Determine starting point \mathbf{x}_c					
3: Compute the objective value of the non-convex program J	c using \mathbf{x}_c				
4: Form a convex approximation of the non-convex parts of t	the inequality constraints using \mathbf{x}_c				
5: Compute the optimal solution \mathbf{x}_{c+1} of the resulting conver	k program				
6: Compute the objective value of the non-convex program J	c_{c+1} using \mathbf{x}_{c+1}				
7: if $J_c - J_{c+1} \leq \epsilon$ then					
8: return \mathbf{x}_{c+1}					
9: end if					
10: c := c + 1					
11: go to 4					



Sequential convex programming – discussion

- Fast (in our applications <100ms)</p>
- Locally optimal solutions of QCQP problem
- SCP sub-problem is restriction of QCQP
 - SCP feasible implies QCQP feasible
 - Feasibility issues, SCP too restrictive
 - Solution: slack variable



Objective Function

- Follow a predefined reference trajectory
 - Minimize the distances between the vehicle position and the reference trajectory

- Only accept small input changes
 - Keep the steering angle changes as small as possible



ontrol Horizon



Model predictive control – vehicle example

Constraints

- Input constraints, do not exceed
 - A maximum steering angle
 - A maximum change of the steering angle per time step
 - A maximum lateral acceleration

- Collision avoidance constraints
 - Do not collide with other vehicles or obstacles





















































• Convergence of SCP: $\widehat{J_c}$, Progress of SCP: J_c





- Predicted and real decrease of the objective value
 - $d_{\hat{J}} \leq d_J$ because approximate program is a restriction





Convergence of the control input (control horizon = 3)





Slack variable, progress of SCP



Alrifaee, Networked Model Predictive Control for Vehicle Collision Avoidance, 2017



Computation time





- Video of "Frogger" simulation
- Video of experimental results
- Video of trust
- Vehicle racing, videos of simulation results
 - https://youtu.be/t4tkZA8yZkg
 - https://youtu.be/ BxhYhlbORk



Sequential convex programming – conclusion

SCP finds a (good) upper bound on the non-convex optimization problem starting from the time-shifted last solution of MPC



Sequential convex programming

MATLAB exercise

- B. Alrifaee. MATLAB Simulation of Networked Model Predictive Control for Vehicle Collision Avoidance, 2017. Available: <u>https://doi.org/10.5281/zenodo.1252992</u>
 - Function \controller\SCP_optimizer.m

