Recent Progress in Information Gathering and Surveillance Missions Planning with Unmanned Aerial Vehicles

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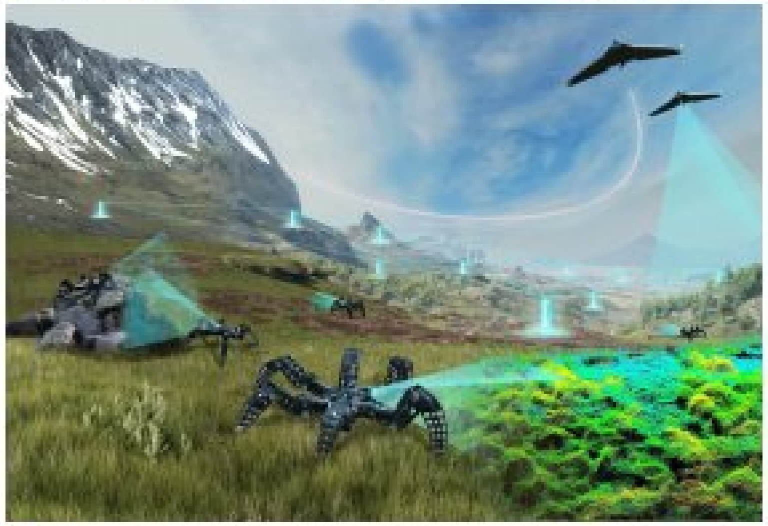
July 20, 2018

Czech Technical University in Prague
Artificial Intelligence Center and Computational Robotics

- Established in 18 January, 1707

  Foundation deed signed by Emperor Joseph I

- About 21 000 students enrolled and 1 9000 academic employees – 8 faculties
- **Faculty of Electrical Engineering** (**FEE**) **Department of Computer Science**
  - First CS department in Czechia established in 1964 http://cs.felk.cvut.cz
- **Artificial Intelligence Center** (**AIC**)
  - Research in AI for more than 20 years http://aic.fel.cvut.cz
- **Computational Robotics Laboratory** (**ComRob**) https://comrob.fel.cvut.cz – established in 2013
  - Focused on robotic information gathering – a problem to create a model of phenomena by autonomous mobile robots performing measurements in dynamic unknown environment.
  - Mostly **aerial** and ground (multi-legged) robotic vehicles



Information Gathering with Unmanned Aerial Vehicles (UAVs) – UAV Mapping and Surveillance Missions

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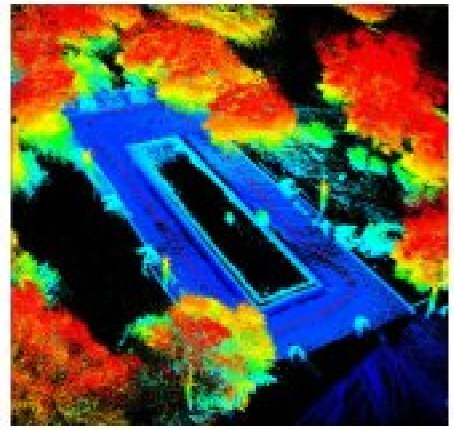
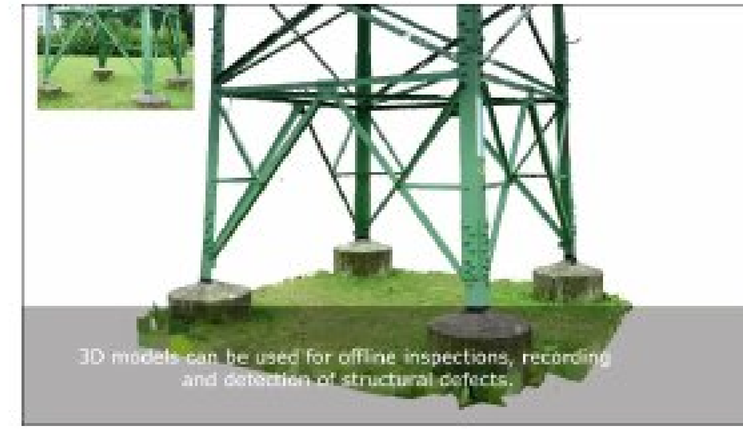
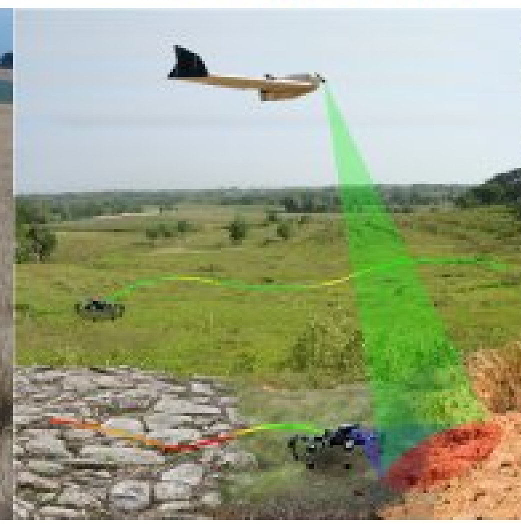
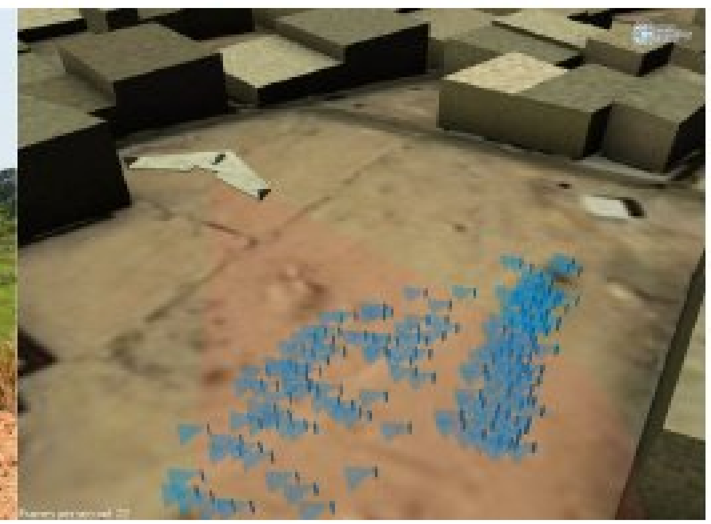
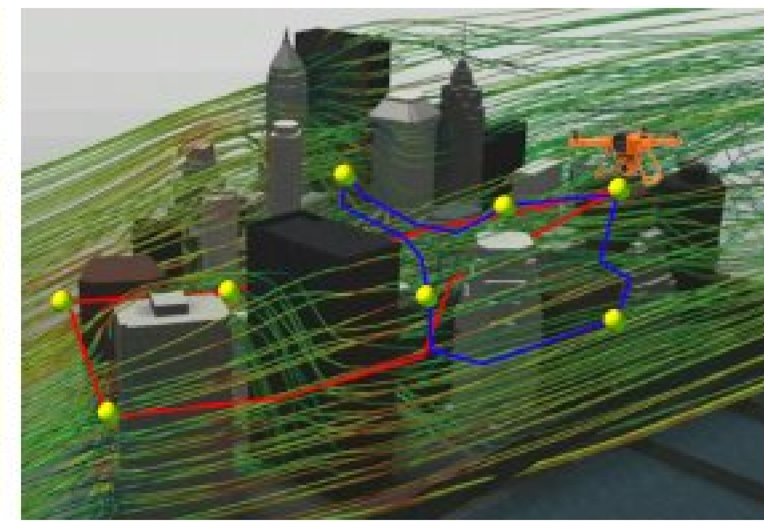
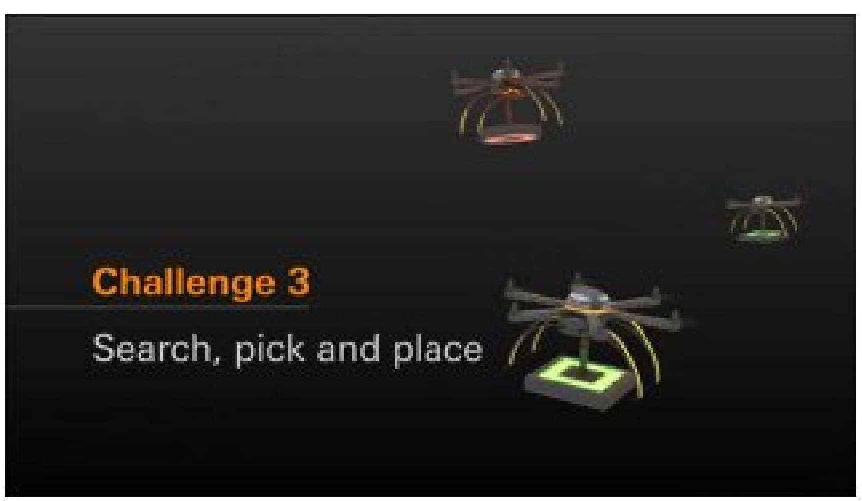




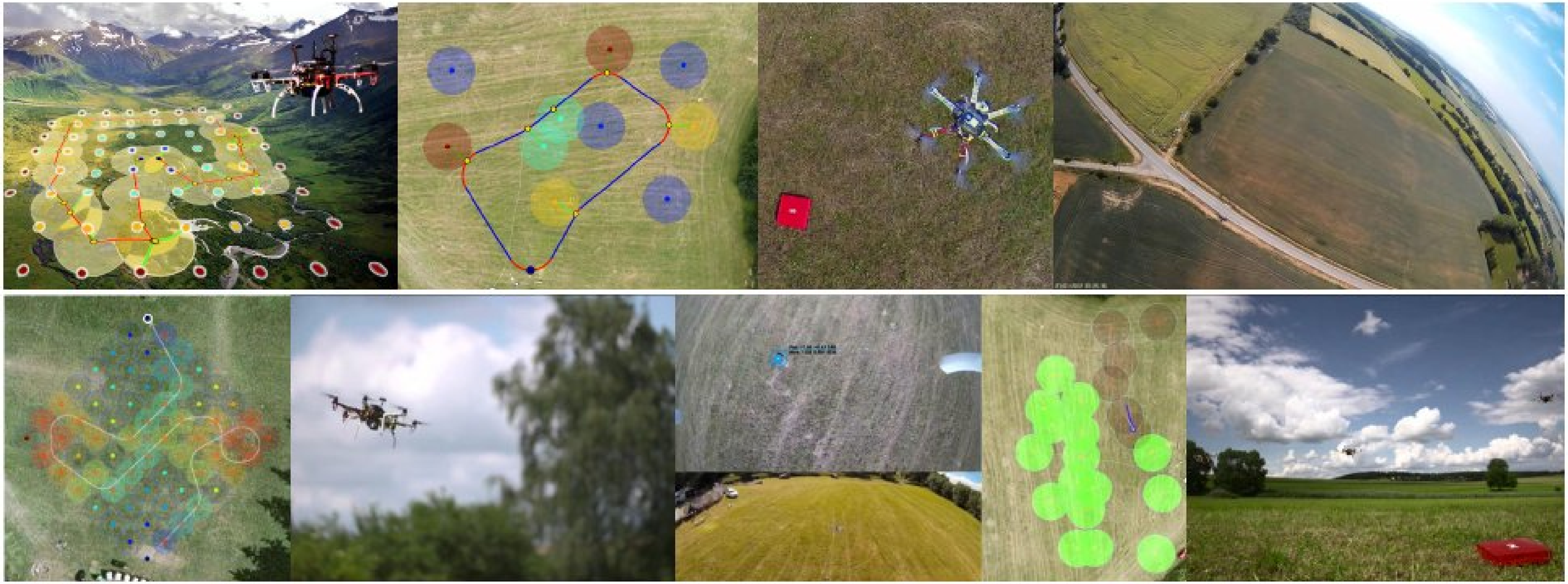







- Surveillance planning in Mohamed Bin Zayed International Robotic Challenge (MBZIRC) 2017

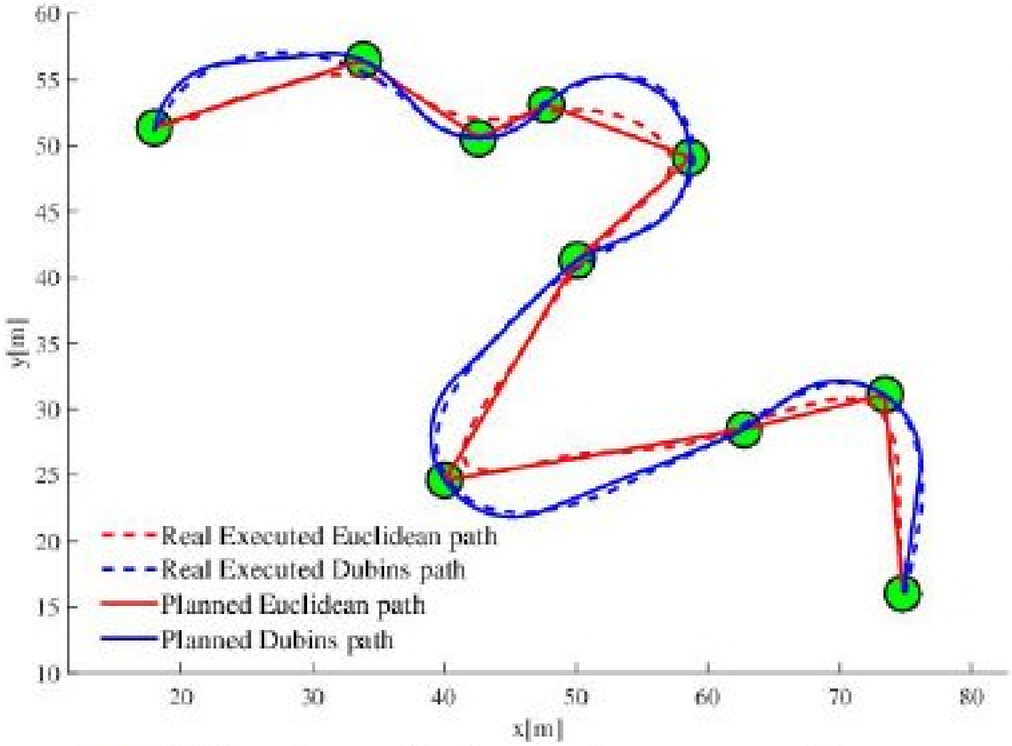
AI CENTER

- Provide **curvature-constrained** path to collect the most valuable measurements with shortest possible path/time or under limited travel budget



- Can be formulated as routing problems with Dubins vehicle
  - **Dubins Traveling Salesman Problem with Neighborhoods**
  - Dubins Orienteering Problem with Neighborhoods

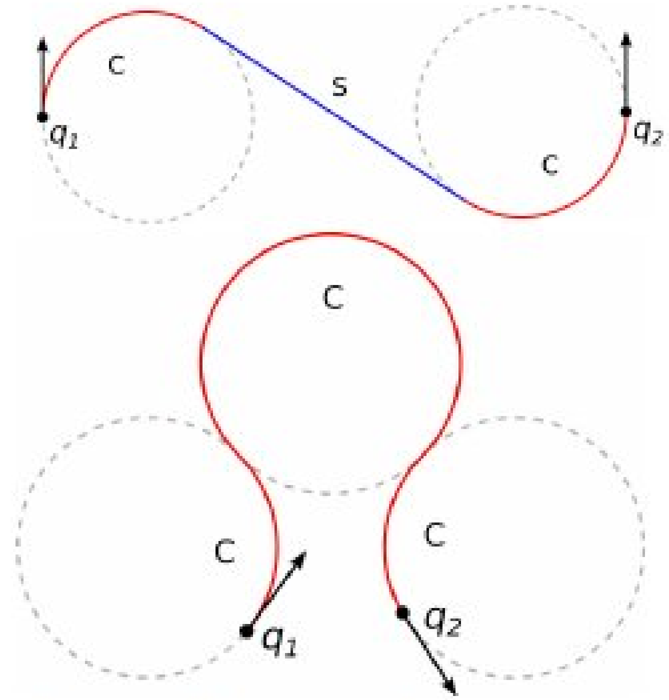
Planning Curvature-Constrained Multi-Goal Path Dubins Vehicle for Fixed-Wing and Multi-Rotor Vehicles



- Sharp turns can lead to high error of visiting the requested goals
- Planned paths should support precise trajectory following by the used controller
- **Dubins vehicle** can be used for curvature-constrained paths

- Minimal turning radius ρ and constant forward velocity v with the state $q = (x, y, \theta)$, $q \in SE(2)$, $(x, y) \in \mathbb{R}^2$ and $\theta \in \mathbb{S}^1$
- **Optimal path connecting** $q_1, q_2 \in SE(2)$ can be found analytically
- Two types of maneuvers: CSC and CCC

(Dubins, 1957)



The main difficulty is to determine the vehicle headings for a given set/sequence of waypoints

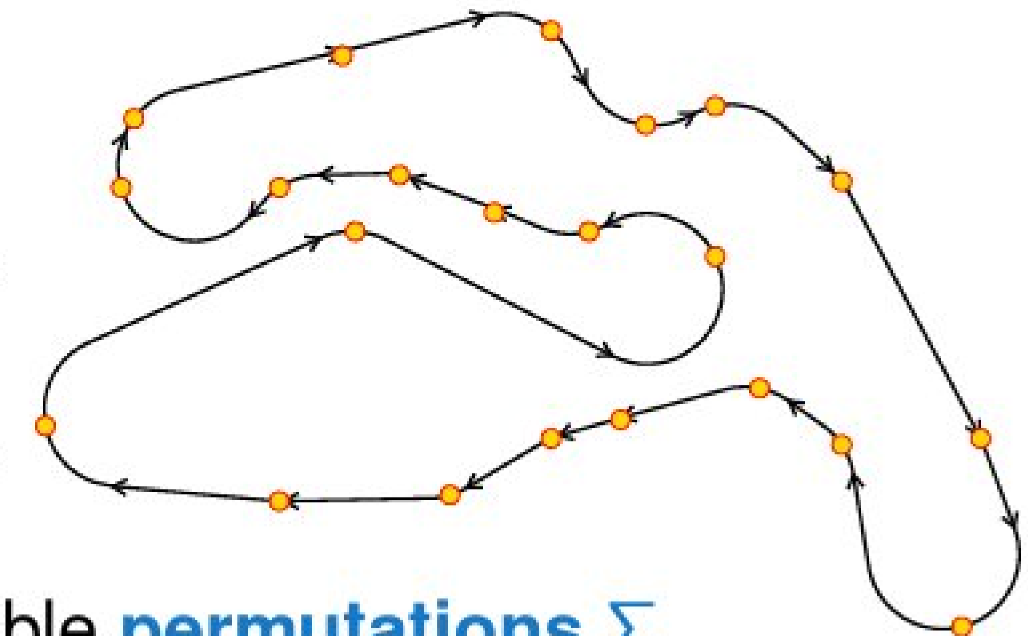
- Having a set of locations to be visited, the problem is to determine a closed shortest Dubins path visiting each location $p_i \in P$ of the given set of n locations $P = \{p_1, \ldots, p_n\}$, $p_i \in \mathbb{R}^2$

