Real-time planning and control: Smarter machines or simpler world

AASS Seminar, Örebro University

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Contents

- Ph.D. work – **Human-robot interaction**
- Current work – **Multi-arm coordination**
- **Future interests**
- A little summary - **Smarter machine or simpler world**

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SHIYU ZHANG
Nov 2017


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APR 2017
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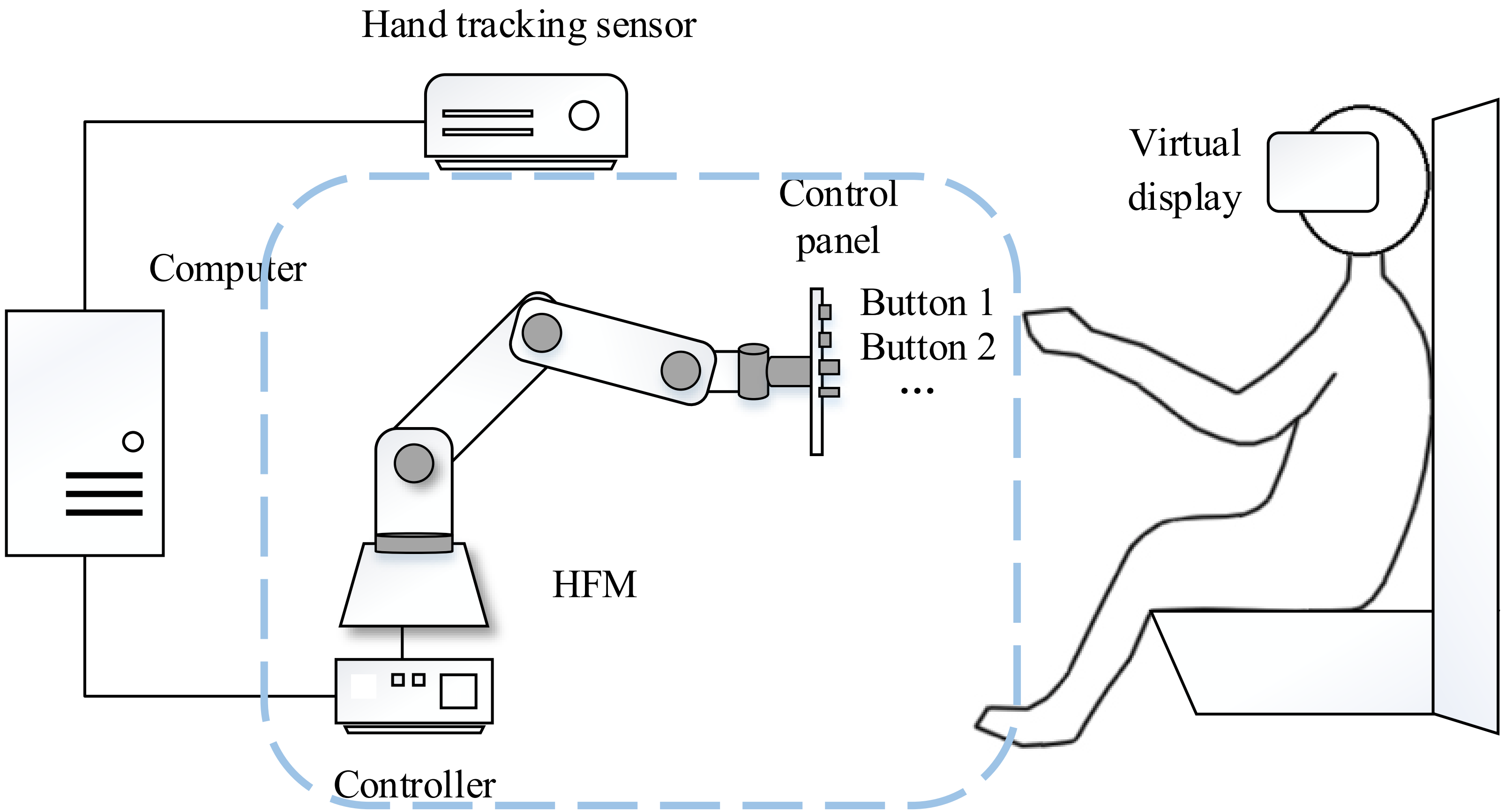
SHIYU ZHANG Feb 2018

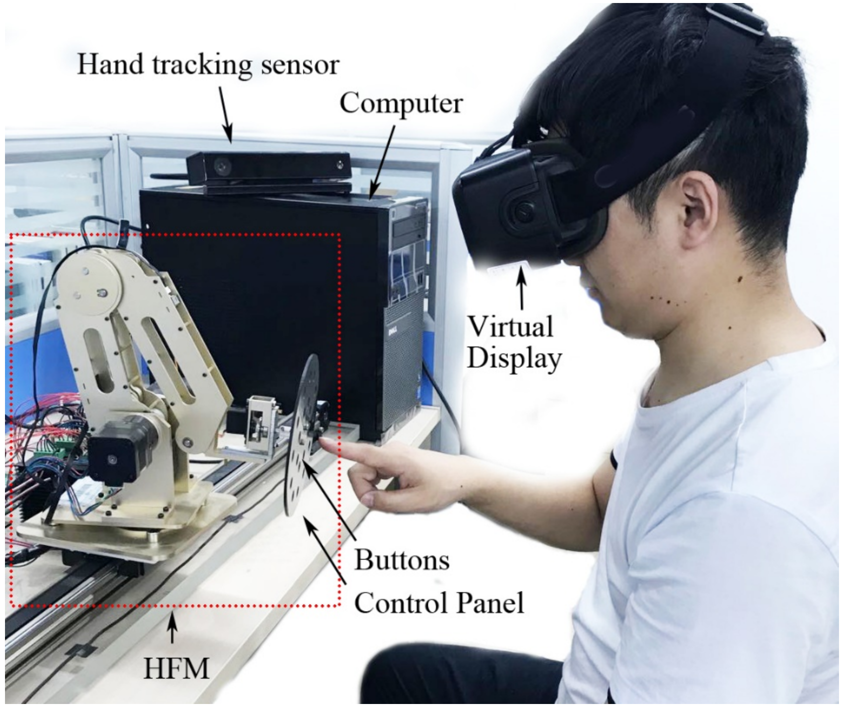
Virtual reality in aerospace application

Traditional flight simulator

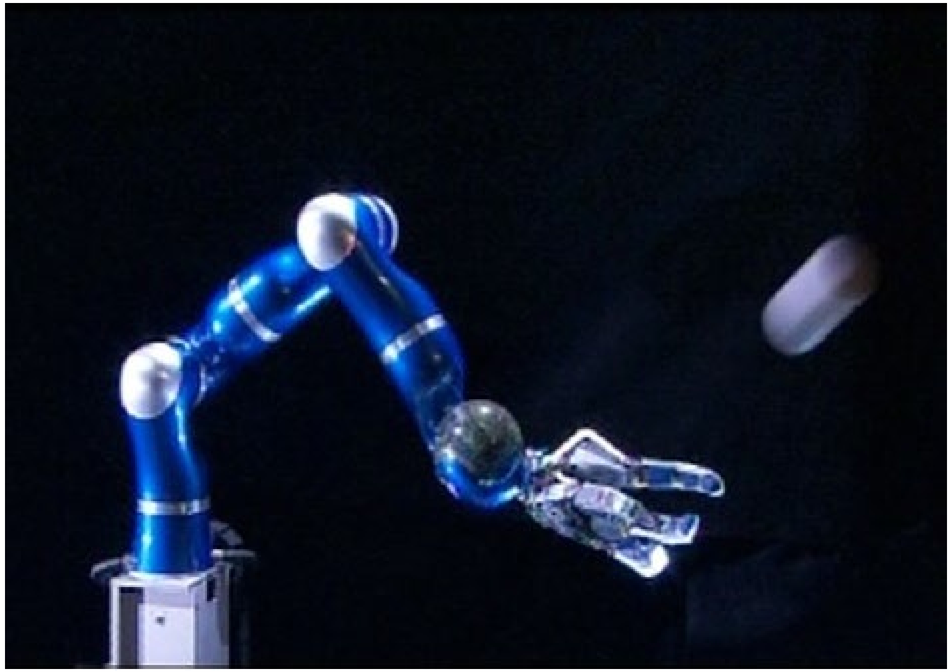
Virtual cockpit system

Haptic interaction based on servo-serial manipulator





Detect the human motion and the environment and accordingly **react** to them in **real-time**