1. Permutation $\Sigma = (\sigma_1, \ldots, \sigma_n)$ of visits

   Sequencing part of the problem – combinatorial optimization

2. Headings $\Theta = \{\theta_{\sigma_1}, \theta_{\sigma_2}, \ldots, \theta_{\sigma_n}\}$ for $p_{\sigma_i} \in P$

   Continuous optimization



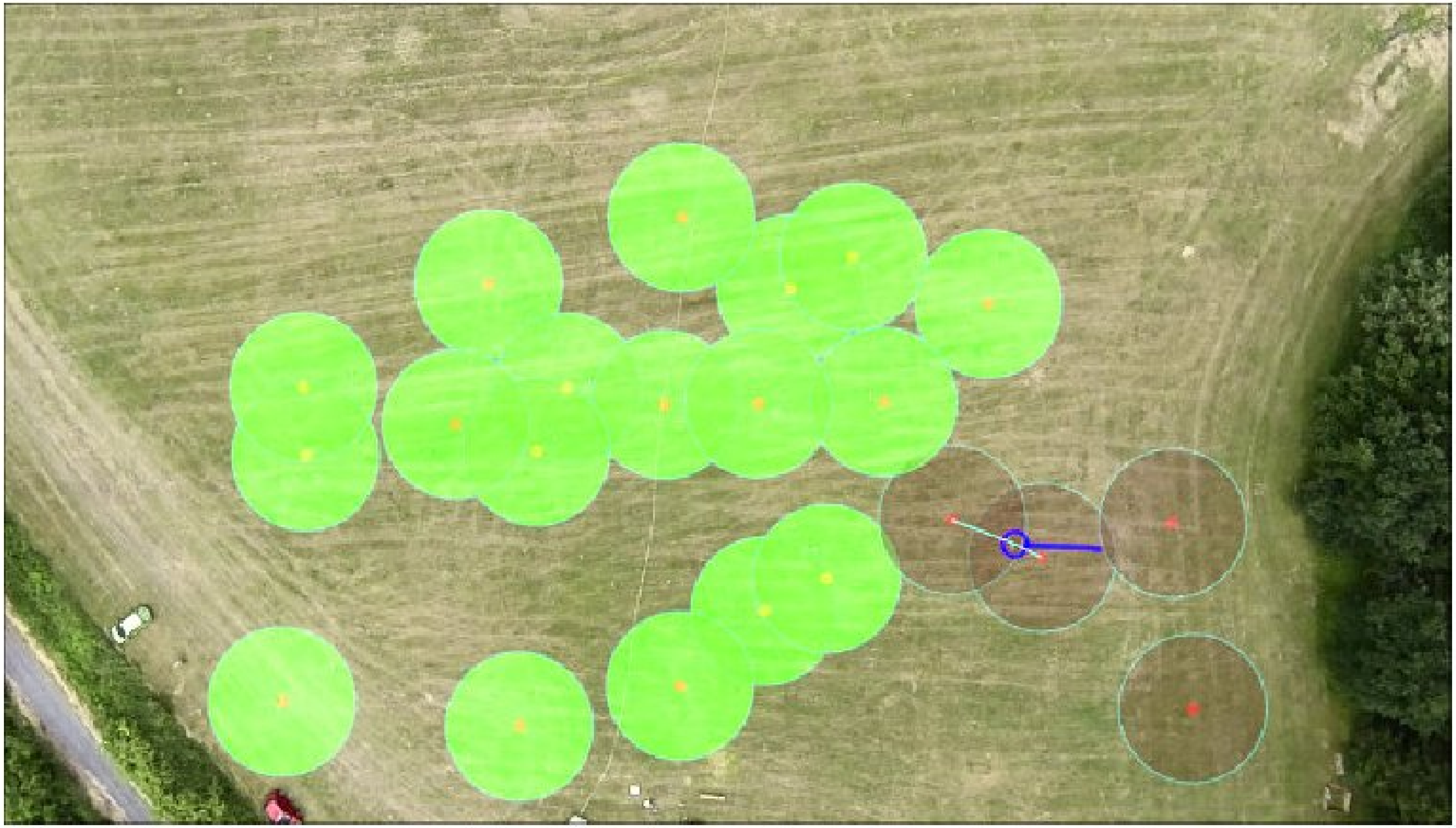
- **DTSP** is an optimization problem over all possible **permutations** Σ and **headings** Θ in the states $(q_{\sigma_1}, q_{\sigma_2}, \ldots, q_{\sigma_n})$ such that $q_{\sigma_i} = (p_{\sigma_i}, \theta_{\sigma_i})$

$$\textit{minimize}_{\Sigma,\Theta} \quad \sum_{i=1}^{n-1} \mathcal{L}(q_{\sigma_i}, q_{\sigma_{i+1}}) + \mathcal{L}(q_{\sigma_n}, q_{\sigma_1}) \qquad (1)$$

$$\textit{subject to} \quad q_i = (p_i, \theta_i) \; i = 1, \ldots, n, \qquad (2)$$

where $\mathcal{L}(q_{\sigma_i}, q_{\sigma_j})$ is the length of Dubins path between q_{σ_i} and q_{σ_j}.

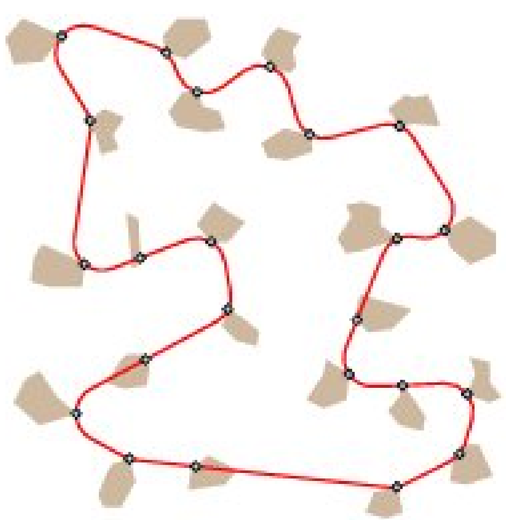
- Exploiting non-zero sensing range δ to shorten the requested multi-goal path

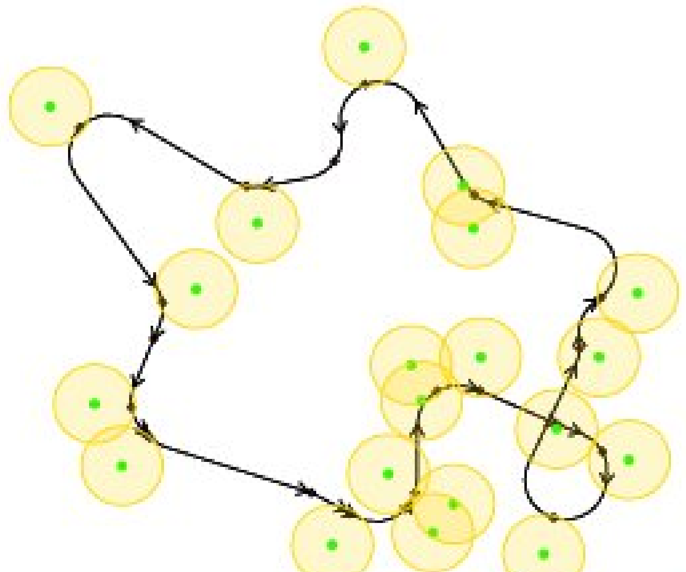


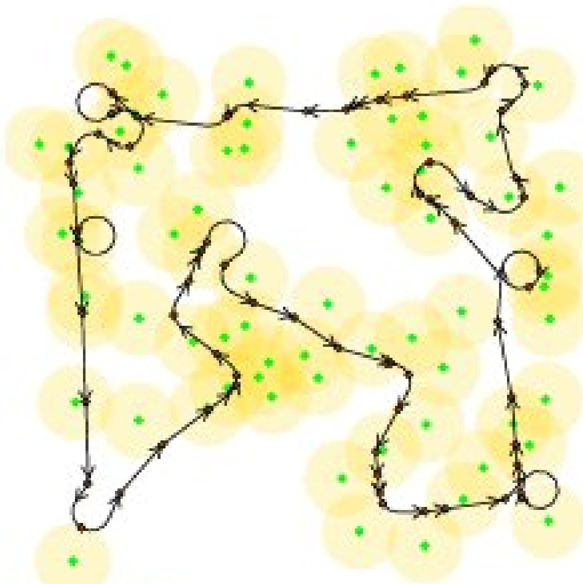
- **Dubins Traveling Salesman Problem with Neighborhoods** (**DTSPN**)
  – determine the sequence of visits Σ, headings Θ, but also the waypoint locations within the respective neighborhoods $P = \{p_1, \ldots, p_n\}$, $p_i \in \mathbb{R}^2$

Existing Approaches to the DTSP(N) Heuristics, Resolution Complete, and Sampling-based

- Sampling-based approaches
  - *Obermeyer, 2009*
  - *Oberlin et al., 2010*
  - *Macharet et al., 2016*
- Convex optimization
  - (Only if the locations are far enough)
  - *Goac et al., 2013*
- Lower-bound for the DTSP
  - Using Dubins Interval Problem (DIP)
  - *Manyam et al., 2016*
- Lower-bound for the DTSPN
  - Using Generalized DIP (GDIP)
  - *Váňa and Faigl, 2018*
- Heuristic approaches
  - *Savla et al., 2005*
  - *Ma and Castanon, 2006*
  - *Macharet et al., 2011*
  - *Macharet et al., 2012*
  - *Ny et al., 2012*
  - *Yu and Hang, 2012*
  - *Macharet et al., 2013*
  - *Zhant et al., 2014*
  - *Macharet and Campost, 2014*
  - *Váňa and Faigl, 2015*
  - *Isaiah and Shima, 2015*
  - ...



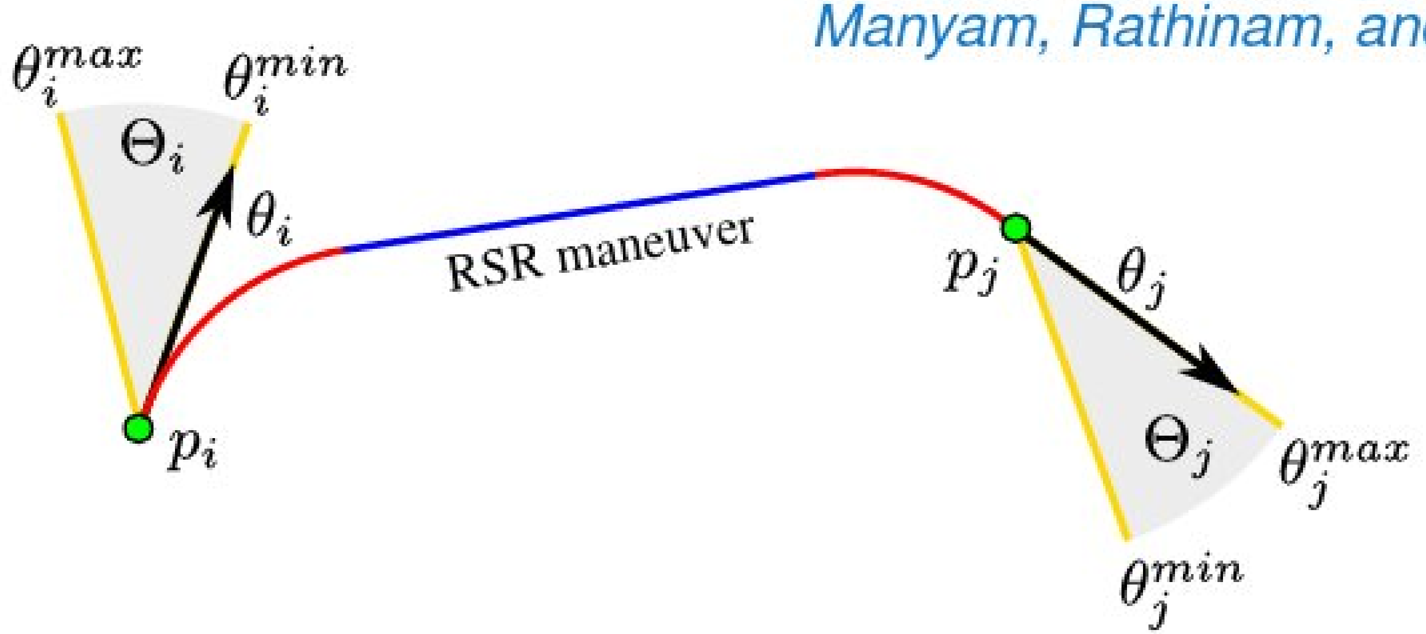




Theoretical Guarantees – Lower-Bound using solution of Dubins Interval Problem (DIP)

- Determine the shortest Dubins maneuver connecting p_i and p_j given the angle intervals $\theta_i \in [\theta_i^{min}, \theta_i^{max}]$ and $\theta_j \in [\theta_j^{min}, \theta_j^{max}]$
- DIP has closed-form solution

Manyam, Rathinam, and Casbeer, 2016

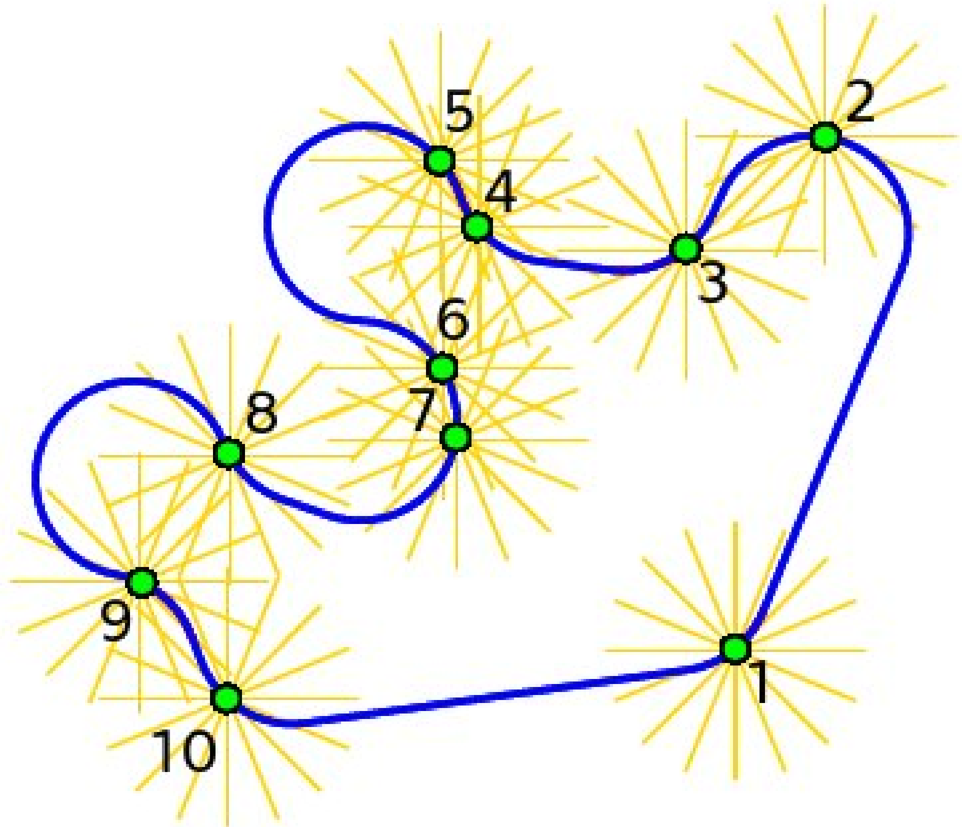


- For the intervals $\Theta_i = \Theta_j = [0, 2\pi)$, the solution is the length of the straight line segment
- It provides lower-bound of the length of the shortest Dubins maneuver connecting p_i and p_j

- For a sequence of the waypoint locations

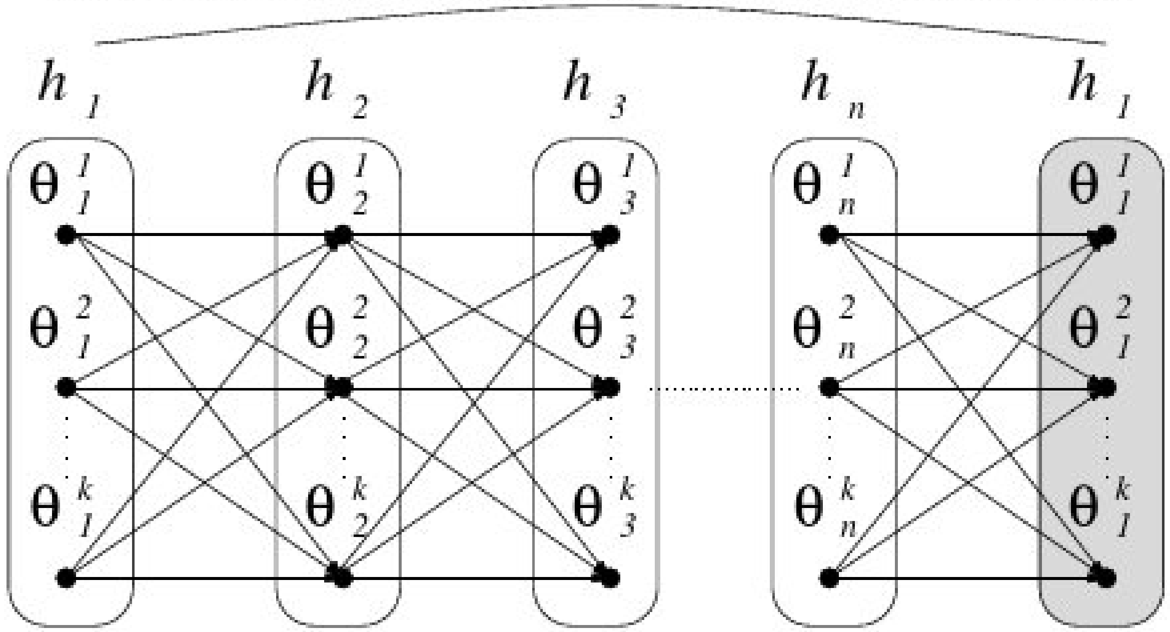
$$P = (p_1, \ldots, p_n)$$

E.g., found as a solution of the Euclidean TSP



- We can sample possible heading values at each location i into a discrete set of k headings, i.e., $h_i = \{\theta_i^1, \ldots, \theta_i^k\}$ and create a graph of all possible Dubins maneuvers

The first layer is duplicated layer to support the forward search method



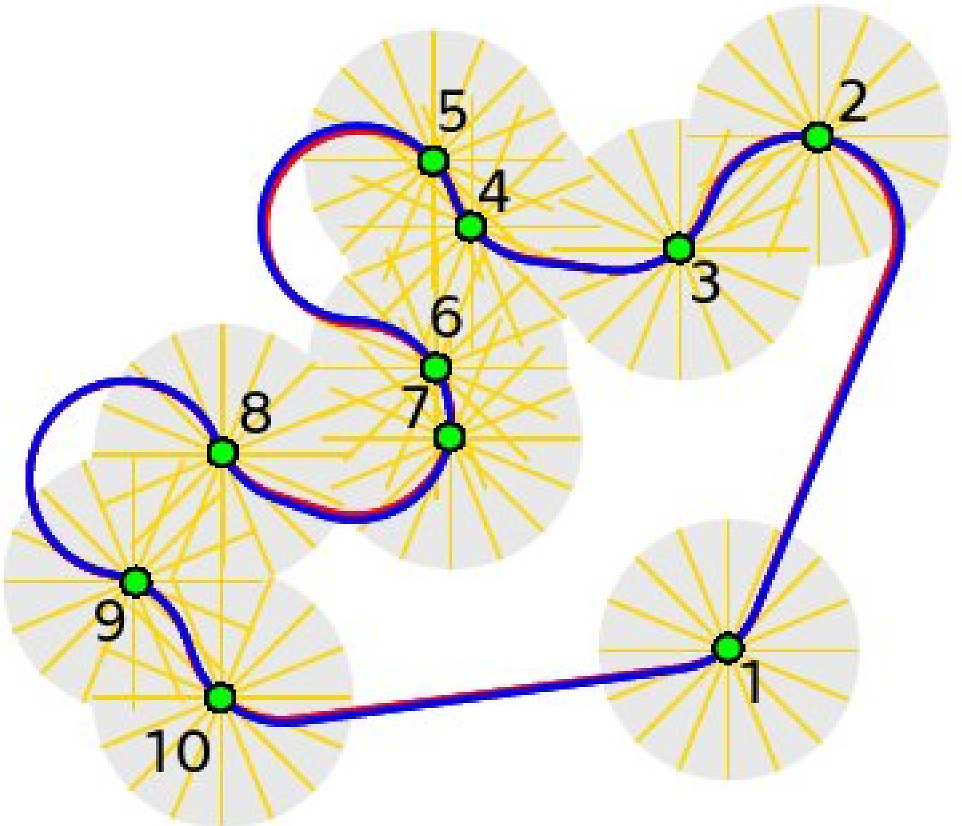
- For a set of heading samples, the optimal solution can be found by a forward search of the graph in $O(nk^3)$
- **The key is to determined the most suitable heading samples per each waypoint**
- The lower bound can be found using DIP

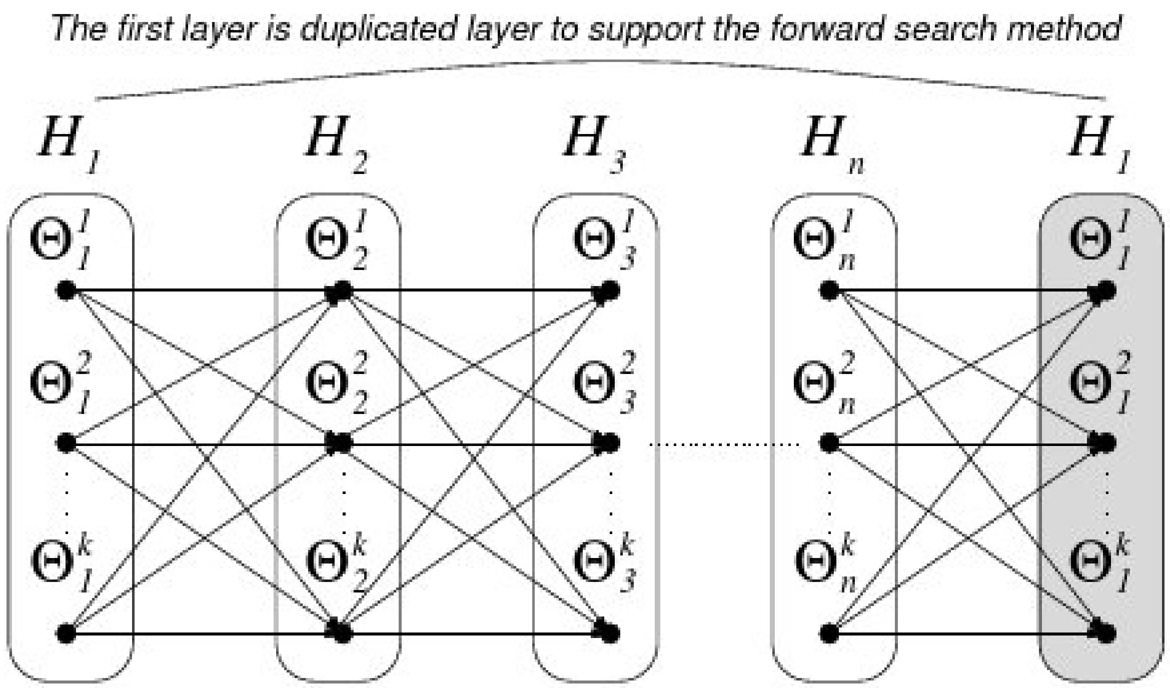
- For a sequence of the waypoint locations

$$P = (p_1, \ldots, p_n)$$

E.g., found as a solution of the Euclidean TSP

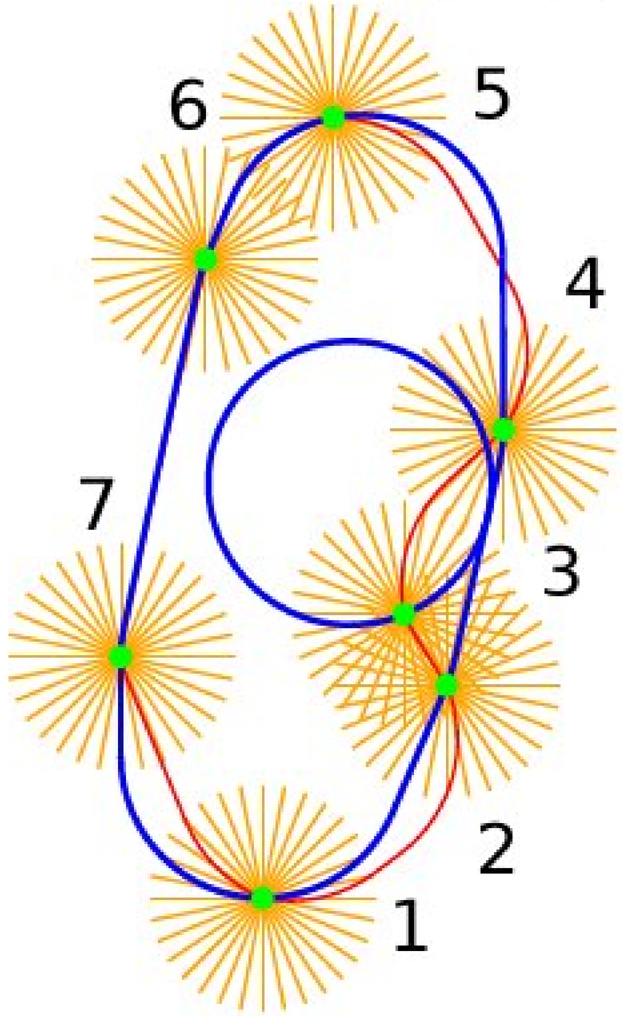
- We can sample possible heading values at each location i into a discrete set of k headings, i.e., $h_i = \{\theta_i^1, \ldots, \theta_i^k\}$ and create a graph of all possible Dubins maneuvers





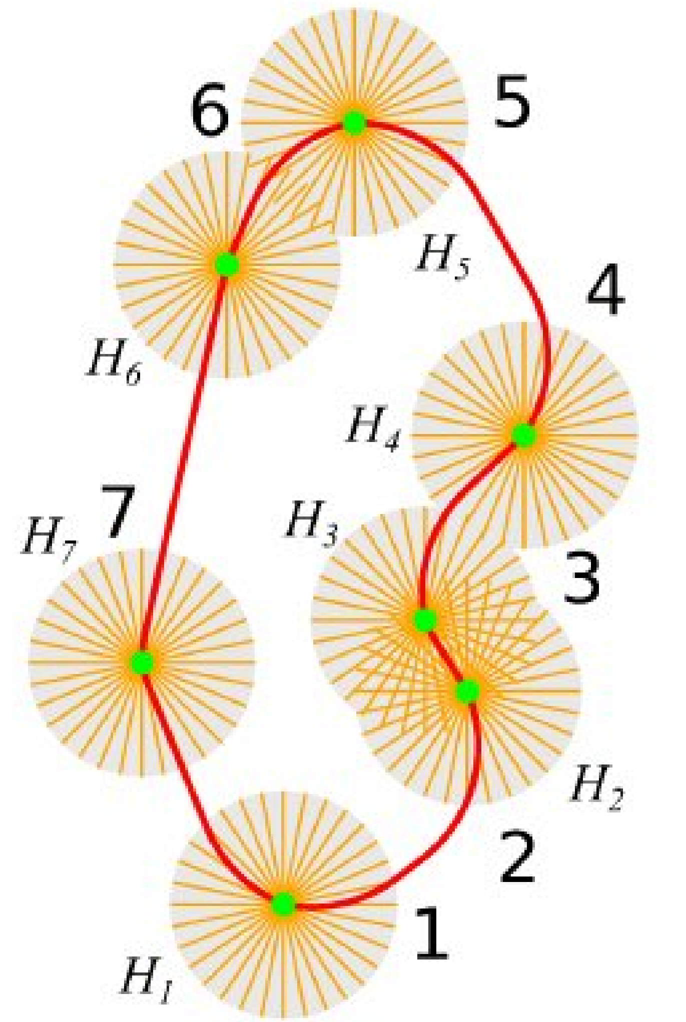
- For a set of heading samples, the optimal solution can be found by a forward search of the graph in $O(nk^3)$
- **The key is to determined the most suitable heading samples per each waypoint**
- The lower bound can be found using DIP

Uniform sampling



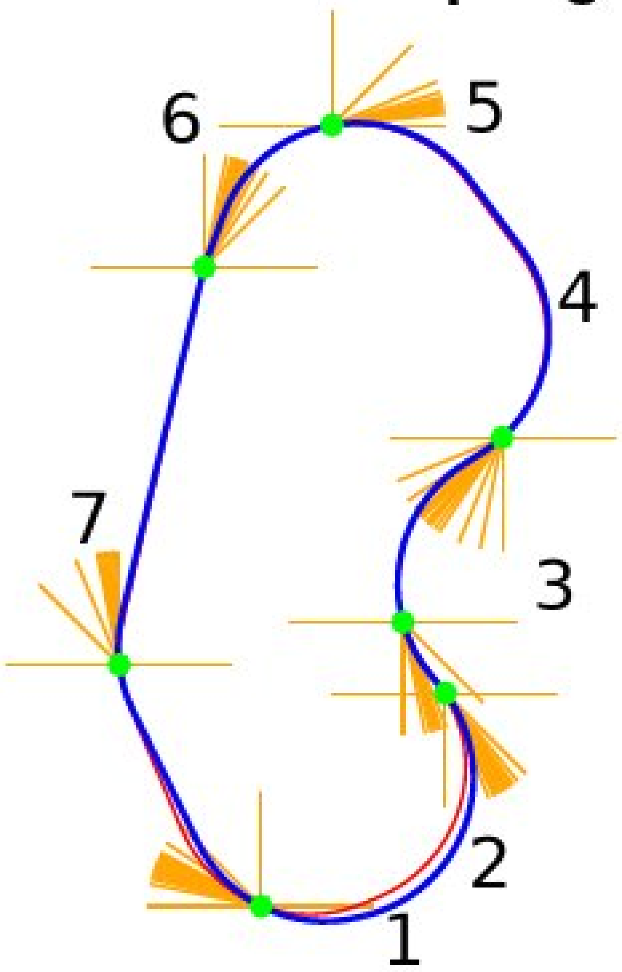
$N = 224$, $T_{cpu} = 128$ ms
$\mathcal{L} = 19.8$, $\mathcal{L}_U = 13.8$,

Lower Bound Solution



Lower bound $\mathcal{L}_U$ based on the Dubins Interval Problem

Informed sampling



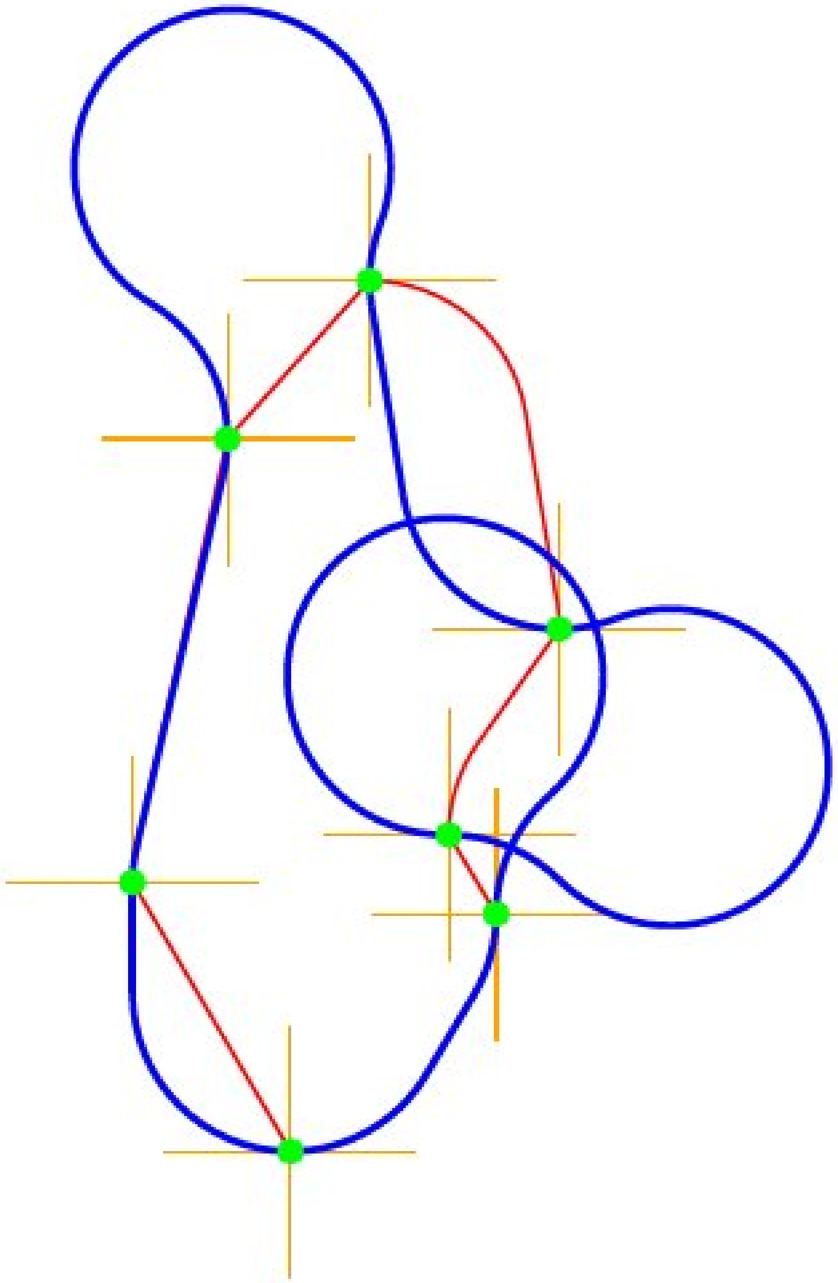
$N = 128$, $T_{cpu} = 76$ ms
$\mathcal{L} = 14.4$, $\mathcal{L}_U = 14.2$,

- N – the total number of samples (up to 32 samples per waypoint)
- $\mathcal{L}$ is the length of the tour (blue) and $\mathcal{L}_U$ is the lower bound (red) determined as a solution of the **Dubins Interval Problem** (**DIP**)

- Faigl et al.: *On solution of the Dubins touring problem.* ECMR 2017.

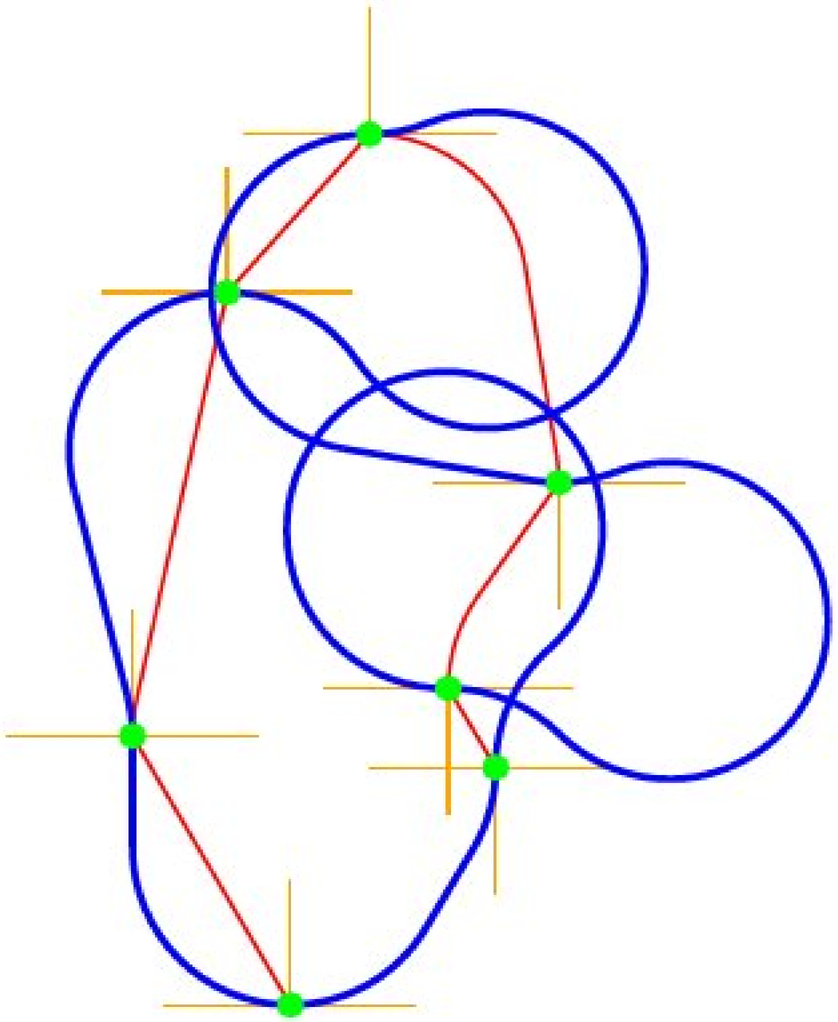
- Refinement iteration 1, the angular resolution $2\pi/4$

Uniform sampling



$\epsilon = 2\pi/4$, $N = 28$, $T_{CPU} = 8$ ms
$\mathcal{L} = 27.9$, $\mathcal{L}_U = 13.2$