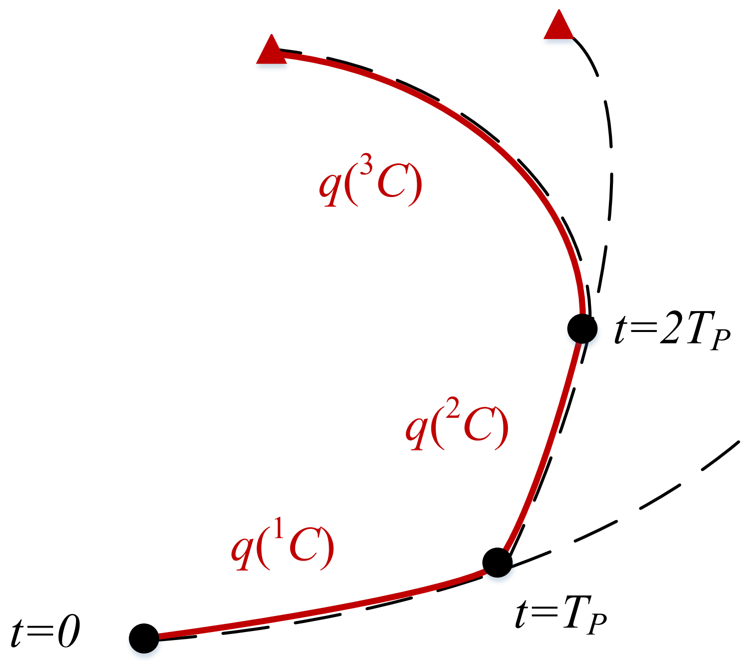
Catching flying objects [1]

Human–robot collaboration [2]

[1] Bäuml B et al. Kinematically optimal catching a flying ball with a hand-arm-system[C]//2010 IEEE/RSJ IROS: 2592-2599.
[2] Ajoudani A et al. Progress and prospects of the human–robot collaboration[J]. Autonomous Robots, 2018, 42(5): 957-975.

Real-time trajectory planning

- Real-time generating new motions for robots to rapidly react to changing external factors



A series of point-to-point trajectory planning problems

- Very short re-planning period T_p
- Each period: need to do the calculation very fast

Point-to-point trajectory planning (joint space)

$$\boldsymbol{X} \rightarrow \boldsymbol{C}_{\boldsymbol{opt}} = O(\boldsymbol{X})$$

$$\boldsymbol{X} \rightarrow \boldsymbol{C}_{\boldsymbol{opt}} = \min_{\boldsymbol{C}} F_{\boldsymbol{X}}(\boldsymbol{C})$$

Objective function

s.t.

$$\boldsymbol{C} \in R^{N_C}$$

Optimization parameter

$${}^{i}H_{\boldsymbol{X}}(\boldsymbol{C}) = 0, \quad i = 1,2,\ldots,N_h$$

Equality constraints

$${}^{i}G_{\boldsymbol{X}}(\boldsymbol{C}) \leq 0, \quad i = 1,2,\ldots,N_g$$

Inequality constraints

- usually **non-linear** and **non-convex**

Input variables $\boldsymbol{X}$

- Motion state
- Human factors
- Environmental factors
- ……

Trajectory parameters $\boldsymbol{C}$

- Position $\boldsymbol{q}(\boldsymbol{C}, t) \in \mathbb{R}^{N_J}$
- Velocity $\dot{\boldsymbol{q}}(\boldsymbol{C}, t) \in \mathbb{R}^{N_J}$
- Acceleration $\ddot{\boldsymbol{q}}(\boldsymbol{C}, t) \in \mathbb{R}^{N_J}$
- ……

Optimization problem

- **Objective function**: safety, rapidity, low power consumption, …
- **Constraints**: Mechanism limits, time limits, safety, …

Specific case

$$\boldsymbol{X} \rightarrow \boldsymbol{C} = O(\boldsymbol{X})$$

Input variables

$$\boldsymbol{X} = (\boldsymbol{q_f}, \boldsymbol{\omega}_0) \in \mathbb{R}^{2N_J}$$

$$\boldsymbol{q_f} = \boldsymbol{q_c} - \boldsymbol{q}_0$$

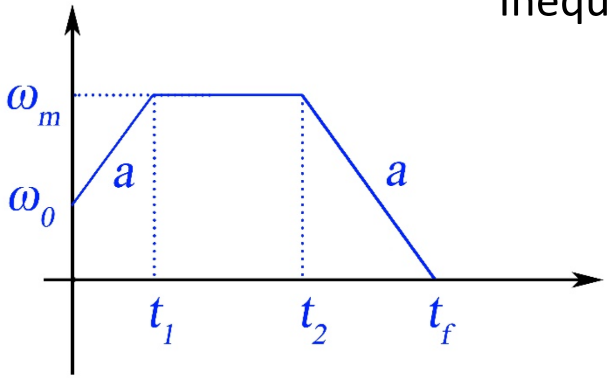
$\boldsymbol{q_0} \in \mathbb{R}^{N_J}$ Initial configuration

$\boldsymbol{q_c} \in \mathbb{R}^{N_J}$ Goal configuration

$\boldsymbol{\omega_0} \in \mathbb{R}^{N_J}$ Initial velocity

Trajectory parameters $\boldsymbol{C}$

$a^j, \omega_m{}^j, t_1{}^j, t_2{}^j, t_f$



Objective function

soft and quick motion

$$F(\boldsymbol{C}) = \frac{(1-\alpha)}{N_J}\sum_{j=1}^{N_J}\left(\frac{a^j}{a_{max}{}^j}\right)^2 + \alpha\left(\frac{t_f}{t_{max}}\right)^2$$

Constraints

Mechanical limits

Trapezoidal profile principle

Application requirement

Equality constraints

$$\frac{1}{2}\omega_m{}^j\left(t_f + t_2{}^j - t_1{}^j\right) + \frac{1}{2}\omega_0{}^j t_1{}^j = q_f{}^j$$

$$\omega_m{}^j = \omega_0{}^j + a^j t_1{}^j$$

$$\left(\omega_m{}^j - \omega_0{}^j\right)\left(t_f - t_2{}^j\right) = \omega_m{}^j t_2{}^j$$