Informed sampling

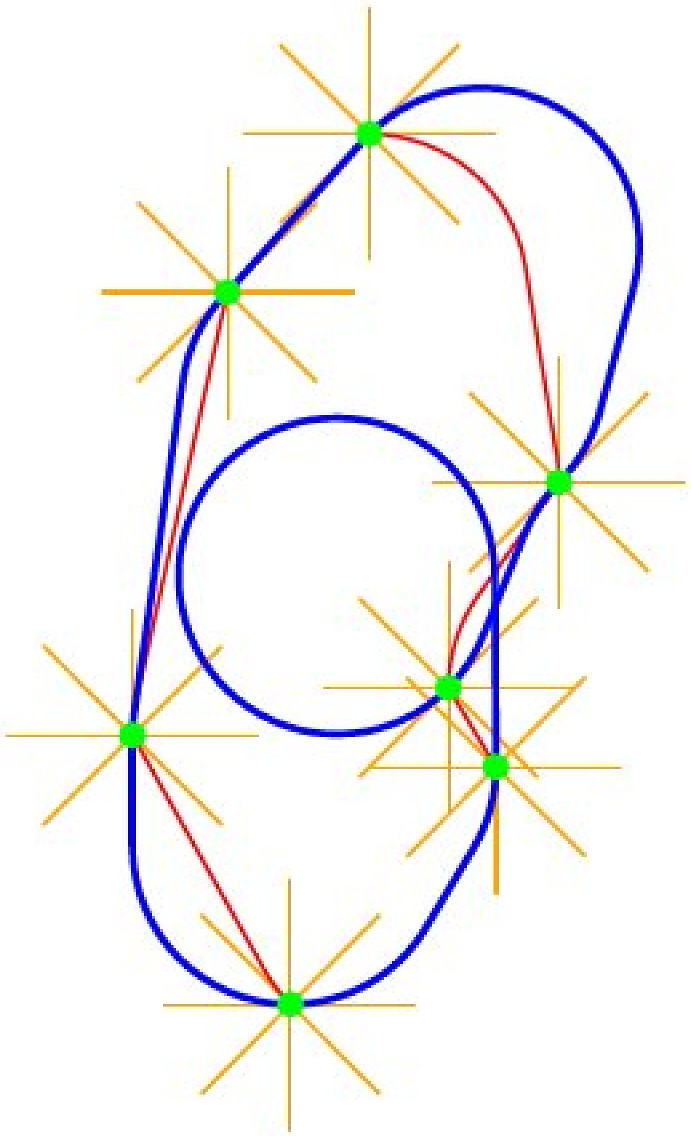


$\epsilon = 2\pi/4$, $N = 21$, $T_{CPU} = 8$ ms
$\mathcal{L} = 29.9$, $\mathcal{L}_U = 13.2$

Solution of the DTSP with Given Sequence of Visits
Uniform vs Informed Sampling

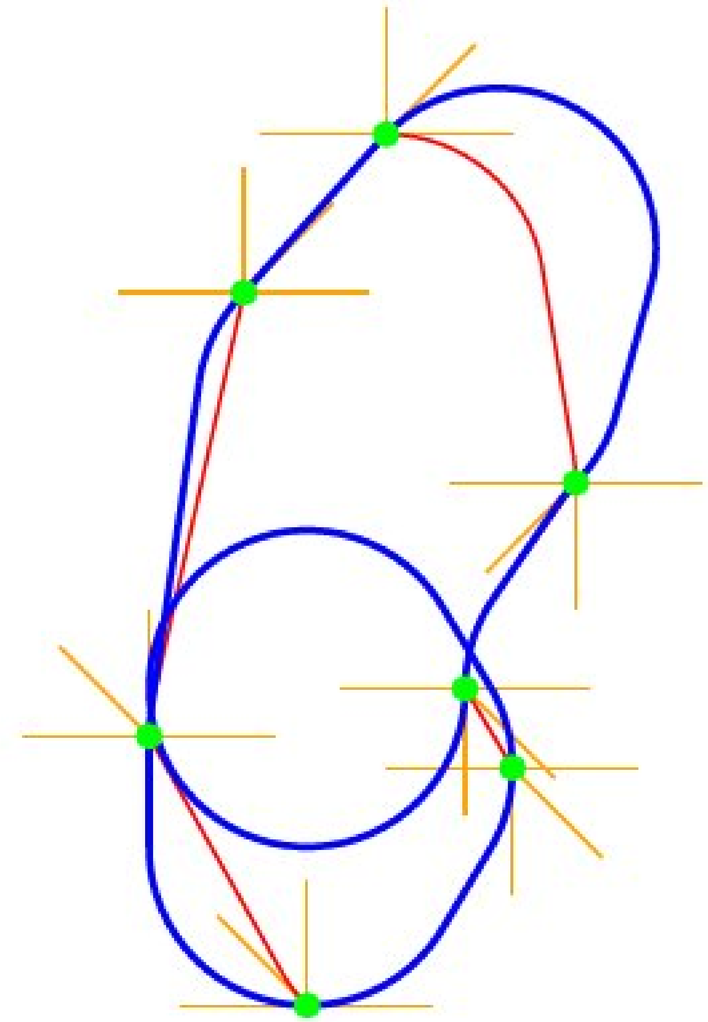
- Refinement iteration 1, the angular resolution $2\pi/8$

Uniform sampling



$\epsilon = 2\pi/8$, $N = 56$, $T_{CPU} = 16$ ms
$\mathcal{L} = 20.8$, $\mathcal{L}_U = 13.2$

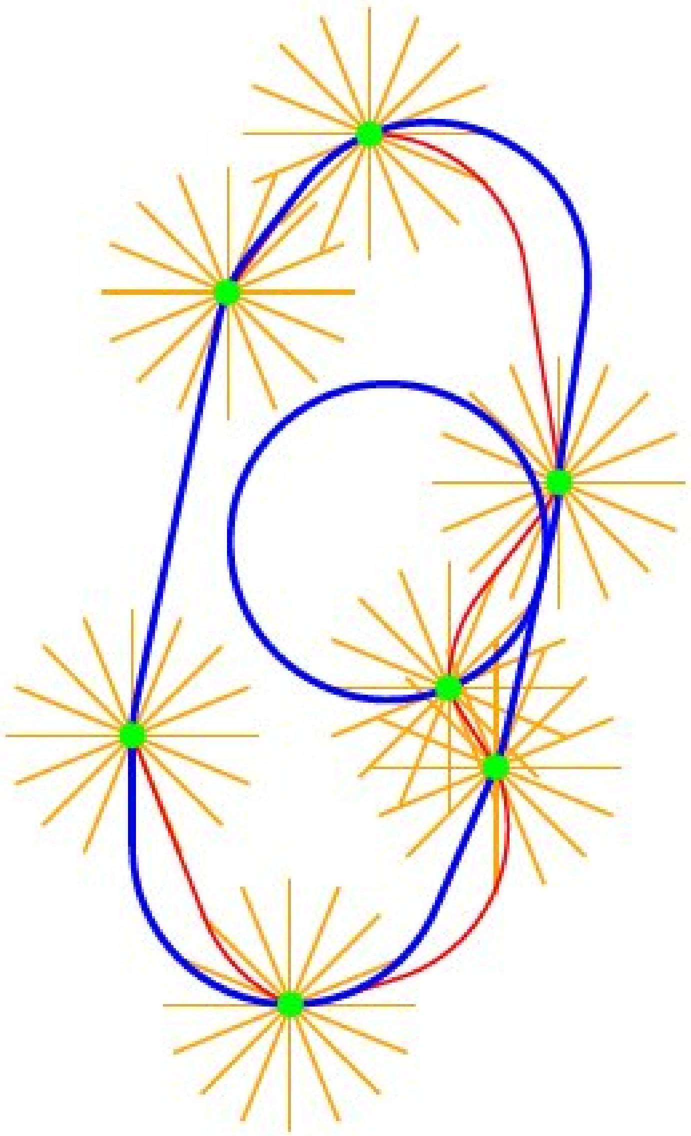
Informed sampling



$\epsilon = 2\pi/8$, $N = 28$, $T_{CPU} = 20$ ms
$\mathcal{L} = 21.0$, $\mathcal{L}_U = 13.2$

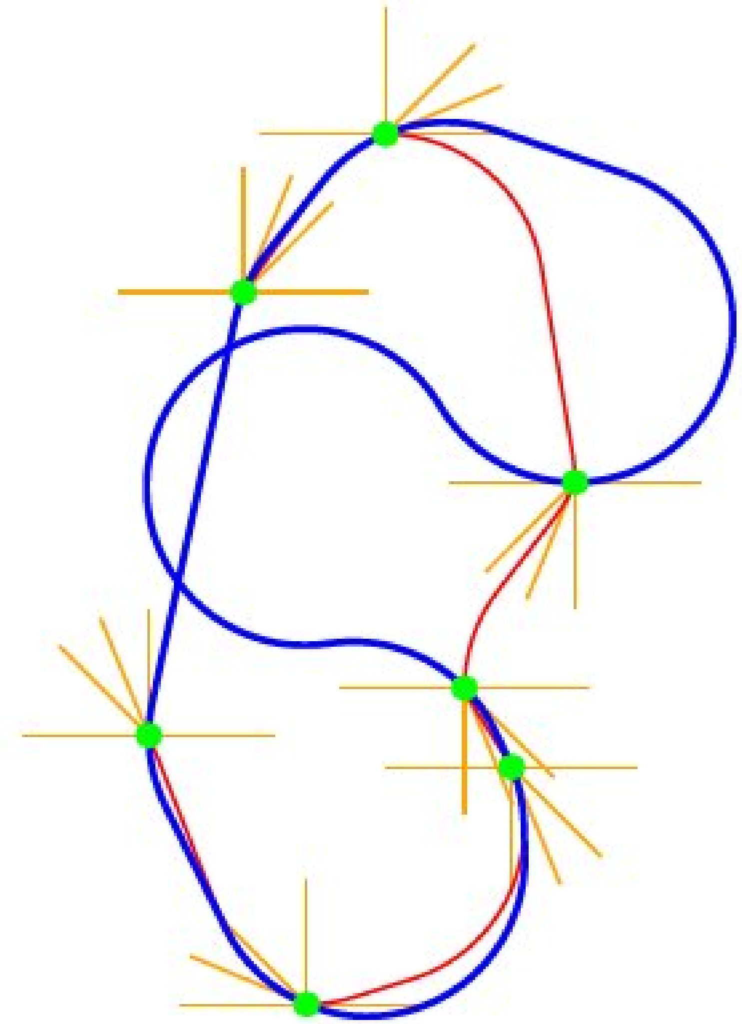
- Refinement iteration 1, the angular resolution $2\pi/16$

Uniform sampling



$\epsilon = 2\pi/16$, $N = 112$, $T_{CPU} = 40$ ms
$\mathcal{L} = 20.3$, $\mathcal{L}_U = 13.5$

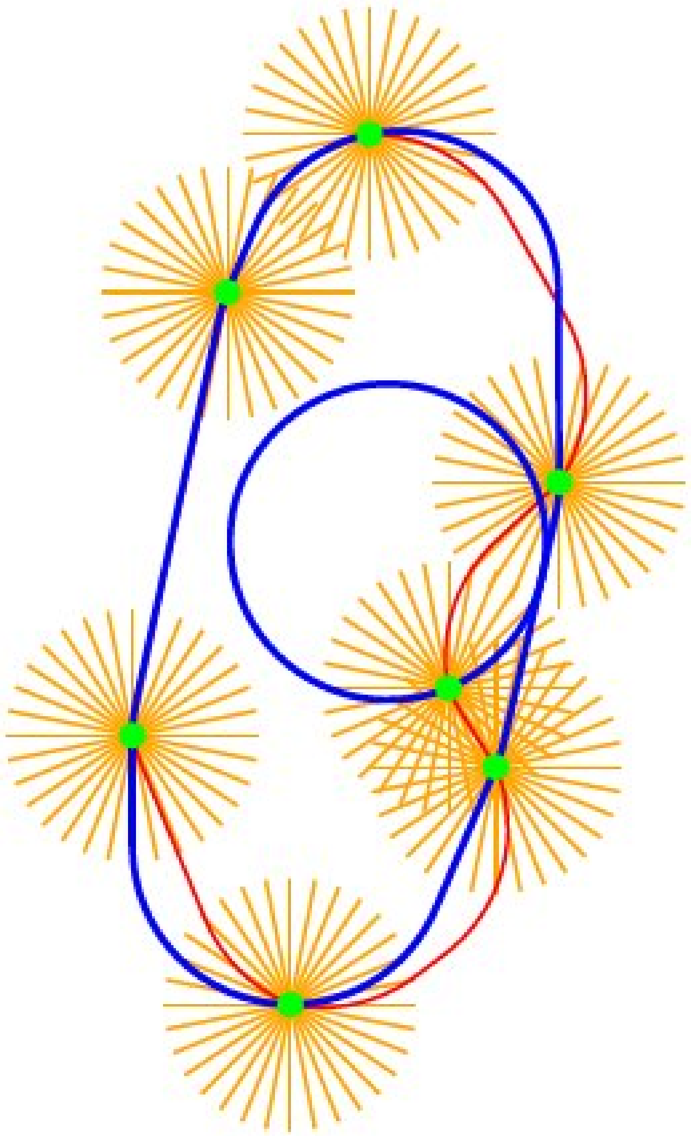
Informed sampling



$\epsilon = 2\pi/16$, $N = 35$, $T_{CPU} = 24$ ms
$\mathcal{L} = 20.1$, $\mathcal{L}_U = 13.5$

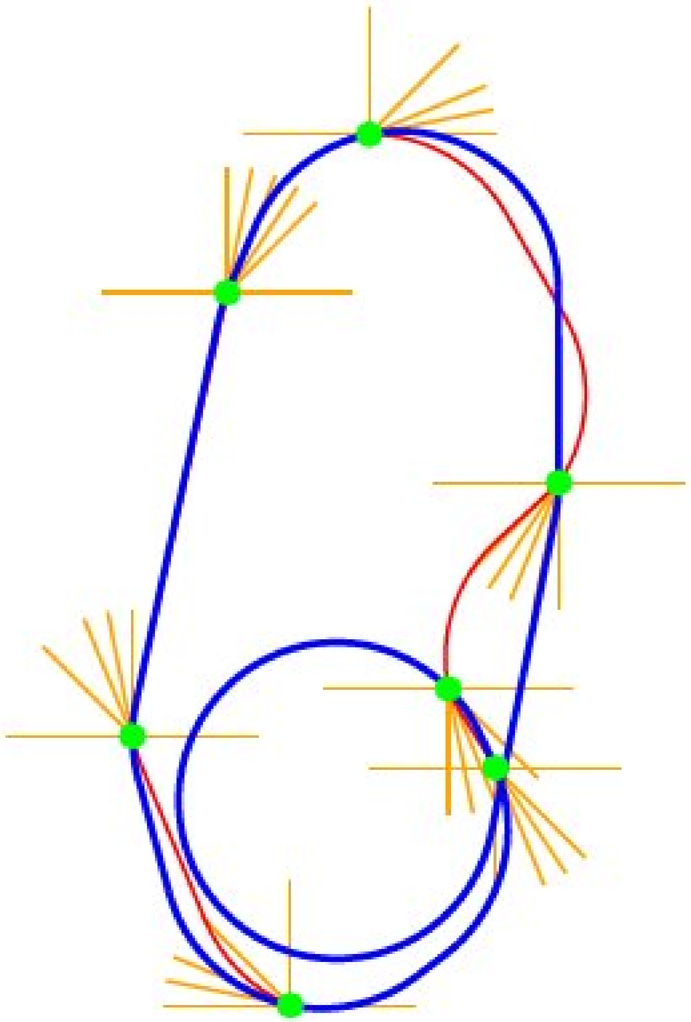
- Refinement iteration 1, the angular resolution $2\pi/32$

Uniform sampling



$\epsilon = 2\pi/32$, $N = 224$, $T_{CPU} = 140$ ms
$\mathcal{L} = 19.8$, $\mathcal{L}_U = 13.8$

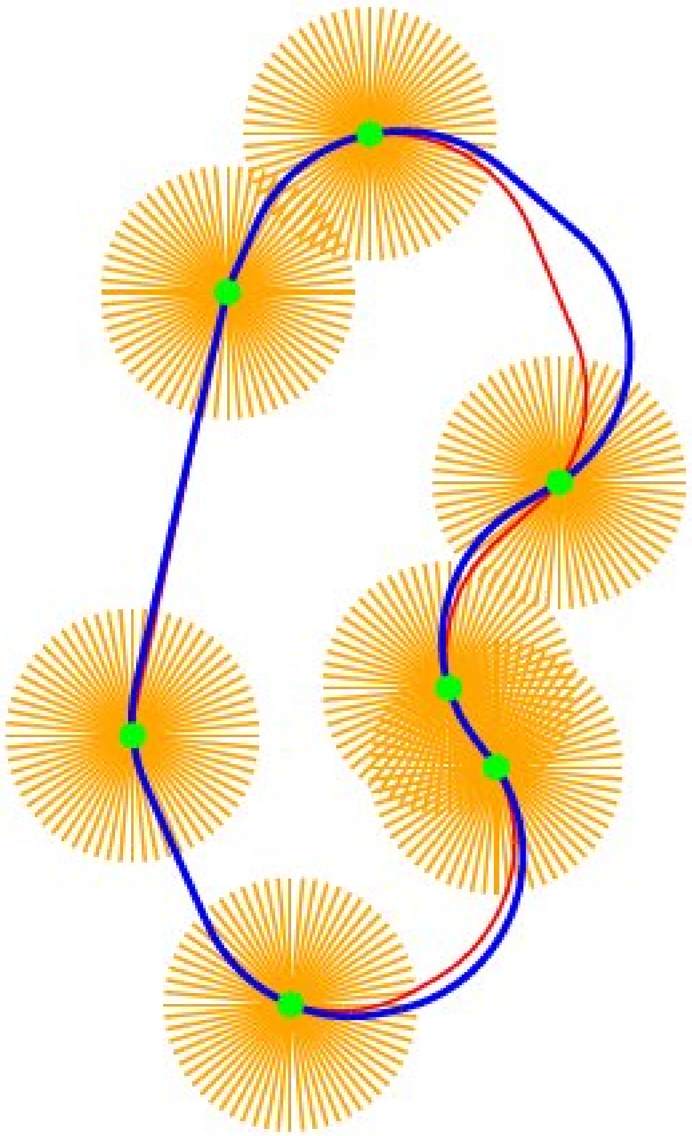
Informed sampling



$\epsilon = 2\pi/32$, $N = 44$, $T_{CPU} = 32$ ms
$\mathcal{L} = 19.9$, $\mathcal{L}_U = 13.8$

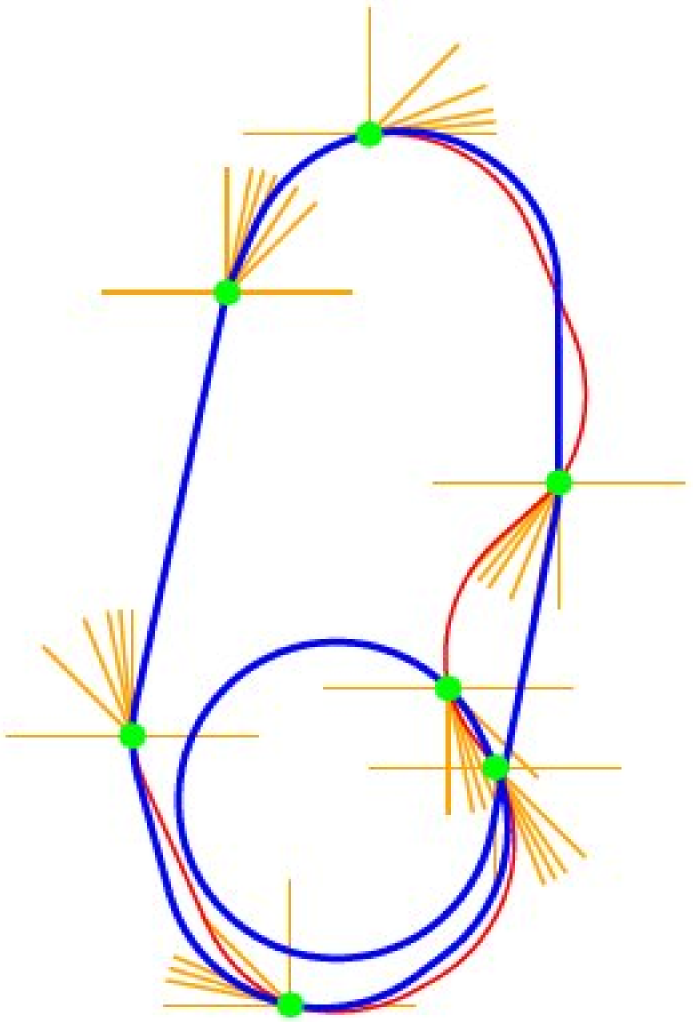
- Refinement iteration 1, the angular resolution $2\pi/64$

Uniform sampling



$\epsilon = 2\pi/64$, $N = 448$, $T_{CPU} = 456$ ms
$\mathcal{L} = 14.5$, $\mathcal{L}_U = 14.5$

Informed sampling



$\epsilon = 2\pi/64$, $N = 51$, $T_{CPU} = 48$ ms
$\mathcal{L} = 19.9$, $\mathcal{L}_U = 13.9$

Solution of the DTSP with Given Sequence of Visits Uniform vs Informed Sampling

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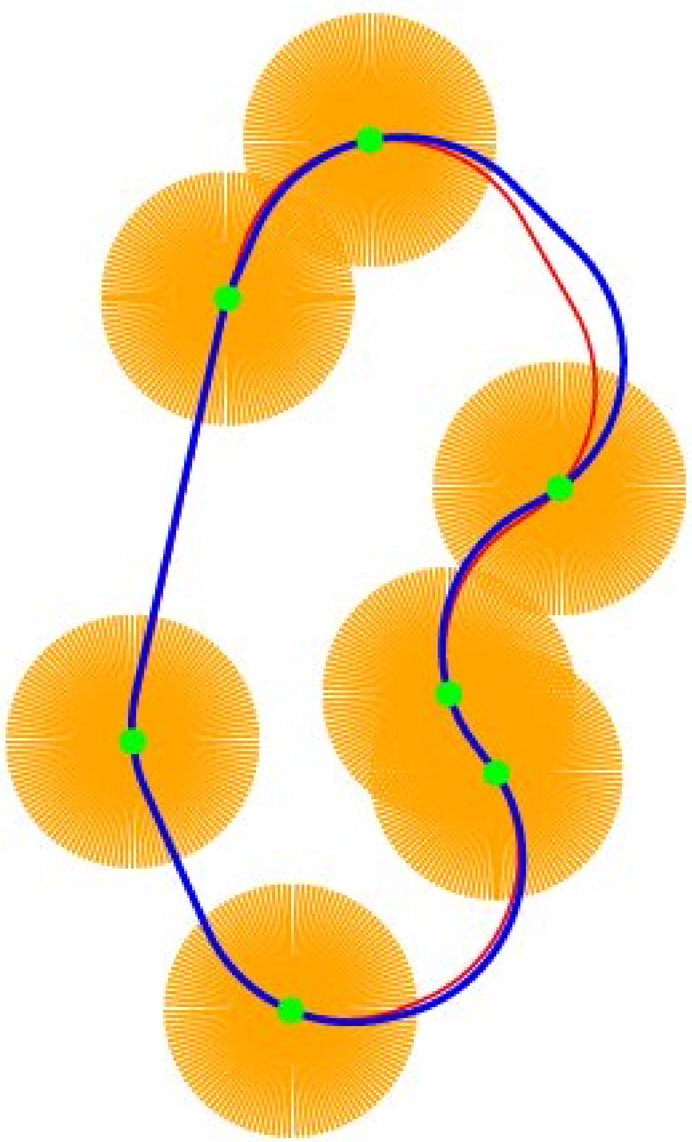
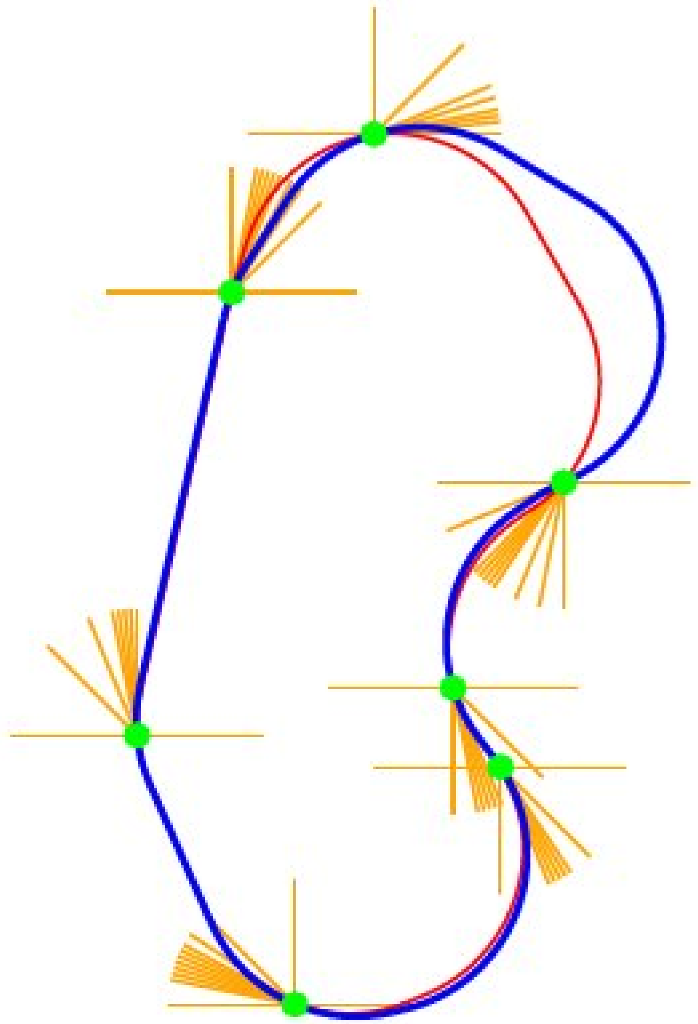
- Refinement iteration 1, the angular resolution $2\pi/128$

Uniform sampling



$\epsilon = 2\pi/128$, $N = 896$, $T_{CPU} = 1620$ ms
$\mathcal{L} = 14.5$, $\mathcal{L}_U = 14.5$

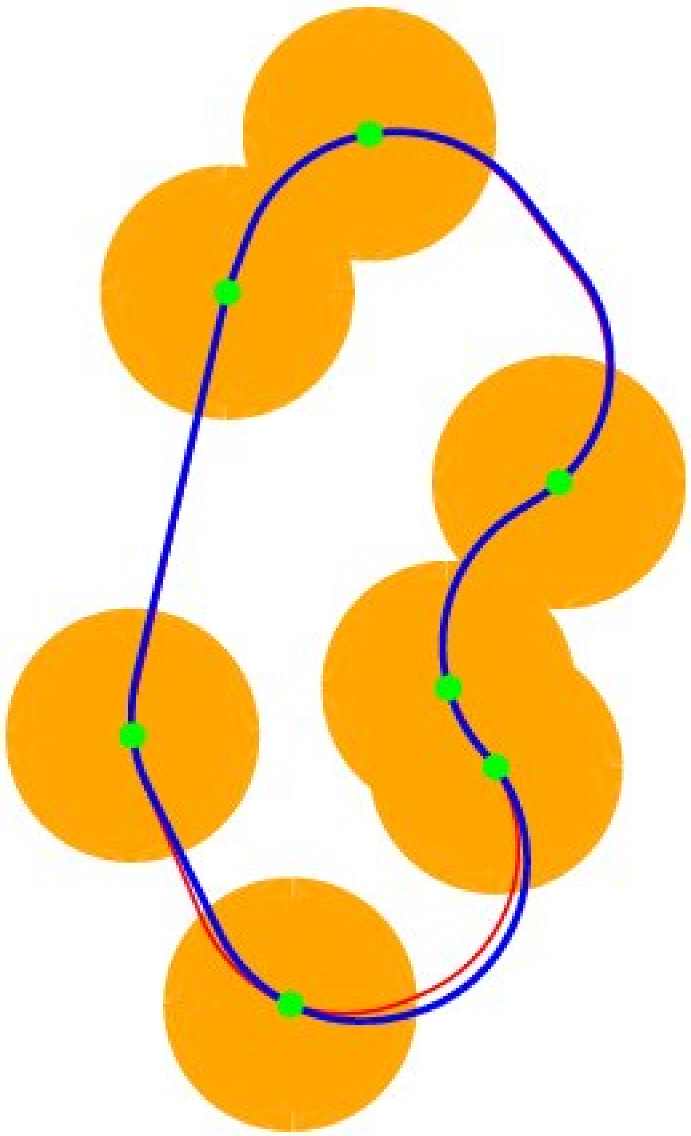
Informed sampling



$\epsilon = 2\pi/128$, $N = 70$, $T_{CPU} = 60$ ms
$\mathcal{L} = 14.8$, $\mathcal{L}_U = 14.1$

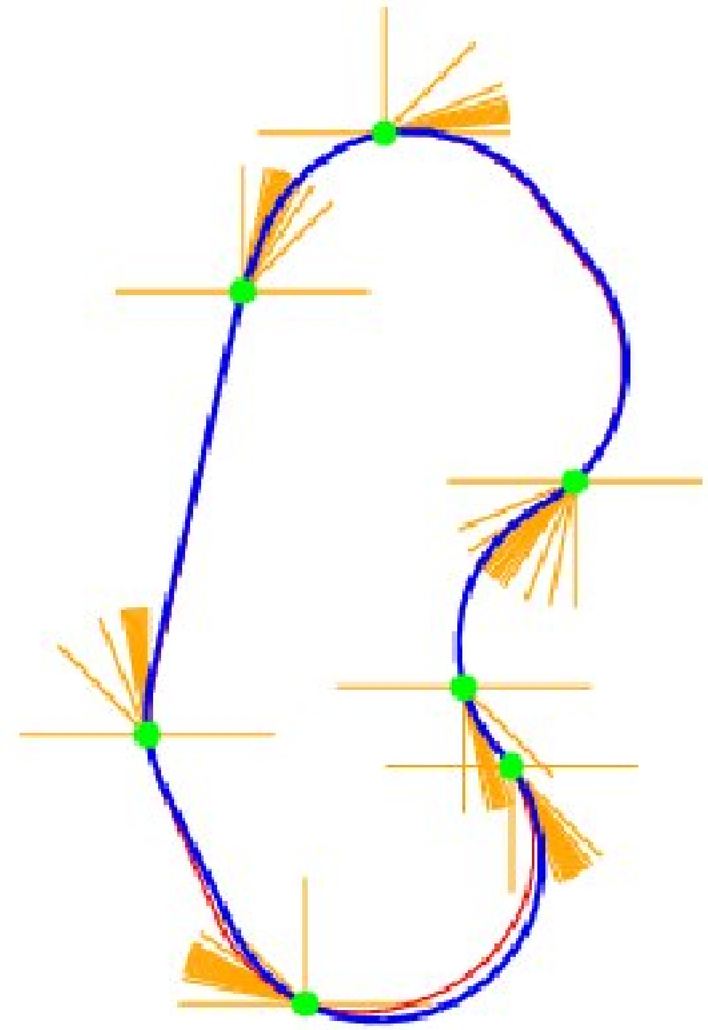
- Refinement iteration 1, the angular resolution $2\pi/256$

Uniform sampling



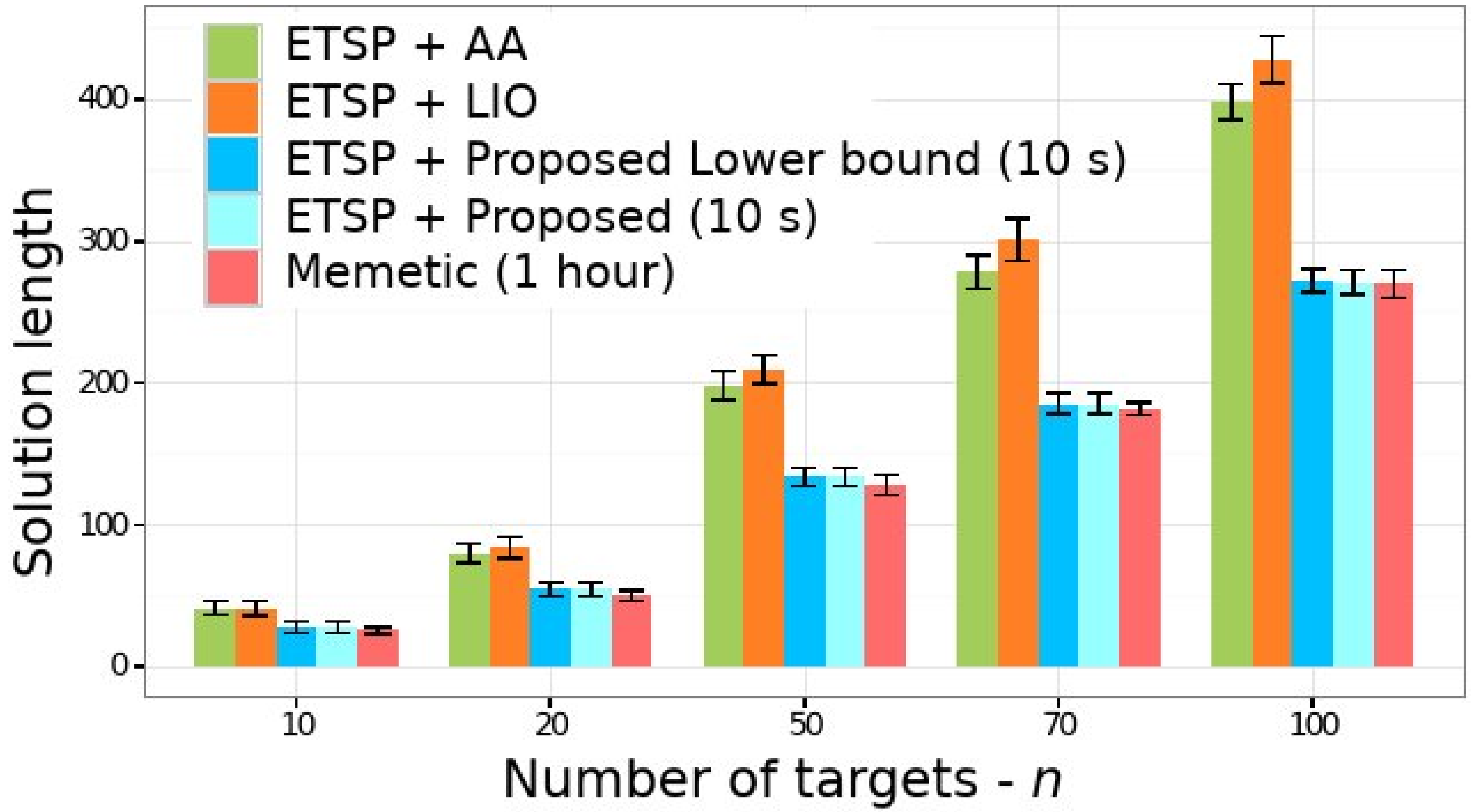
$\epsilon = 2\pi/256$, $N = 1792$, $T_{CPU} = 6784$ ms
$\mathcal{L} = 14.4$, $\mathcal{L}_U = 14.3$

Informed sampling



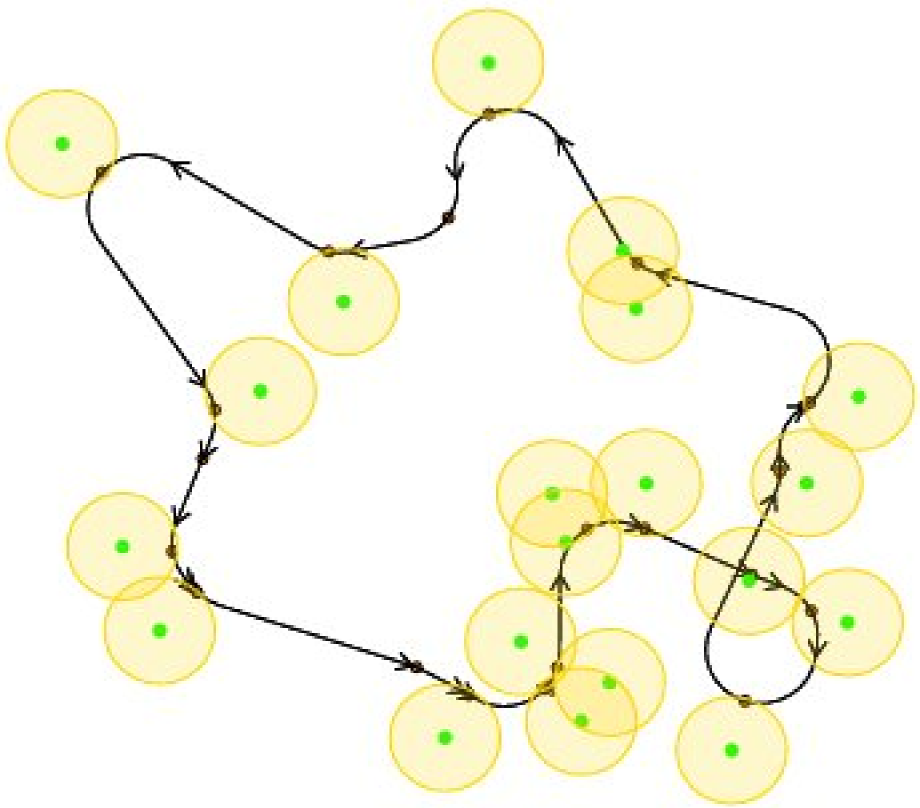
$\epsilon = 2\pi/256$, $N = 100$, $T_{CPU} = 88$ ms
$\mathcal{L} = 14.4$, $\mathcal{L}_U = 14.3$

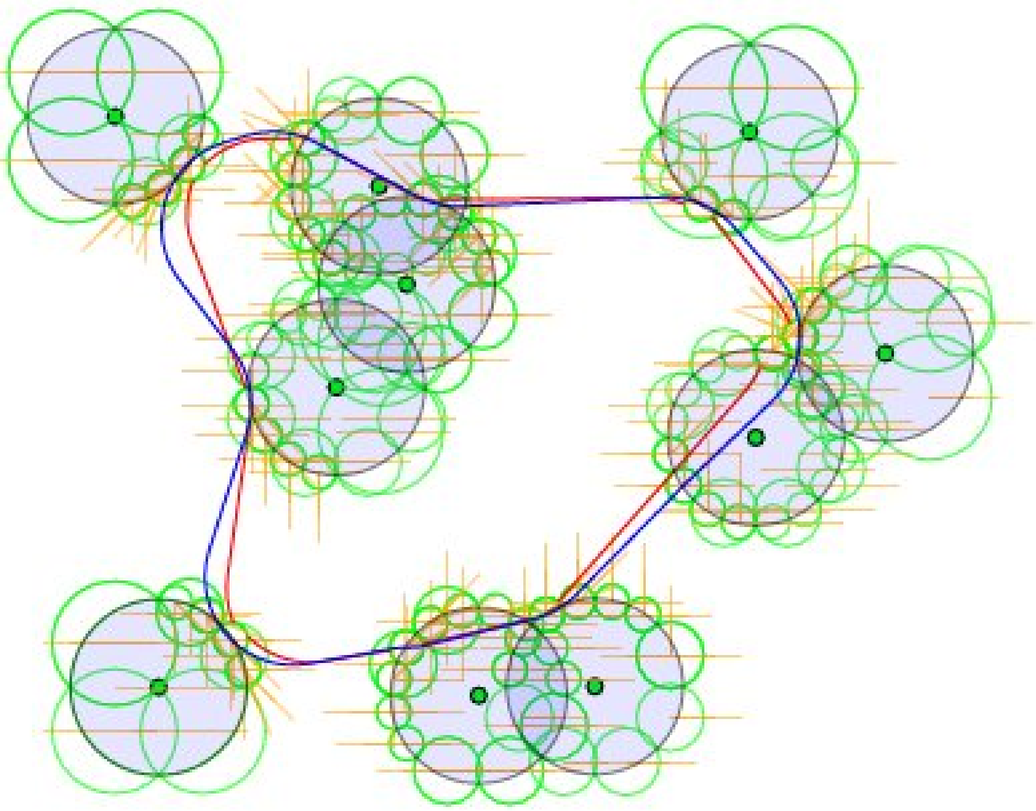
- Comparison with the Alternating Algorithm (AA), Local Iterative Optimization (LIO), and Memetic algorithm — AA – Savla et al., 2005, LIO – Váňa & Faigl, 2015, Memetic – Zhang et al. 2014
- A sequence of the waypoint locations is determined as the Euclidean TSP (ETSP) — *E.g., as in the Alternating Algorithm (AA)*
- In Memetic algorithm, similarly to the sampling-based approaches that solve the Generalized TSP, the best sequence of visits is determined during the solution



- Faigl et al.: *On solution of the Dubins touring problem.* ECMR 2017.