Inequality constraints

$$0 \leq a^j \leq a_{max}{}^j$$

$$\max(0, \omega_0{}^j) \leq \omega_m{}^j \leq \omega_{max}{}^j$$

$$t_1{}^j \leq t_2{}^j$$

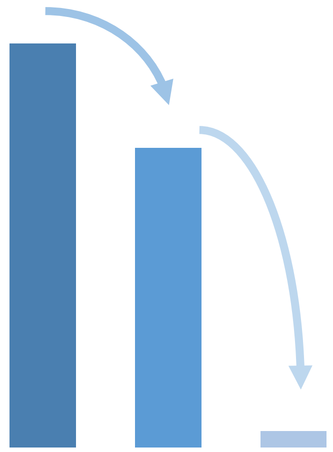
$$0 < t_f \leq t_{max}$$

Challenge

- **Efficiently solve the complex optimization problems**

Methods

- Learning for optimization
- Non-convex transformation
- Joint decoupling



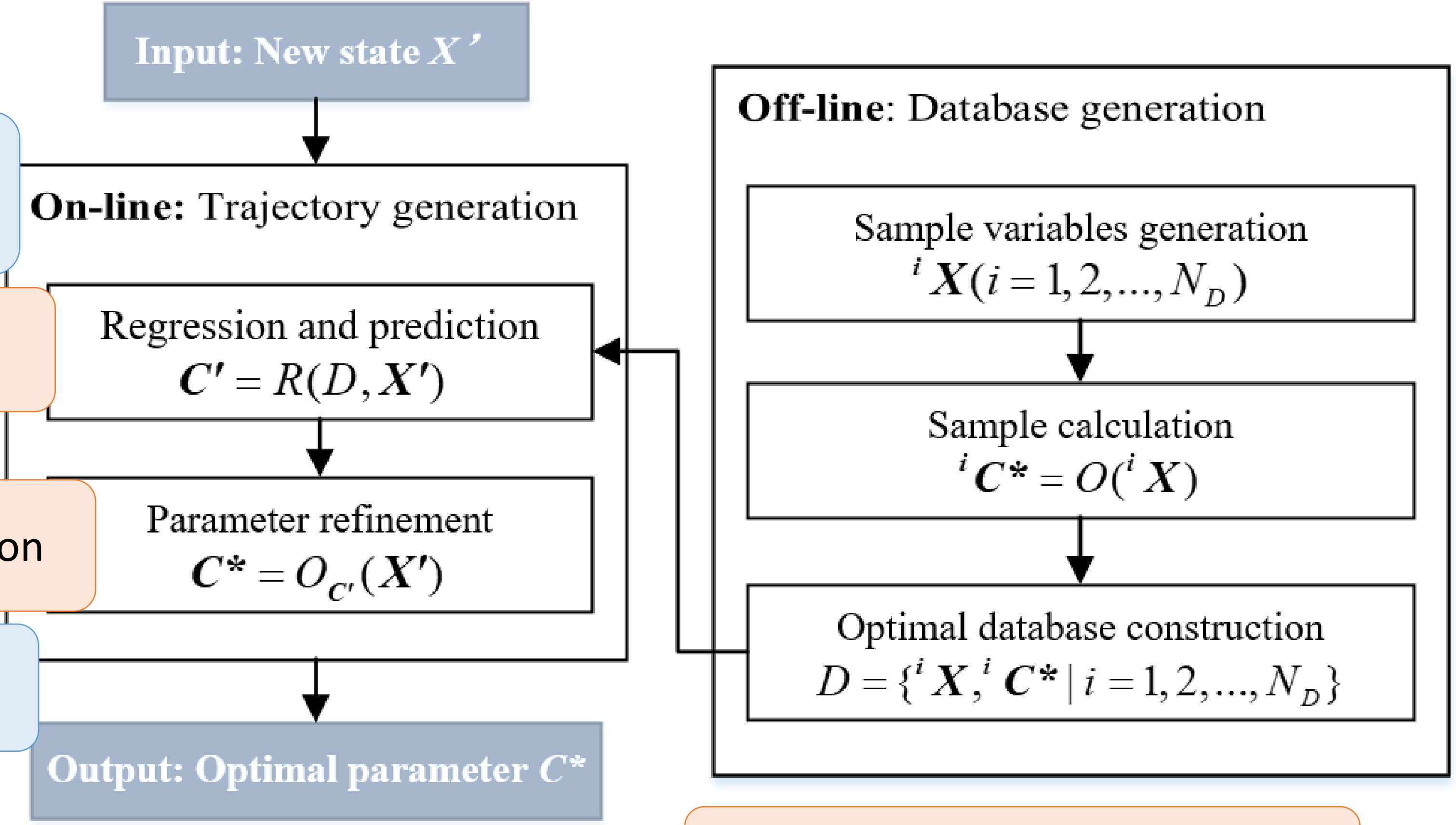
Method 1: Learning for optimization

Independently select features and build regression models

Multiple-dimensional output space

Not guarantee a fast enough optimization iteration

Make **simplifications** of the **objective function**



High-dimensional input space

Map input space to other space

Difficulties in implementation

Solutions

Method 1: Learning for optimization

Learning optimization model

$$\mathcal{L}(D, R, O)$$

- D - Database
- R - Regression method
- O – Parameter refinement

Performance evaluation indices

- Feasible success rate

Feasibility

$$R_s = \frac{N_{r1}}{N_r}$$

- Learning time

Efficiency

$$T_L = T_R + T_O$$

- Cost increase rate

Accuracy

$$e_F = \frac{1}{N_r}\sum_{i=1}^{N_r}\left|\frac{{F_p}^i - {F_a}^i}{{F_a}^i}\right|$$

Another challenge: Non-convex optimization model

- Has **multiple local minima**
- An arbitrary initialization could not guarantee the **global solution**
- **Learned initialization** is helpful to improve the accuracy and efficiency, but there's still **no guarantee**

Method 2: Non-convex transformation

$$\boldsymbol{X} \rightarrow \boldsymbol{C} = O(\boldsymbol{X})$$

Input variables

$$\boldsymbol{X} = (\boldsymbol{q}_f, \boldsymbol{\omega}_0) \in \mathbb{R}^{2N_J}$$

$\boldsymbol{q}_f = \boldsymbol{q}_c - \boldsymbol{q}_0$

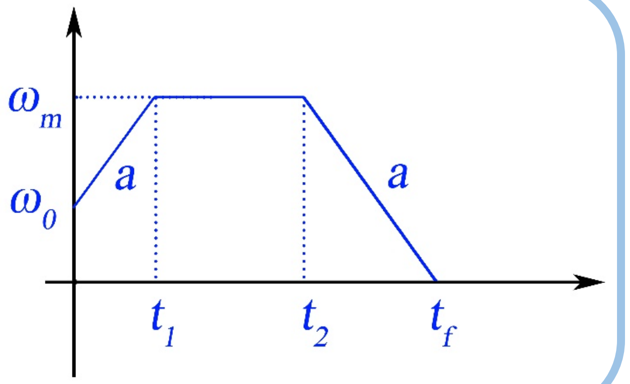
$\boldsymbol{q}_0 \in \mathbb{R}^{N_J}$ Initial configuration

$\boldsymbol{q}_c \in \mathbb{R}^{N_J}$ Goal configuration

$\boldsymbol{\omega}_0 \in \mathbb{R}^{N_J}$ Initial velocity

Trajectory parameters $\boldsymbol{C}$

$a^j, \omega_m{}^j, t_1{}^j, t_2{}^j, t_f$



Objective function

$$F(\boldsymbol{C}) = \frac{(1-\alpha)}{N_J}\sum_{j=1}^{N_J}\left(\frac{a^j}{a_{max}{}^j}\right)^2 + \alpha\left(\frac{t_f}{t_{max}}\right)^2$$

Constraints

Equality constraints

$$\frac{1}{2}\omega_m{}^j\left(t_f + t_2{}^j - t_1{}^j\right) + \frac{1}{2}\omega_0{}^j t_1{}^j = q_f{}^j$$

$$\omega_m{}^j = \omega_0{}^j + a^j t_1{}^j$$

$$\left(\omega_m{}^j - \omega_0{}^j\right)\left(t_f - t_2{}^j\right) = \omega_m{}^j t_2{}^j$$

Inequality constraints

$$0 \leq a^j \leq a_{max}{}^j$$

$$\max(0, \omega_0{}^j) \leq \omega_m{}^j \leq \omega_{max}{}^j$$

$$t_1{}^j \leq t_2{}^j$$

$$0 < t_f \leq t_{max}$$

Method 2: Non-convex transformation

- Unique local minimum
- Guarantee a **global solution**
- Converge more efficiently with **learned initializations**

Optimization parameter

$$\boldsymbol{C} = (a^1, \dots, a^{N_J}, t_f) \in \mathbb{R}^{N_J+1}$$

$$a^j \in [0, a_{max}{}^j]$$

$$t_f \in [0, t_{max}]$$

- simple and intuitive
- obvious convex objective function

Objective function

$$F(\boldsymbol{C}) = \frac{(1-\alpha)}{N_J} \sum_{j=1}^{N_J} \left(\frac{a^j}{a_{max}{}^j}\right)^2 + \alpha \left(\frac{t_f}{t_{max}}\right)^2$$

Inequality constraints

$$\omega_m{}^j \le \omega_{max}{}^j$$

$$\omega_0{}^j \le \omega_m{}^j$$

Where

$$\omega_m{}^j = \frac{(a^j t_f + \omega_0{}^j) - \sqrt{(a^j t_f + \omega_0{}^j)^2 - 2(\omega_0{}^j)^2 - 4 q_f{}^j a^j}}{2}$$

- Extremely complex inequality constraints
- **Non-convex** optimization model
- **Solutions highly rely on initializations**

Optimization parameter

$$\boldsymbol{C} = (\omega_m{}^1, \dots, \omega_m{}^{N_J}, t_f) \in \mathbb{R}^{N_J+1}$$

$$\omega_m{}^j \in [\max(0, \omega_0{}^j), \omega_{max}{}^j]$$

$$t_f \in [0, t_{max}]$$

Objective function

$$F(\boldsymbol{C}) = \frac{(1-\alpha)}{N_J} \sum_{j=1}^{N_J} \left(\frac{a^j}{a_{max}{}^j}\right)^2 + \alpha \left(\frac{t_f}{t_{max}}\right)^2$$