- In the DTSPN, we need to determined not only the **headings**, but the waypoint locations themselves
- Dubins Interval Problem is not sufficient to provide tight lower-bound

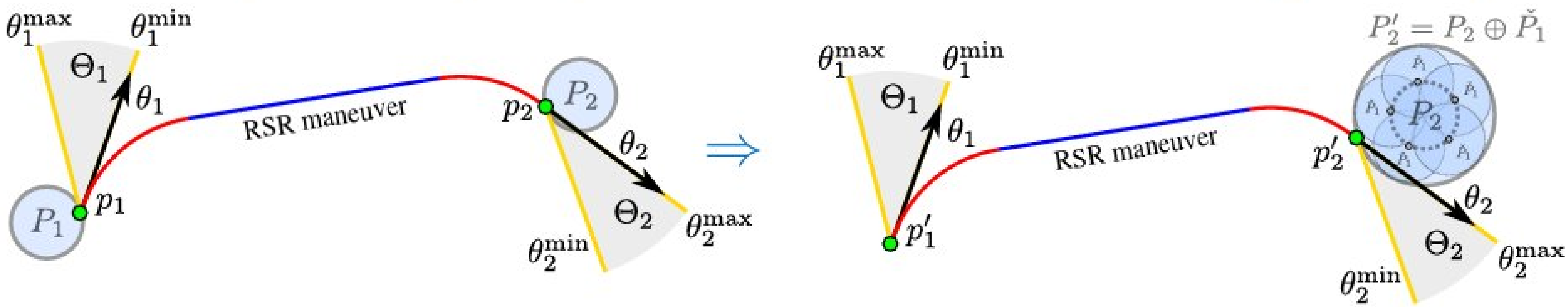




- **Generalized Dubins Interval Problem** (**GDIP**) can be utilized for the DTSPN similarly as the DIP for the DTSP

- Determine the shortest Dubins maneuver connecting P_i and P_j given the angle intervals $\theta_i \in [\theta_i^{min}, \theta_i^{max}]$ and $\theta_j \in [\theta_j^{min}, \theta_j^{max}]$

Full problem (GDIP) **One-side version (OS-GDIP)**

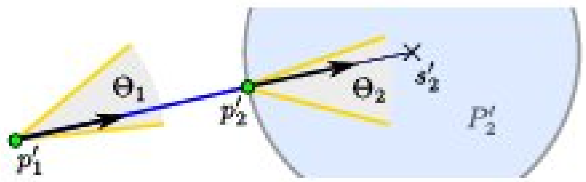


- Transformation from the GDIP to the OS-GDIP:
  - $P_1' = \{p_1'\} = \{(0,0)\}$
  - $P_2' = P_2 \oplus \check{P}_1 = \cup\{p_b - p_a, p_a \in P_1, p_b \in P_2\}$
- A closed-form solution can be found for the OS-GDIP

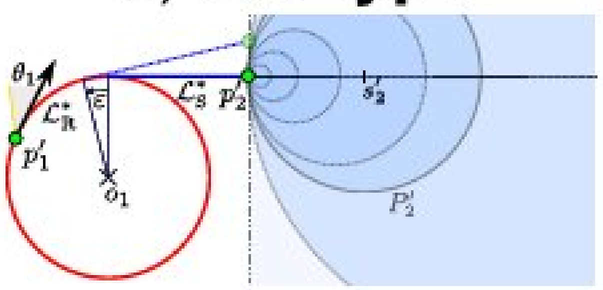
- Váňa and Faigl: *Optimal Solution of the Generalized Dubins Interval Problem*, RSS 2018.

Closed-form expressions (1-6)

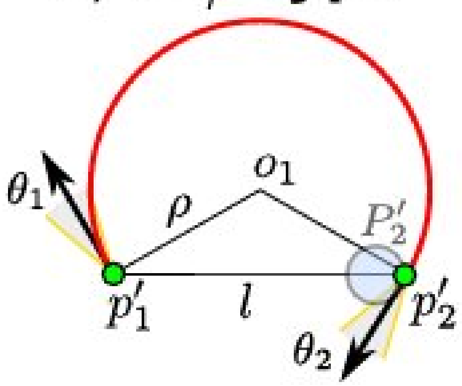
1) **S type**



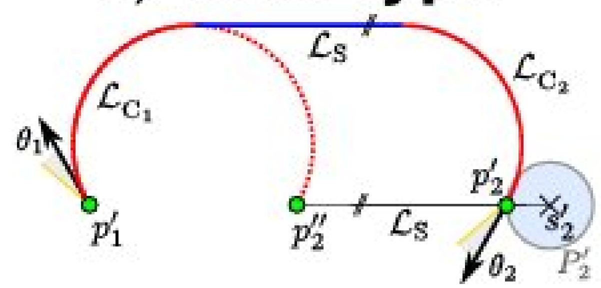
2) **CS type**



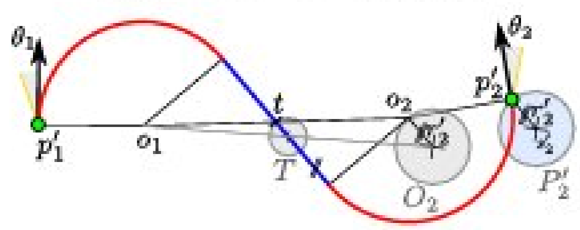
3) **C_ψ type**



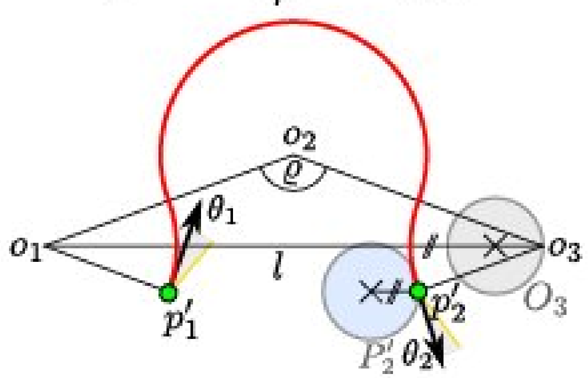
4) **CSC type**



5) **CS$\overline{\text{C}}$ type**

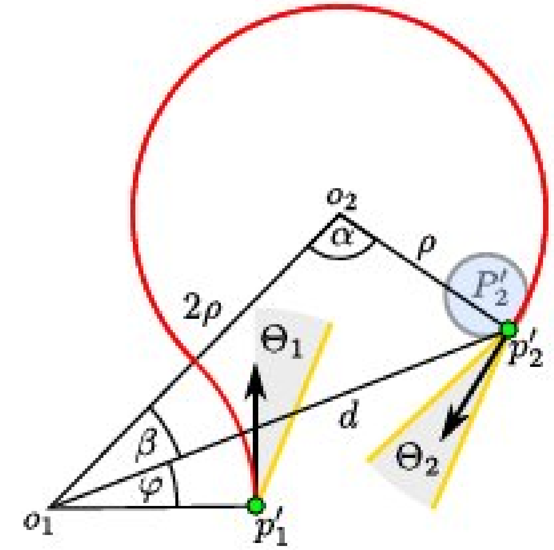


6) **C$\overline{\text{C}}_\psi$C type**



Convex optimization (7)

7) **C$\overline{\text{C}}_\psi$ type**



Average computational time

Problem	Time [μs]	Ratio
Dubins maneuver	0.58	1.00
DIP	2.86	4.93
GDIP	12.63	21.78

https://github.com/comrob/gdip

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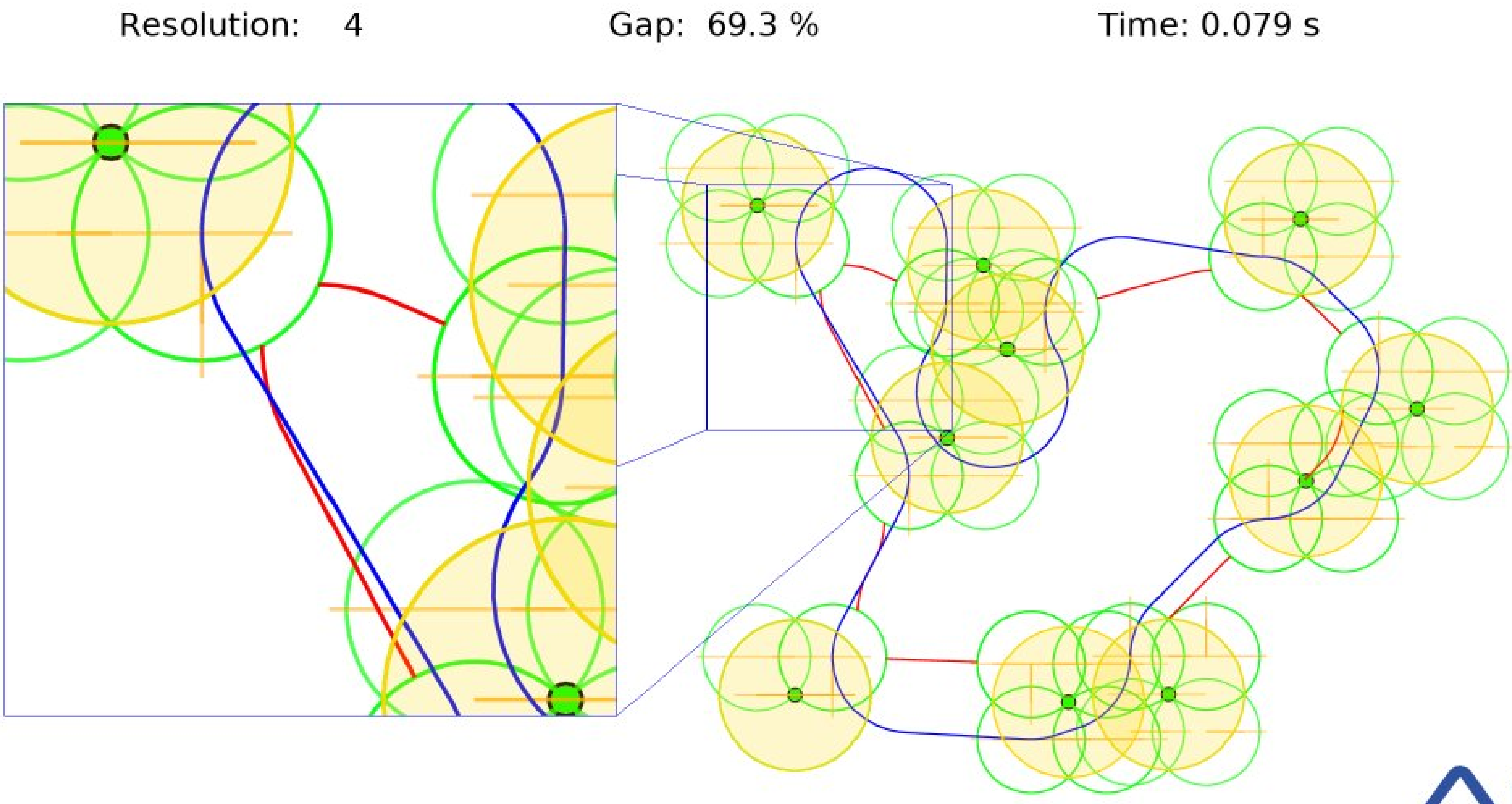
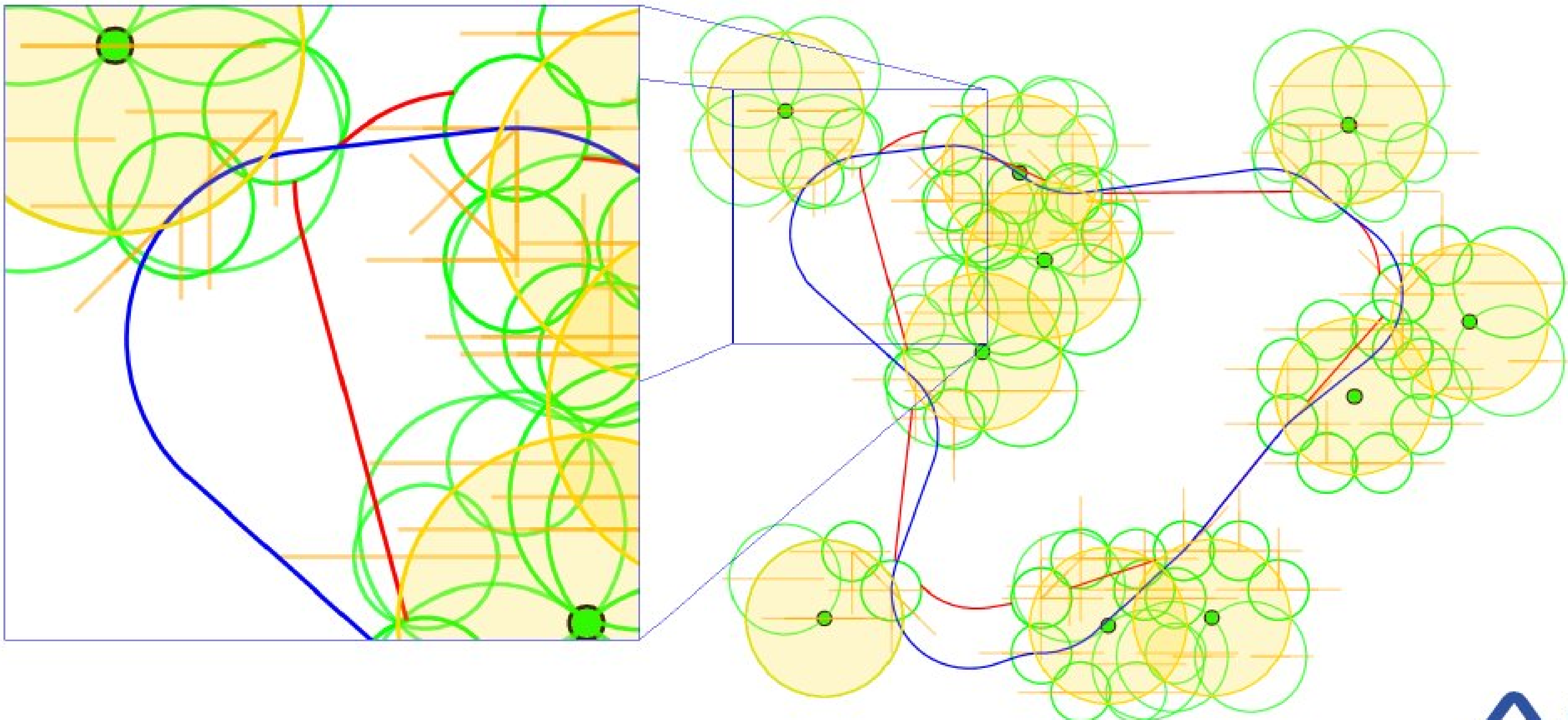
- Iterative refinement of the neighborhood samples and heading samples



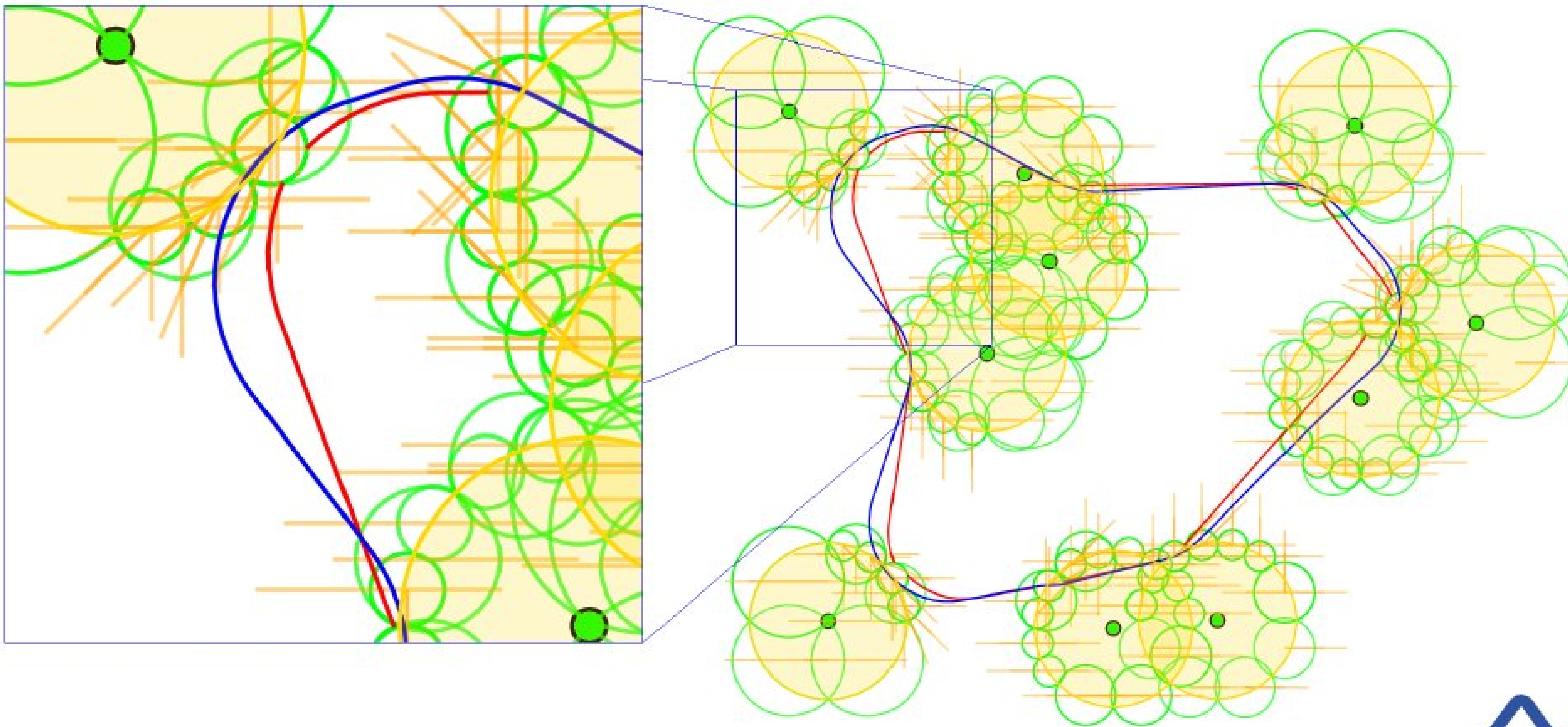
- Iterative refinement of the neighborhood samples and heading samples

Resolution: 8 Gap: 39.4 % Time: 0.211 s



- Iterative refinement of the neighborhood samples and heading samples

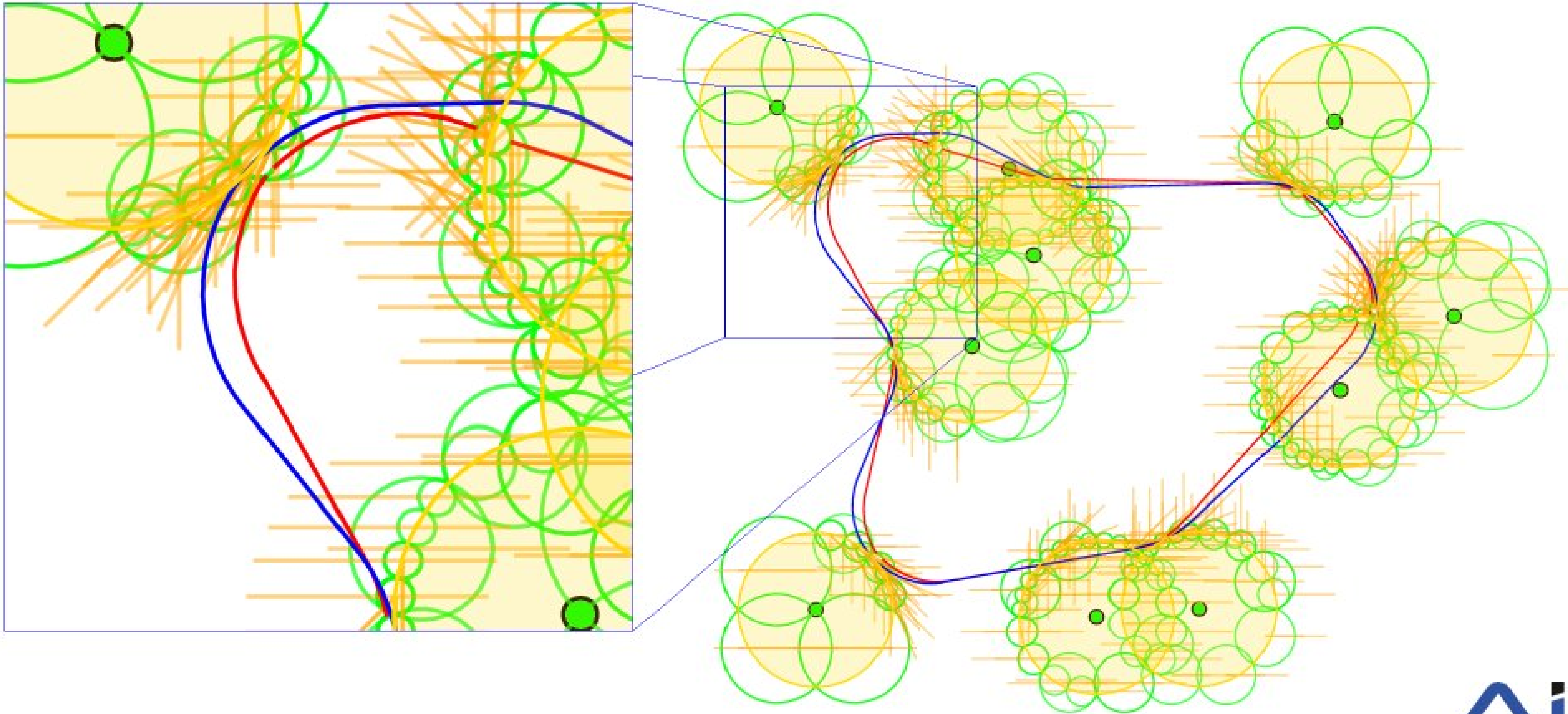
Resolution: 16 Gap: 19.9 % Time: 0.552 s



GDIP-based Informed Sampling for the DTSPN

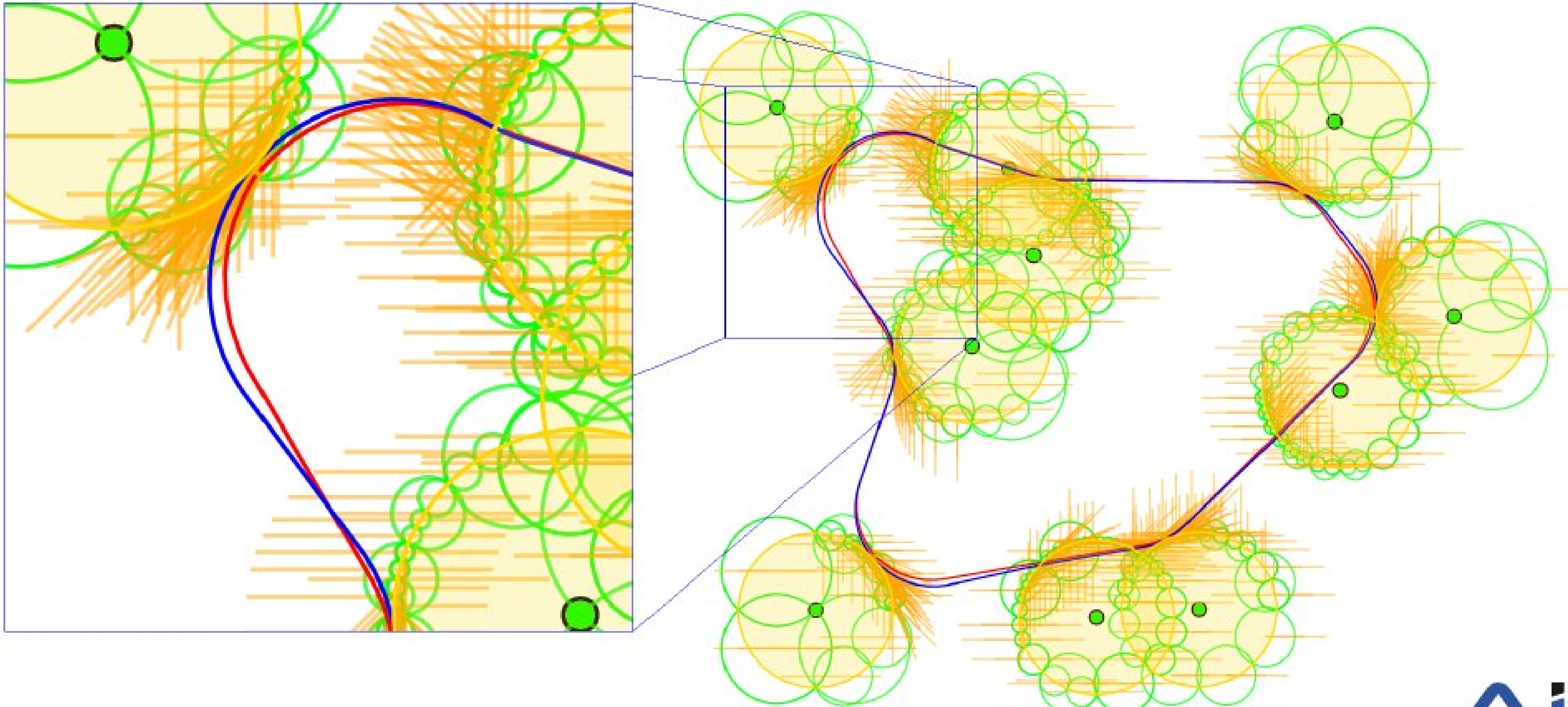
- Iterative refinement of the neighborhood samples and heading samples

Resolution: 32 Gap: 10.7 % Time: 1.292 s

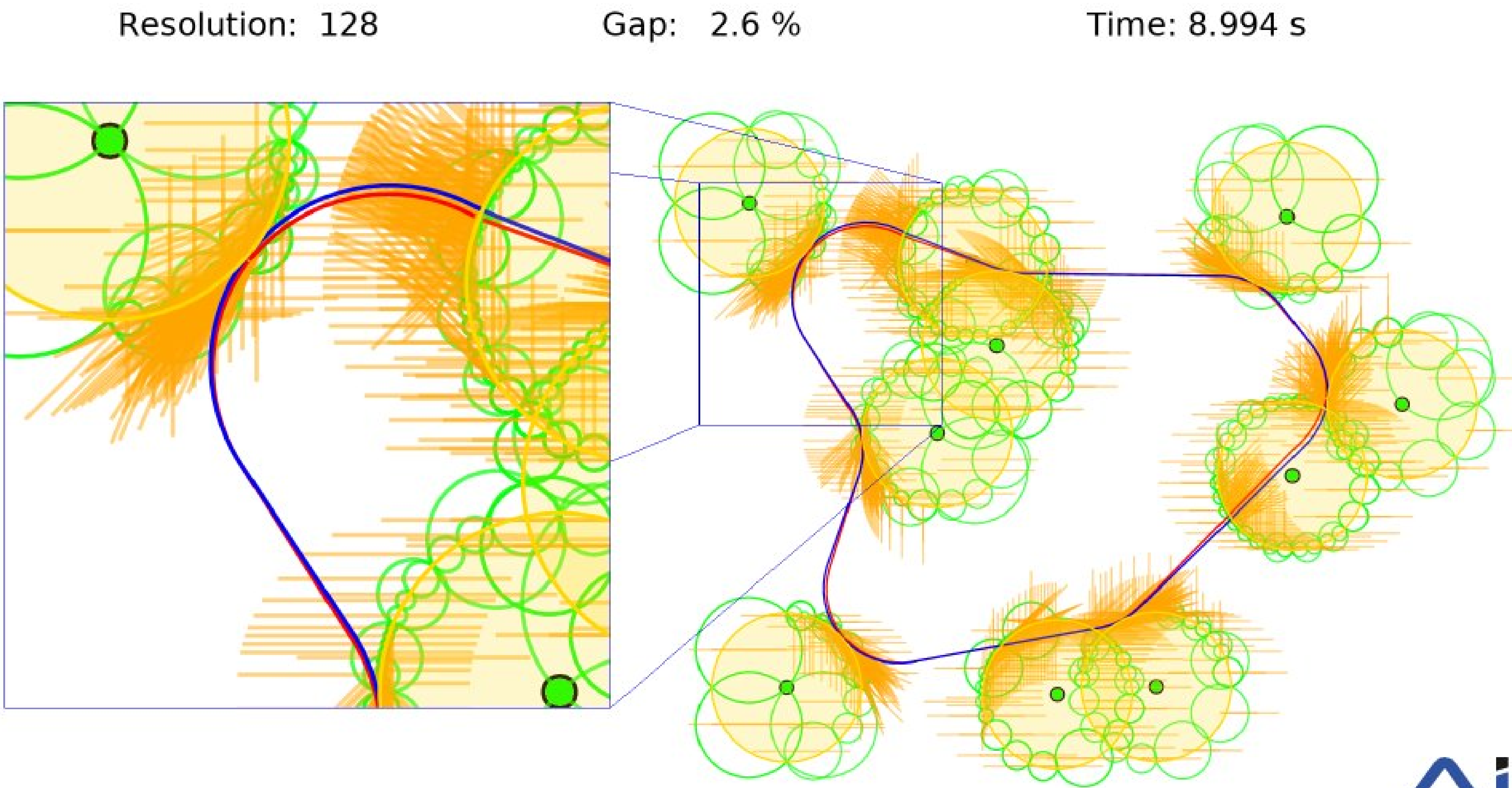


- Iterative refinement of the neighborhood samples and heading samples

Resolution: 64 Gap: 5.3 % Time: 3.183 s



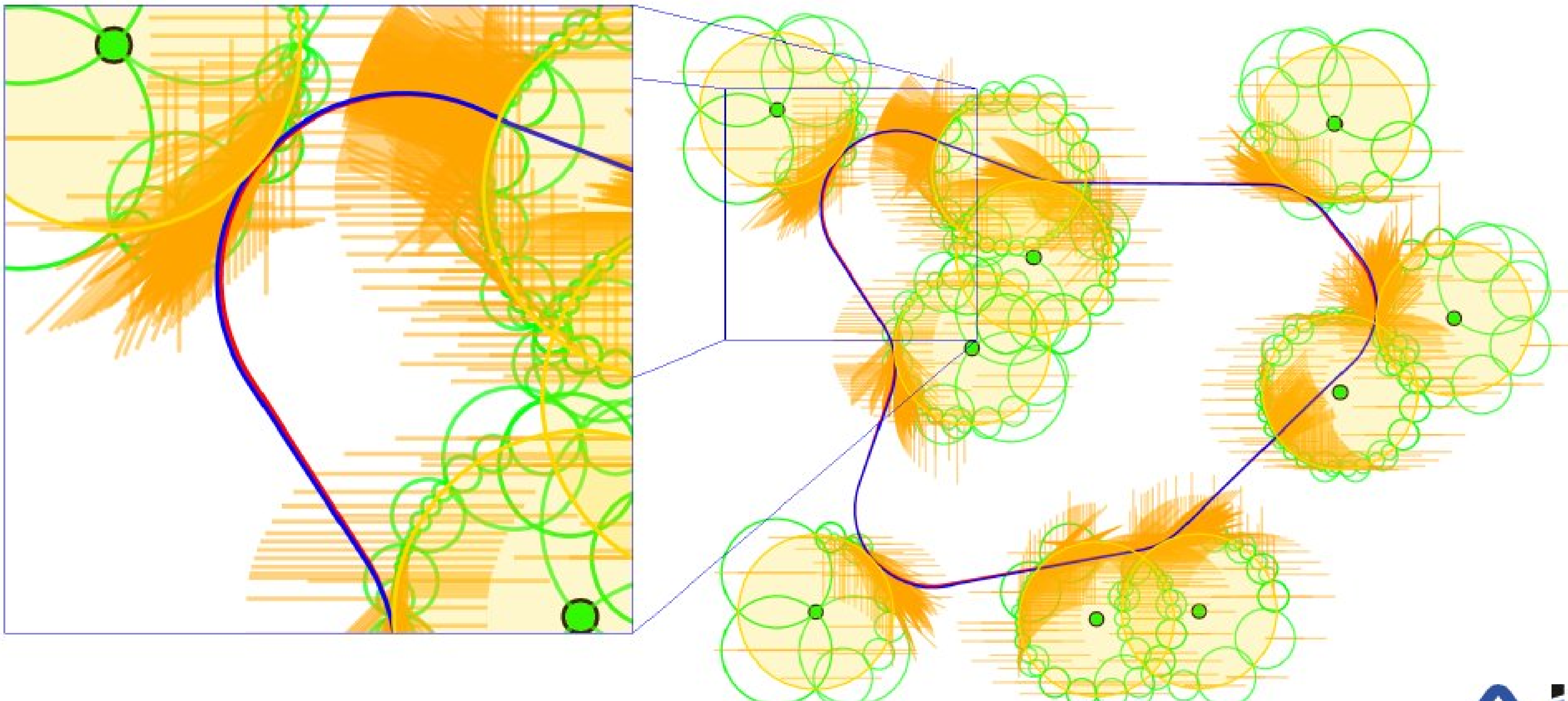
- Iterative refinement of the neighborhood samples and heading samples



GDIP-based Informed Sampling for the DTSPN

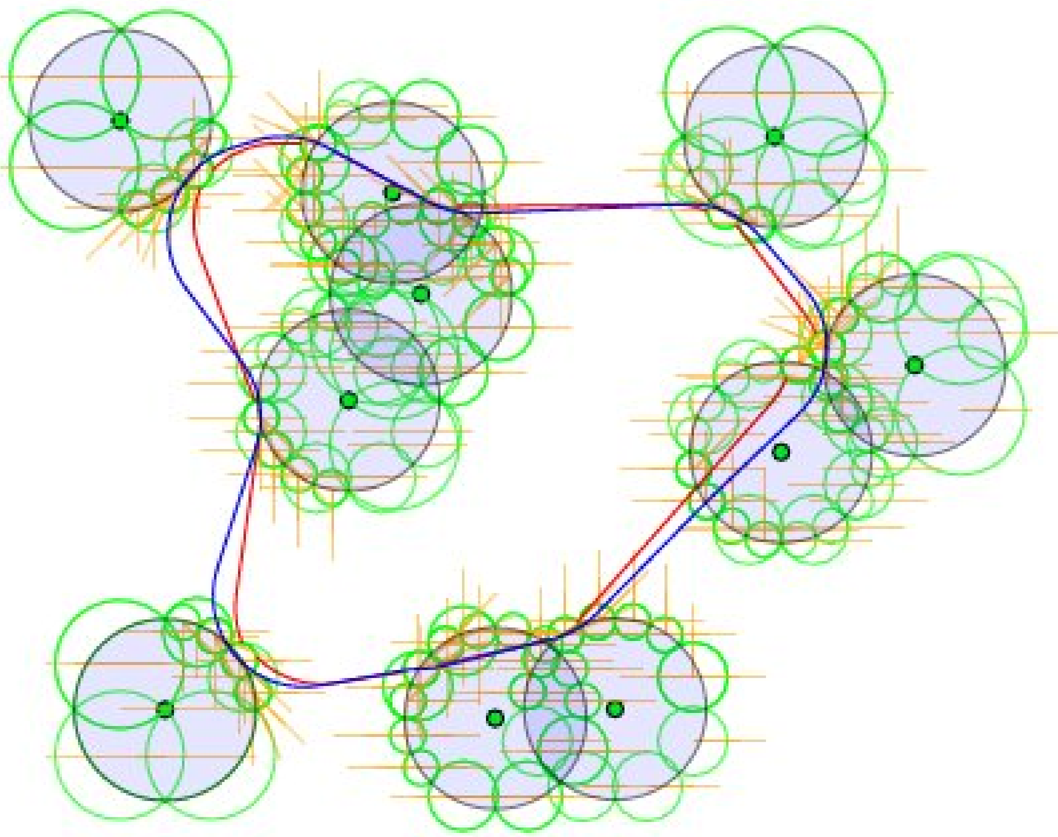
- Iterative refinement of the neighborhood samples and heading samples