Inequality constraints

$$q_f{}^j - \omega_m{}^j t_f < 0 \ (0 < a^j)$$

$$a^j - a_{max}{}^j \le 0$$

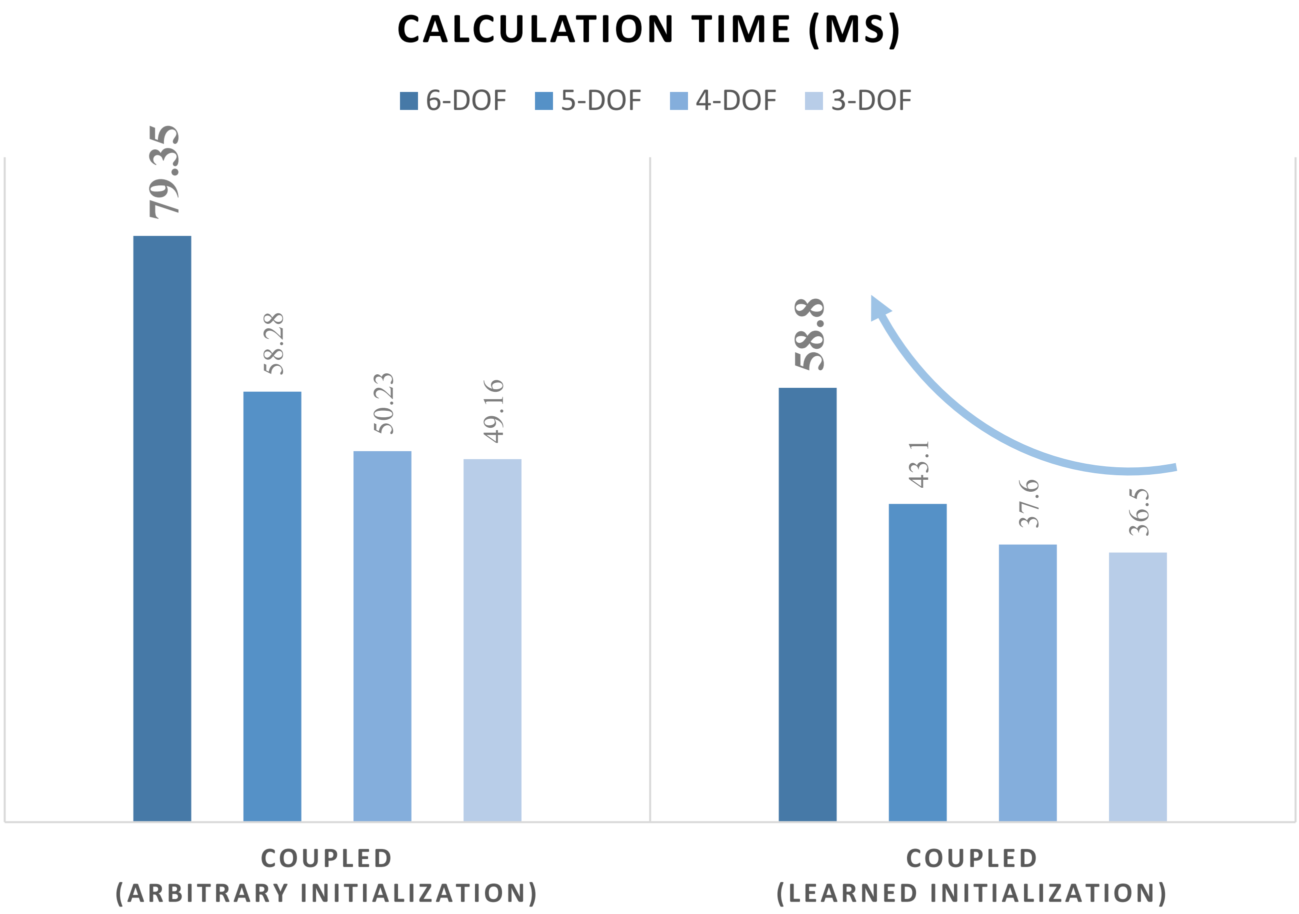
$$2\omega_m{}^j - \omega_0{}^j - a^j t_f \le 0 \ (t_1{}^j \le t_2{}^j)$$

where

$$a^j = \frac{(\omega_m{}^j)^2 + (\omega_0{}^j)^2/2 - \omega_0{}^j \omega_m{}^j}{\omega_m{}^j t_f - q_f{}^j}$$

Still didn't reach the real-time requirement

System sampling time: **4ms**



- Computational efficiency **greatly limited by high dimension** of the problem
- The **increase of the dimension of DOFs** will lead to the **super linear increase** of computational complexity

Method 3: Joint decoupling

Coupled optimization

$$\boldsymbol{X} \rightarrow \boldsymbol{C} = O_{cpl}(\boldsymbol{X})$$

Joint-independent optimization 1

$$(\boldsymbol{X}, \boldsymbol{C}_{cpl}) \rightarrow \boldsymbol{C_J}^{1} = O_{ind}{}^{1}(\boldsymbol{C_J}^{1})$$

n 2

… …

ization NJ

$$(\boldsymbol{X}, \boldsymbol{C}_{cpl}) \rightarrow \boldsymbol{C_J}^{NJ} = O_{ind}{}^{NJ}(\boldsymbol{C_J}^{NJ})$$

Optimization parameter classification

$$\boldsymbol{C} = (\boldsymbol{C_J}^{1}, \ldots, \boldsymbol{C_J}^{N_J}, \boldsymbol{C}_{cou})$$

Coupling parameter

- apply to **all of the joints** simultaneously

Joint parameter

- only appear in the expression of the **certain joint**
- not only related with the certain joint, **affected by other joints indirectly** through the **coupling parameter**

Finding an appropriate coupling parameter

- Learn a feasible and near-optimal coupling parameter

Method 3: Joint decoupling

Coupled optimization

Optimization parameter

$$\boldsymbol{C} = (\omega_m{}^1, \dots, \omega_m{}^{N_J}, t_f) \in \mathbb{R}^{N_J+1}$$
$$\omega_m{}^j \in [\max(0, \omega_0{}^j), \omega_{max}{}^j]$$
$$t_f \in [0, t_{max}]$$

Objective function

$$F(\boldsymbol{C}) = \frac{(1-\alpha)}{N_J}\sum_{j=1}^{N_J}\left(\frac{a^j}{a_{max}{}^j}\right)^2 + \alpha\left(\frac{t_f}{t_{max}}\right)^2$$

Inequality constraints

$$q_f{}^j - \omega_m{}^j t_f < 0 \ (0 < a^j)$$
$$a^j - a_{max}{}^j \leq 0$$
$$2\omega_m{}^j - \omega_0{}^j - a^j t_f \leq 0 \ (t_1{}^j \leq t_2{}^j)$$

where

$$a^j = \frac{(\omega_m{}^j)^2 + (\omega_0{}^j)^2/2 - \omega_0{}^j\omega_m{}^j}{\omega_m{}^j t_f - q_f{}^j}$$

- NJ+1 dimensional
- Needs iterative solver

Optimization parameter classification

$$C_{cpl} = t_f \in \mathbb{R}$$
$$C_J{}^j = \omega_m{}^j \in \mathbb{R}$$

Joint-independent optimization

$$(q_f{}^j, \omega_0{}^j, t_{syn}) \rightarrow \omega_m{}^j = O_{ind}{}^j(\omega_m{}^j)$$

Objective function

$$F^j(\omega_m{}^j) = a^j = \frac{(\omega_m{}^j)^2 + (\omega_0{}^j)^2/2 - \omega_0{}^j\omega_m{}^j}{\omega_m{}^j t_{syn} - q_f{}^j}$$

Constraints

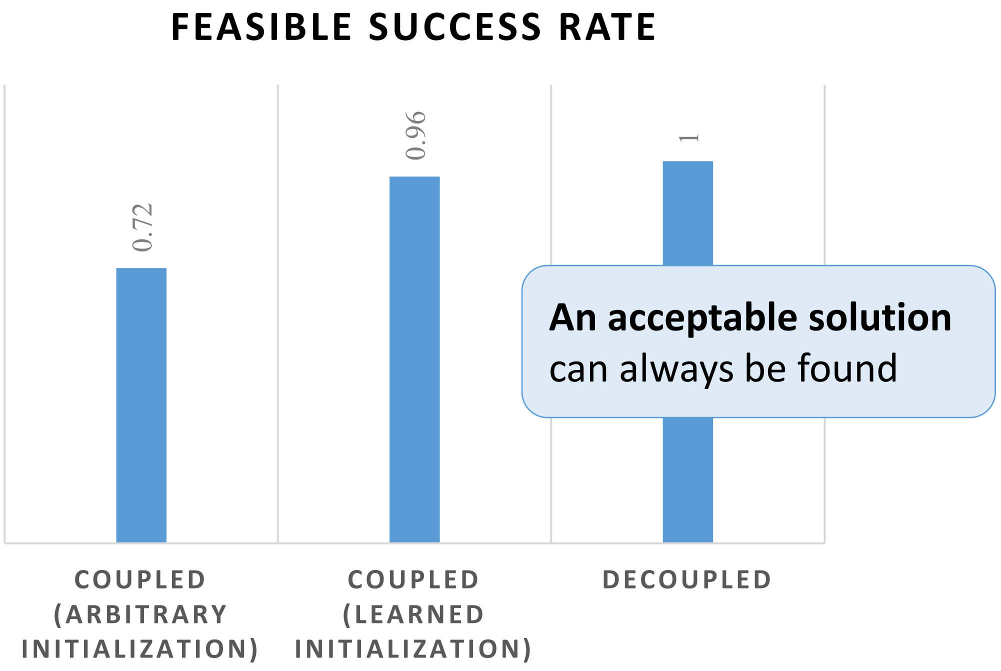
$$\max(\omega_0{}^j, 0) \leq \omega_m{}^j \leq \omega_{max}{}^j$$
$$q_f{}^j - \omega_m{}^j t_{syn} < 0 \ (a^j > 0)$$
$$a^j - a_{max}{}^j \leq 0$$
$$2\omega_m{}^j - \omega_0{}^j - a^j t_{syn} \leq 0 \ (t_1{}^j \leq t_2{}^j)$$

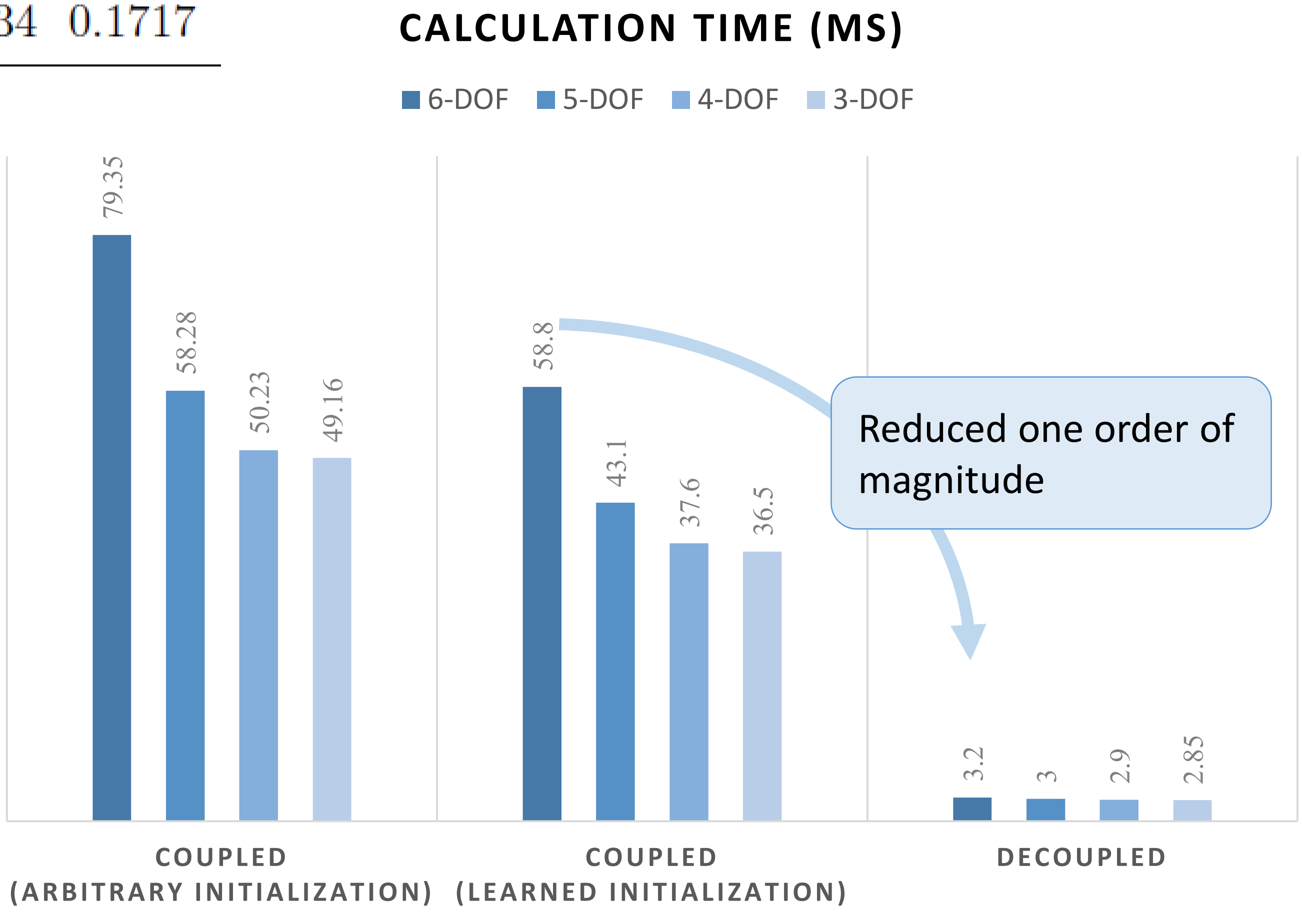
- 2 dimensional
- Could be analytically solved

Method 3: Joint decoupling

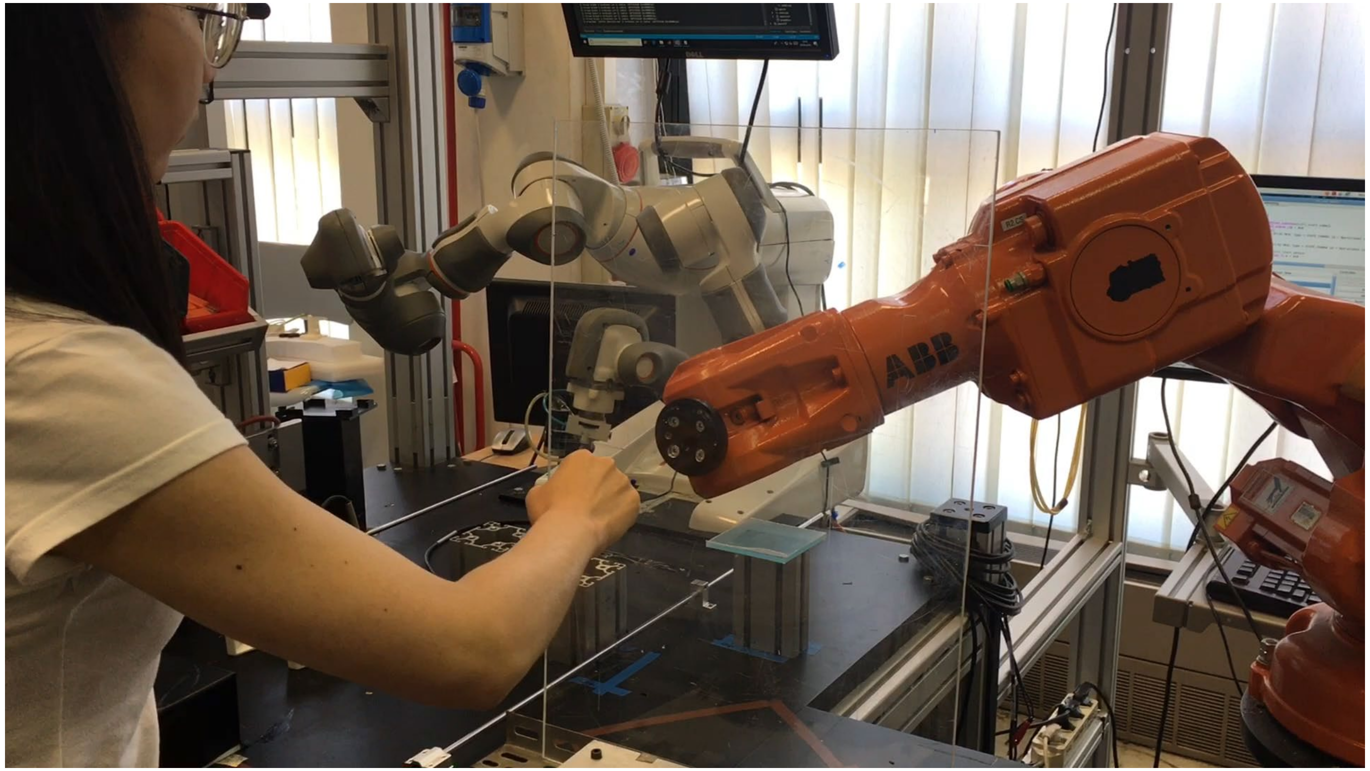
ERROR WITH OPTIMAL SOLUTION

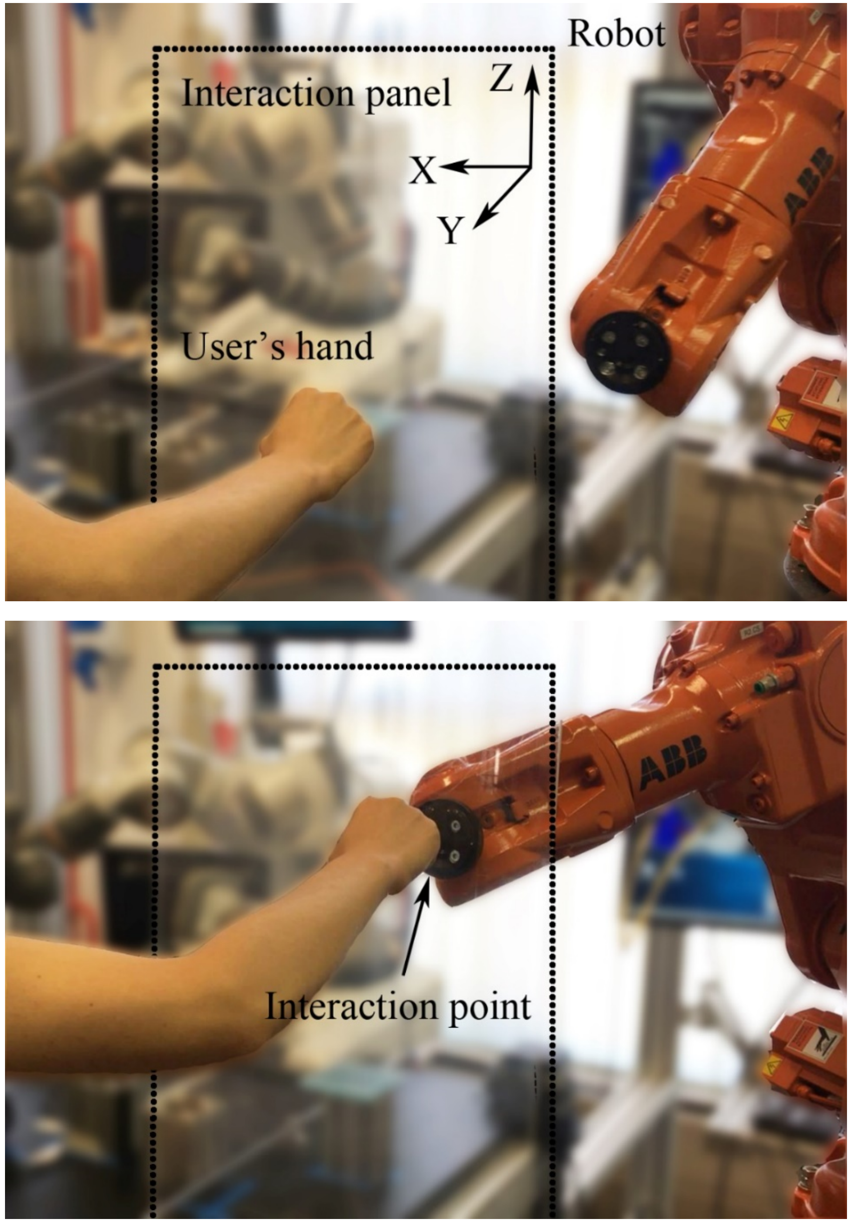
e_F				e_C			
0.1758	0.1694	0.2579	0.1649	0.1652	0.2518	0.2134	0.1717





Haptic interaction demo



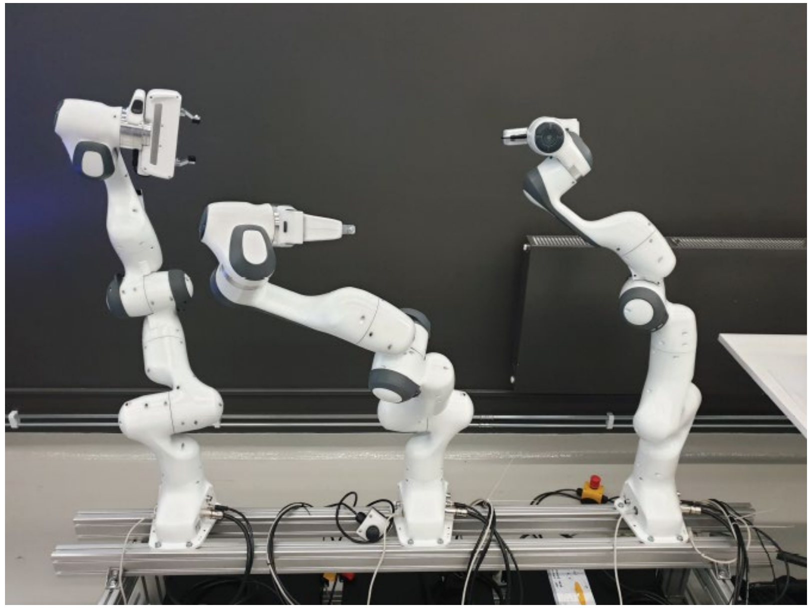


Multi-arm coordination

AutoBoomer - Automated Drill Planning for Multiple-Boom Rigs in Underground Mining

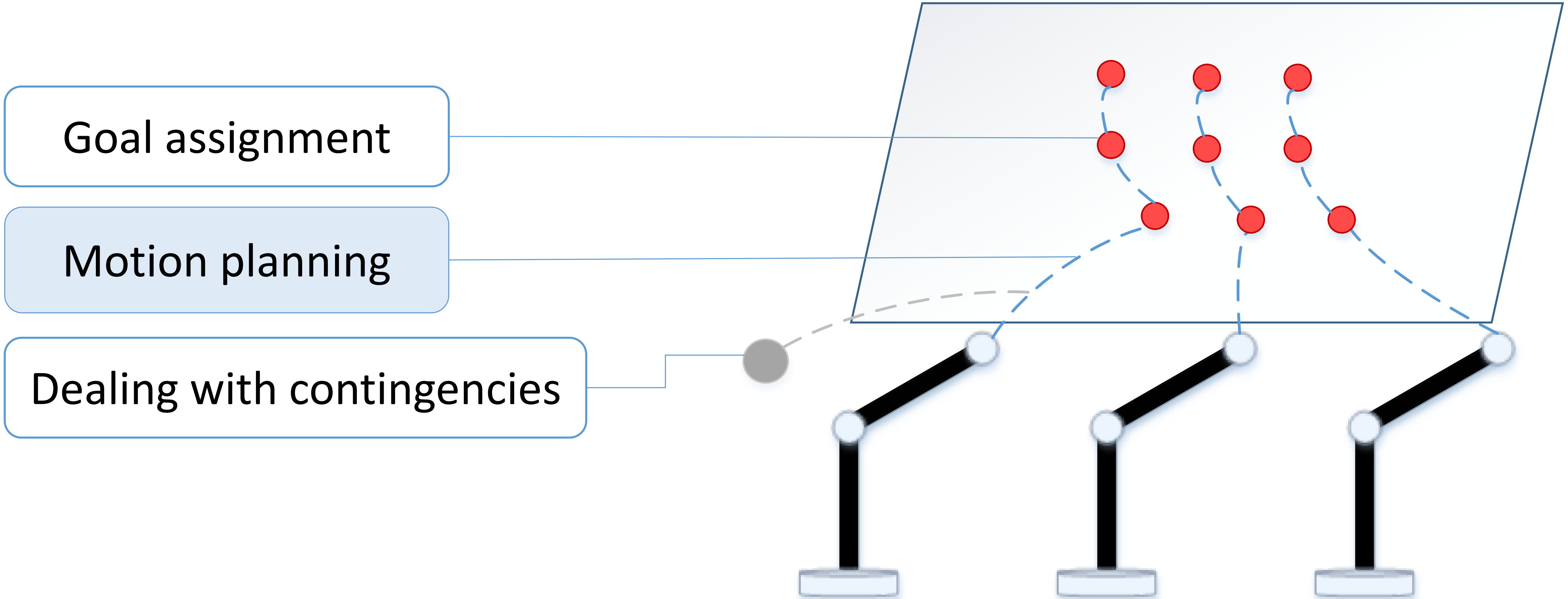
Funders VINNOVA SIP STRIM

Partners Örebro Universitet, Epiroc, Zinkgruvan Mining a subsidiary of lundin mining, Alfred Nobel Science Park

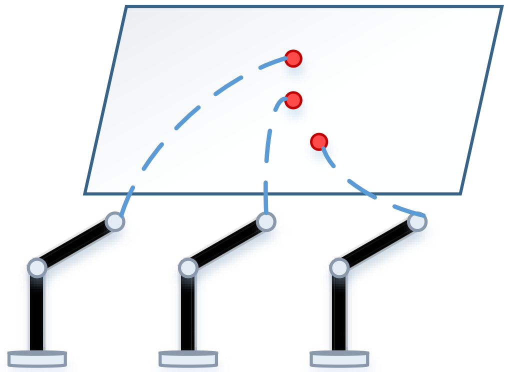


Multi-arm coordination

AutoBoomer - Automated Drill Planning for Multiple-Boom Rigs in Underground Mining



Collision and deadlock free motion planning for multiple robot arms in shared workspace



Assumption

- The goal for each robot has already been assigned

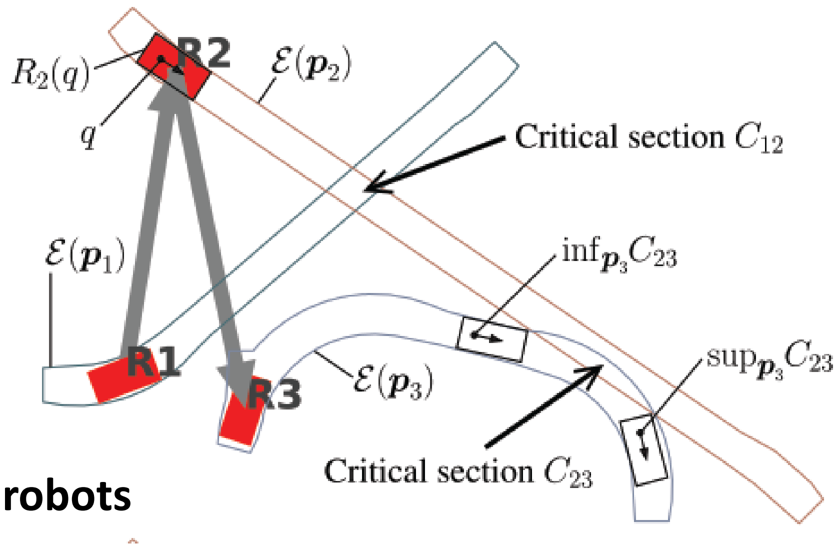
Objective

- To bring all the robots to goal configurations in **minimal time** without collisions

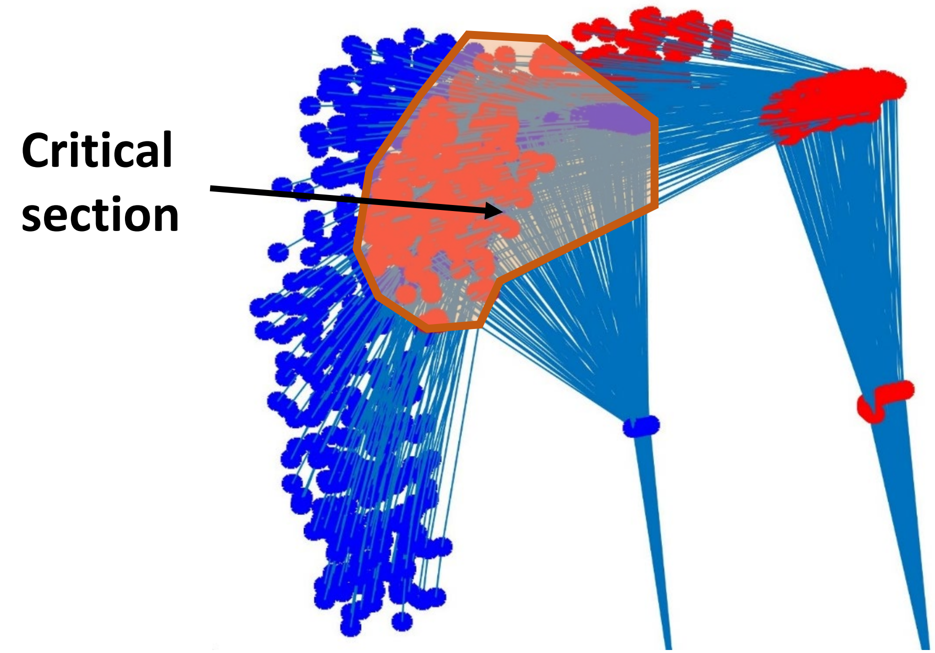
Challenge

- Dealing with the interference of each other, avoiding **collisions and deadlocks**

Extend coordination_oru framework* to robot arms



Mobile robots



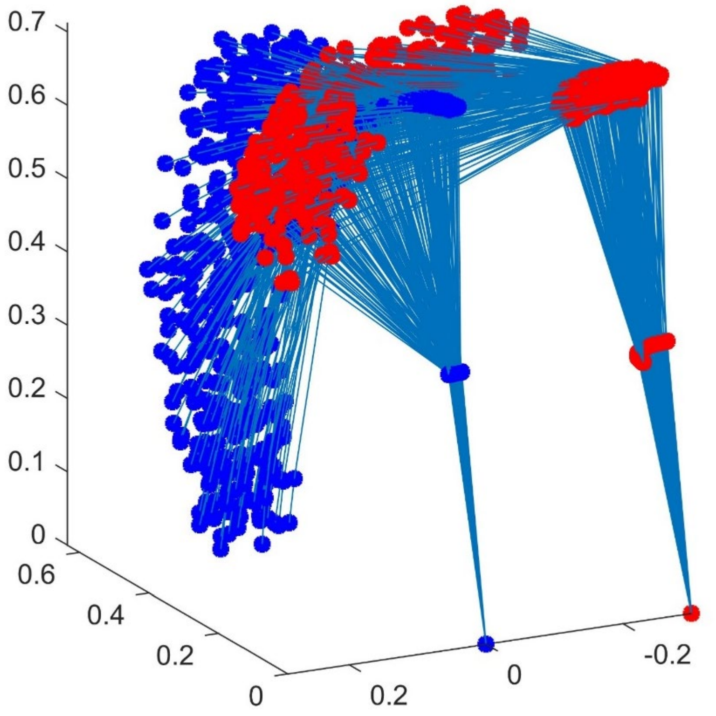
Robot arms

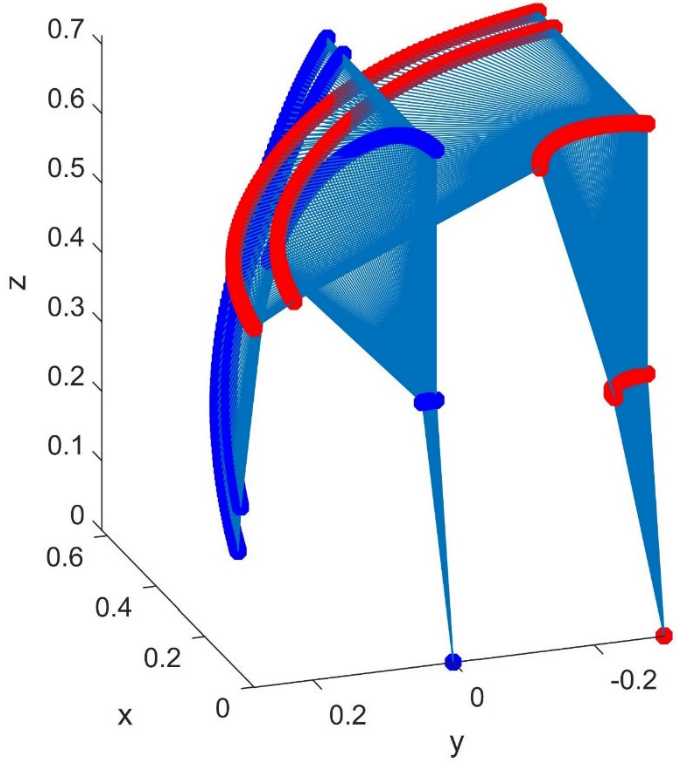
Hard to get the **accurate boundary** of collision region and whether a configuration is in the region

- Complex **geometric shape**
- Transformation between **joint space** and **task space**

* Pecora F, Andreasson H, Mansouri M, et al. **A Loosely-Coupled Approach for Multi-Robot Coordination, Motion Planning and Control** [C] //Twenty-Eighth International Conference on Automated Planning and Scheduling. 2018.

Modifications and adaptation to robot arms

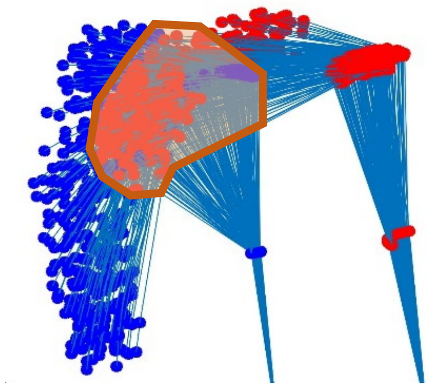




All the possible configurations

Configurations along an initial trajectory

Coordination Matrix Transform the complex geometry to **linear space**



R2 – robot with lower priority

C1 C2 … (equal time interval)

R1 – robot with higher priority

	C1	C2	…									
C1	0	0	0	0	1	1	1	1	1	1	1	0
C2	0	0	0	0	1	1	1	1	1	1	1	0
…	0	0	0	0	0	1	1	1	1	1	0	0
	0	0	0	0	0	0	1	1	1	1	0	0
	0	0	0	0	0	0	1	1	1	1	0	0
	0	0	0	0	0	0	0	1	1	0	0	0
	0	0	0	0	0	0	0	1	1	0	0	0
	0	0	0	0	0	0	0	0	1	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0	0

1 **collision** between two configurations

0 **no collision** between two configurations

Collision-free region

Critical section

Boundary

Coordination Matrix

- **Collision**: Diagonal elements
- **Avoid collision** : Stretch/ Add columns
- **Deadlock**: Full “0” route from start to end
- **Change priority**: Transpose
- ……

R2 – robot with lower priority

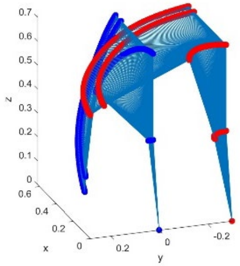
C1 C2 … (equal time interval)

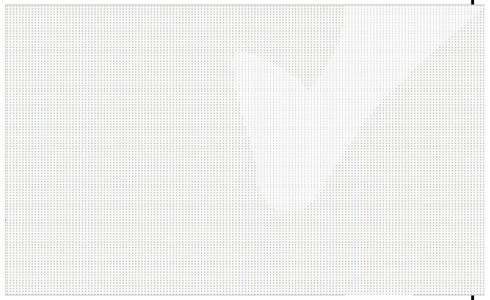
R1 – robot with higher priority

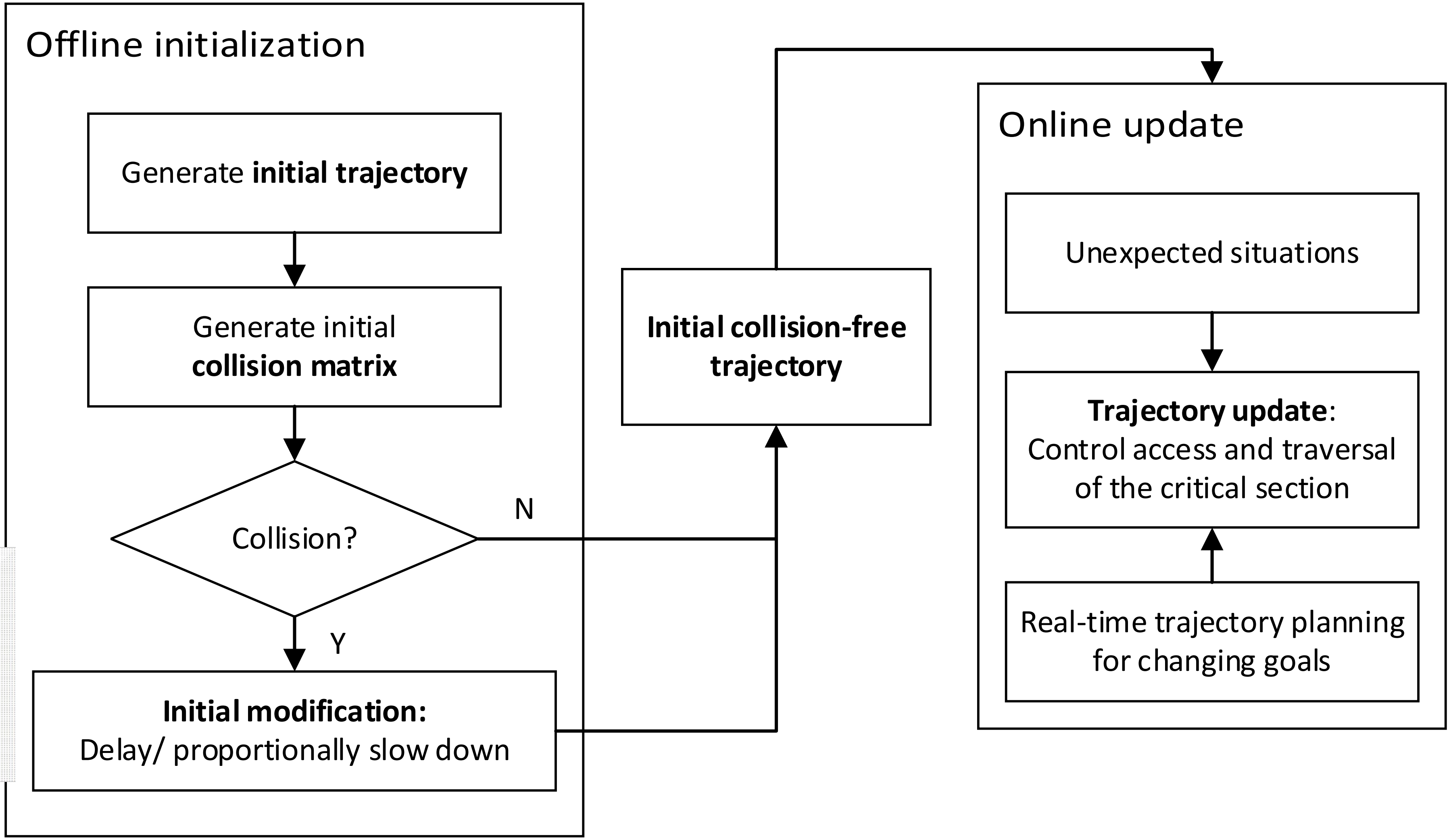
C1 C2 …

0	0	0	0	1	1	1	1	1	1	1	0
0	0	0	0	1	1	1	1	1	1	1	0
0	0	0	0	0	1	1	1	1	1	0	0
0	0	0	0	0	0	1	1	1	1	0	0
0	0	0	0	0	0	1	1	1	1	0	0
0	0	0	0	0	0	0	1	1	0	0	0
0	0	0	0	0	0	0	1	1	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0

Coordination process







Future challenges

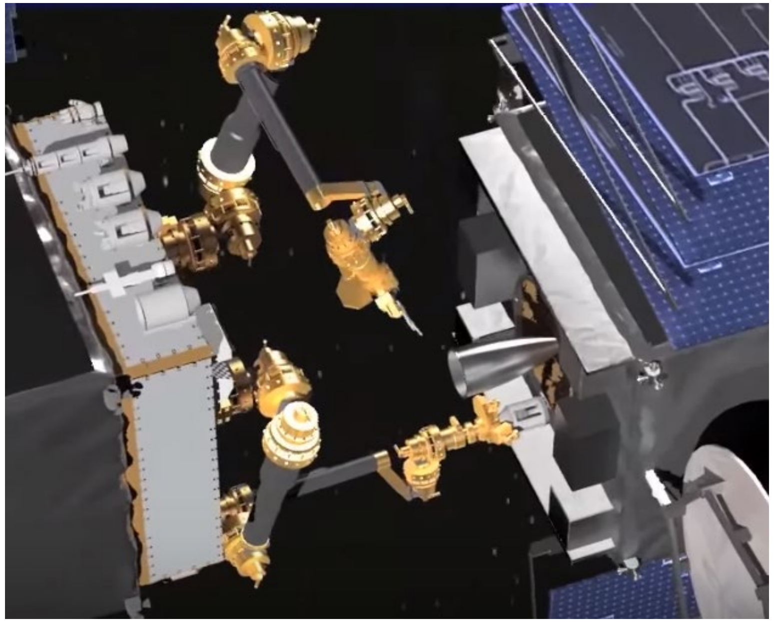
- Velocity profile for each joint changes – reference configuration changes
- More than 2 robots
- Change path/ goal
- Non-void workspace
- Long duration operation
- Learn cooperative pattern
- …

Applications

Exploring the remote places

Underground mining [1]

South pole station construction [2]



On-orbit service [3]

[1] Epiroc https://www.epiroc.com/
[2] Mega Structures: South pole station
[3] DARPA Robotic Servicing of Geosynchronous Satellites (RSGS) https://www.darpa.mil/program/robotic-servicing-of-geosynchronous-satellites

Challenges

- Large size
- Harsh working environment
- Long-duration operation
- …

Technologies

- Real-time planning and control based on perception
- Multi-robot systems
- Low level control with physical contacts
- Modeling and control of novel designed field mechanisms

Basis and Foundation

- Modeling and efficient algorithms for complex real-world problems
- Safe and reliable learning techniques for planning and control

VINNOVA

KK-stiftelsen

Stiftelsen för Strategisk Forskning

European Commission

Horizon 2020
European Union funding
for Research & Innovation

Vetenskapsrådet

Smarter machines

- Reuse previous experience
- Feed robot knowledge

Simpler world

- Non-convex - convex
- Coupled - decoupled
- Non-linear - linear

* When the **linear-programming model** and **simplex algorithm** first delivered by **George Dantzig** at a meeting, it was criticized by a noted scholar, **Harold Hotelling**,

"But we all know the world is nonlinear."

At this moment, **John von Neumann** replied for him, "The speaker titled his talk linear programming and carefully stated his axioms. If you have an application that satisfies the axioms, well use it. If it does not, then don't."

Fortunately for the world, many of its complexities can in fact be described in sufficient detail by linear models.

The episode is later summed up nicely by a cartoon hanging outside Dantzig's office.
The caption reads,

Happiness is
assuming **the world is linear.**

* Cook W J. **In pursuit of the traveling salesman: mathematics at the limits of computation**[M]. Princeton University Press, 2011

Thank you!