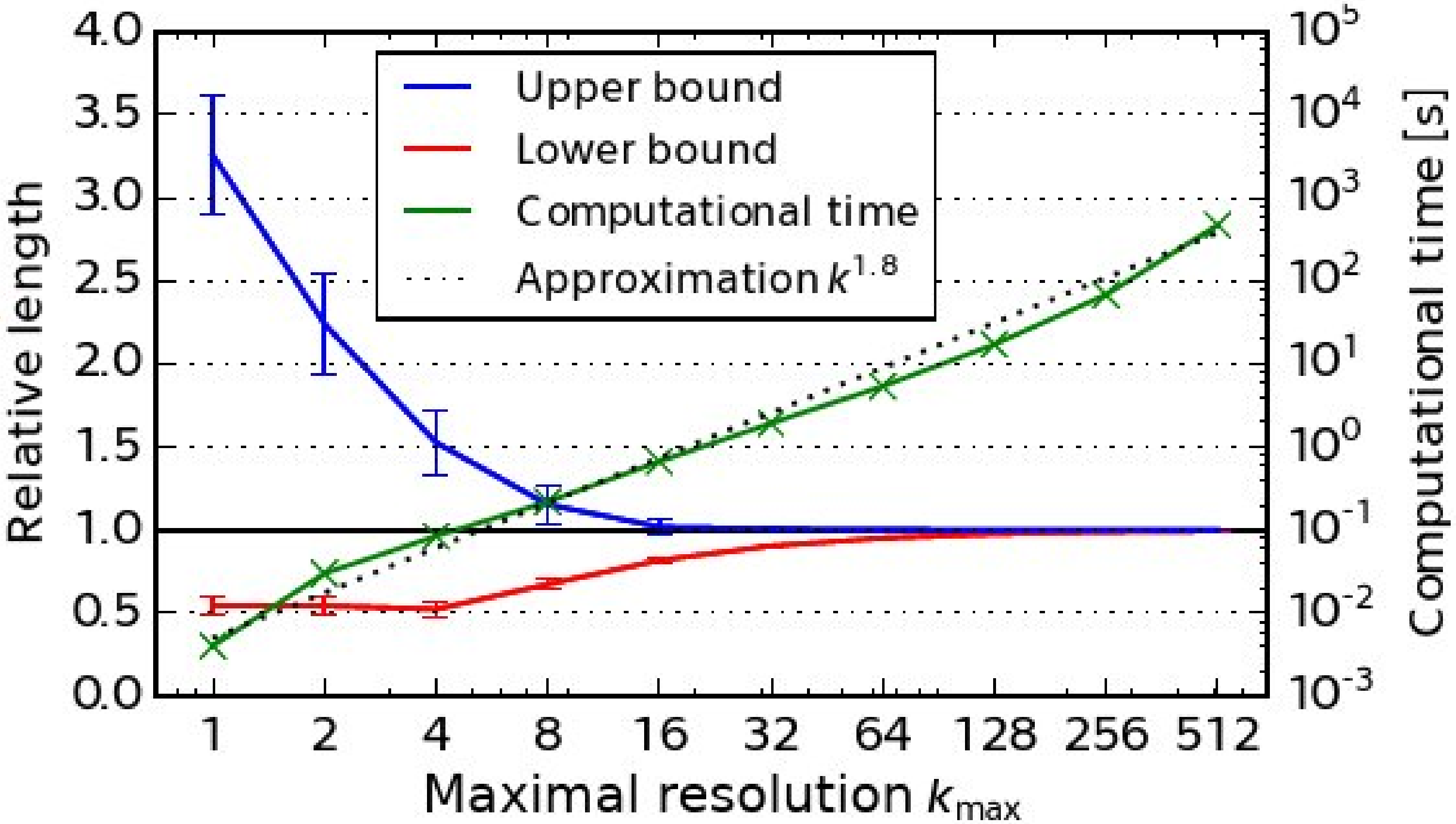
Resolution: 256 Gap: 1.3 % Time: 33.474 s



DTSPN – Convergence to the Optimal Solution

- For a given sequence of visits to the target regions (locations)





- The algorithm scales linearly with the number of locations
- Complexity of the algorithm is approximately $\mathcal{O}(nk^{1.8})$

https://github.com/comrob/gdip

- Váňa and Faigl: *Optimal Solution of the Generalized Dubins Interval Problem*, RSS 2018.

Motivation for Surveillance Planning with Multiple UAVs in MBZIRC 2017 Scenario

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- Provide **curvature-constrained** paths for a team of autonomous unmanned aerial vehicles to verify expected objects of interest

$v = 5$ m.s^{-1}, 80 m $\times$ 60 m testing site for experimental verification of our system for the Mohamed Bin Zayed International Robotics Challenge (MBZIRC)

- Sampling-based methods are relatively slow
- Desired properties of the requested surveillance mission planner are: **fast trajectories and low computational time ($\leq$ 1 s)**

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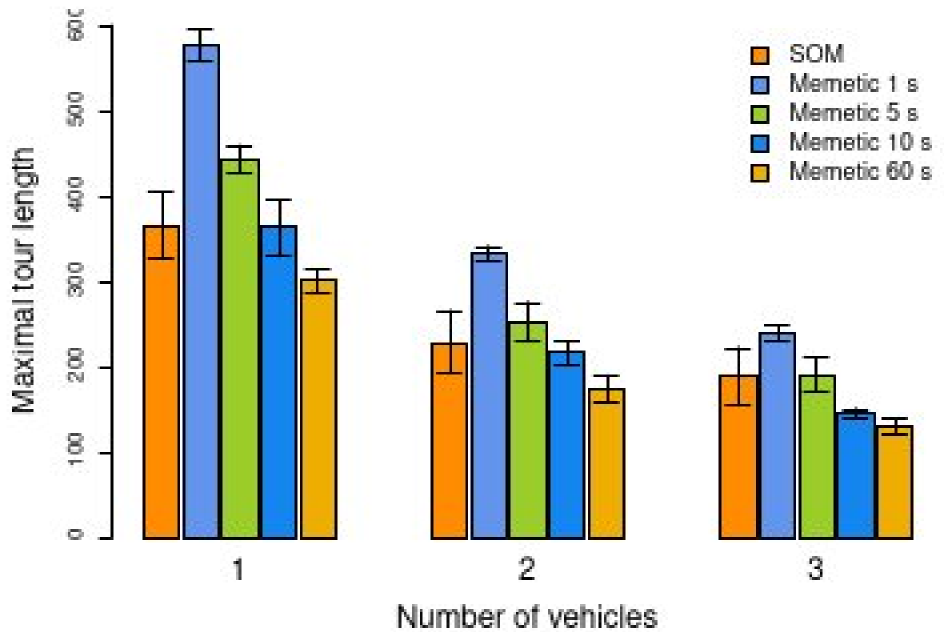
Unsupervised Learning for Surveillance Planning with Team of Aerial Vehicles

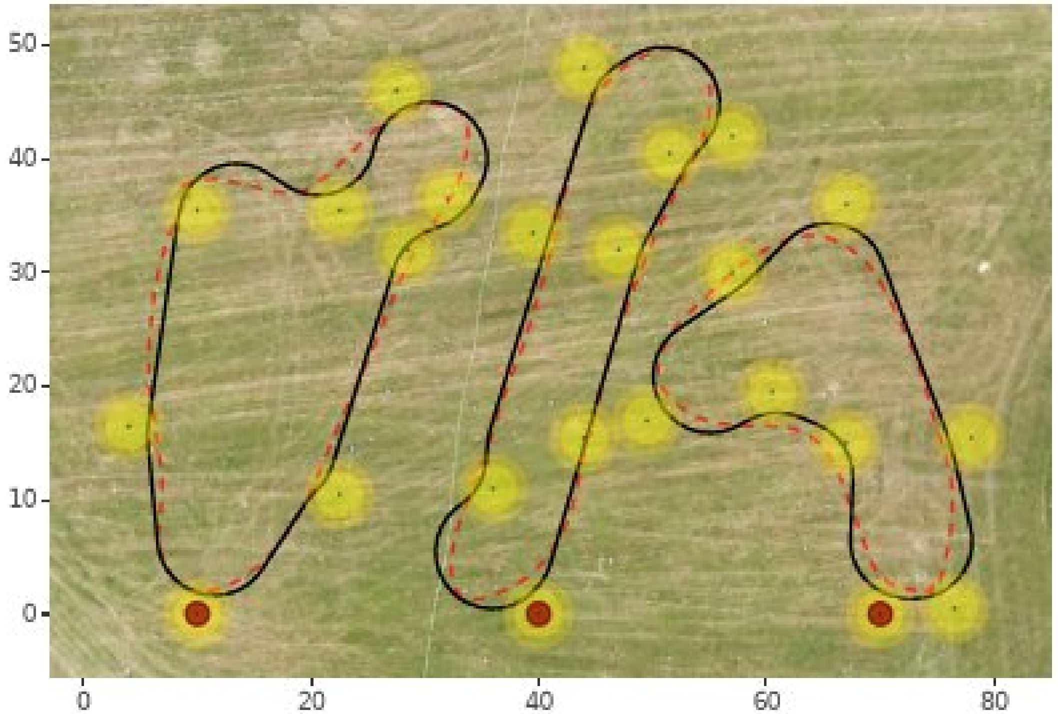
- **Fast heuristic solution based on unsupervised learning** for routing problems

  Solutions found in less than 0.6 second for the MBZIRC 2017 scenarios

- Comparison with Memetic algorithm (Zhang et al., 2014) restricted to the maximal computational time $T_{max} \in \{1, 5, 10, 60\}$ seconds and k vehicles

k	**Memetic 1 s**	**Memetic 10 s**	**Unsupervised Learning**	
	L_{max} [m]	L_{max} [m]	L_{max} [m]	T [s]
1	586.01 (24.22)	376.52 (27.17)	**363.38** (36.56)	**0.55** (0.07)
2	335.83 (10.67)	**212.18** (18.73)	*223.76* (40.76)	**0.53** (0.01)
3	240.67 (6.63)	**153.37** (12.79)	*180.12* (29.49)	**0.53** (0.03)





- Faigl and Váňa: *Unsupervised learning for surveillance planning with team of aerial vehicles.* IJCNN 2017.
- Faigl: *GSOA: Growing Self-Organizing Array–Unsupervised Learning for the Close-Enough Traveling Salesman Problem and Other Routing Problems.* Neurocomputing 2018.

3D Data Collection Planning with Dubins Airplane Model
Dubins Traveling Salesman Problem (DTSPN) in 3D

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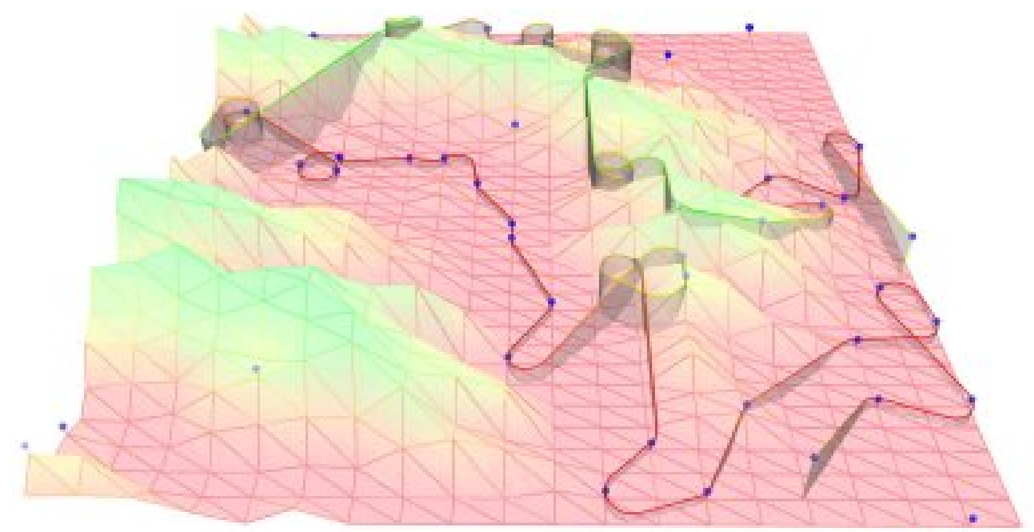
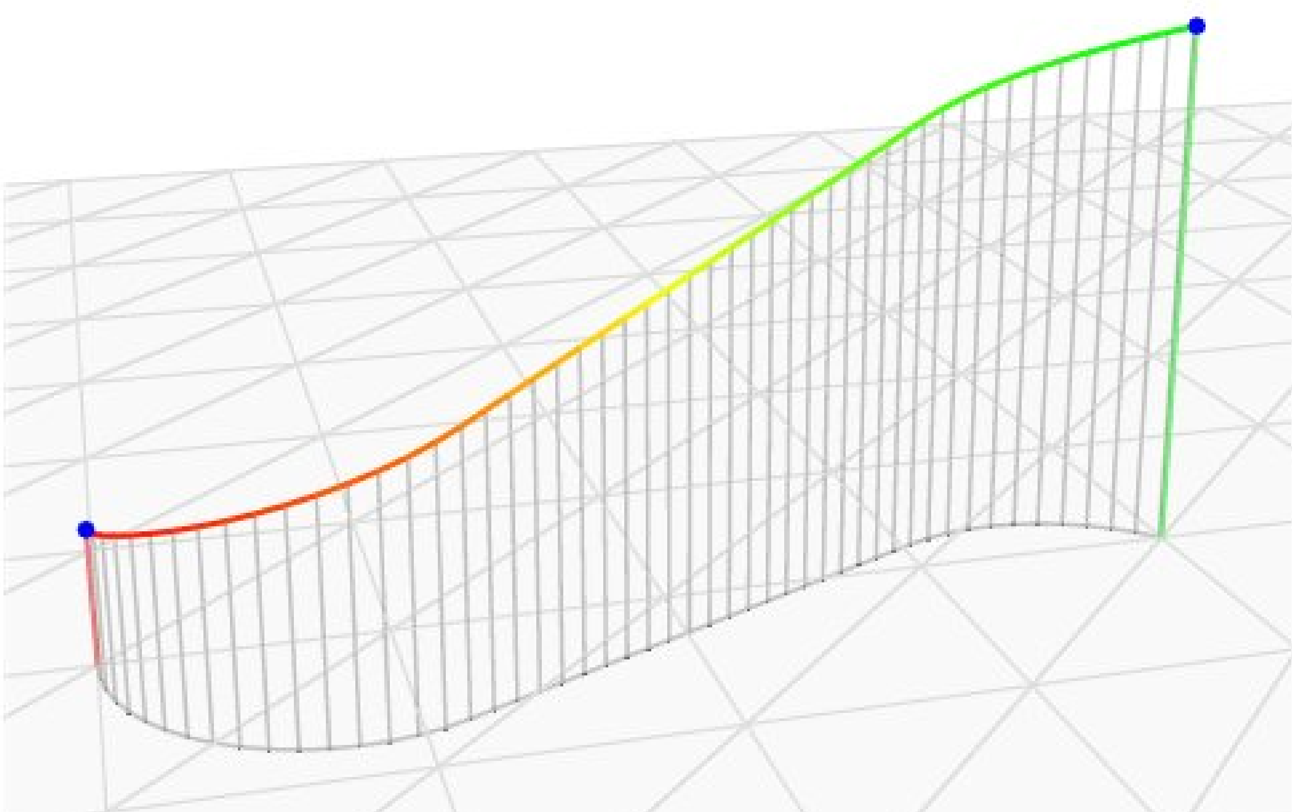
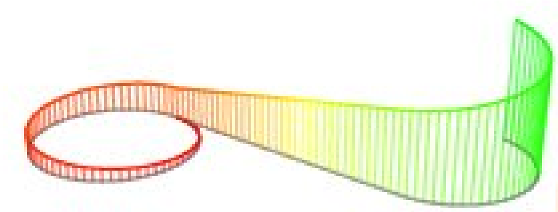
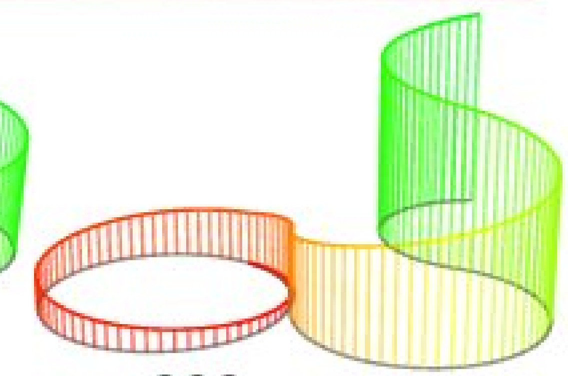
- **Dubins Airplane** model describes the vehicle state $q = (p, \theta, \psi)$, $p \in \mathbb{R}^3$ and $\theta, \psi \in \mathbb{S}^1$ as Chitsaz, H., LaValle, S.M. (2017)
- Constant forward velocity v, the minimal turning radius ρ, and limited pitch angle, i.e., $\psi \in [\psi_{min}, \psi_{max}]$





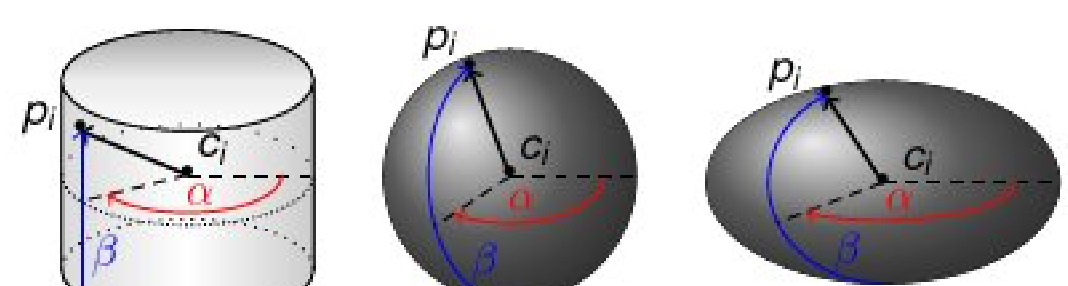


CSC maneuver



CCC maneuver

- Parametrization of 3D regions to be visited



- Váňa and Faigl: *The Dubins Traveling Salesman Problem with Neighborhoods in the Three-Dimensional Space.* ICRA 2018.

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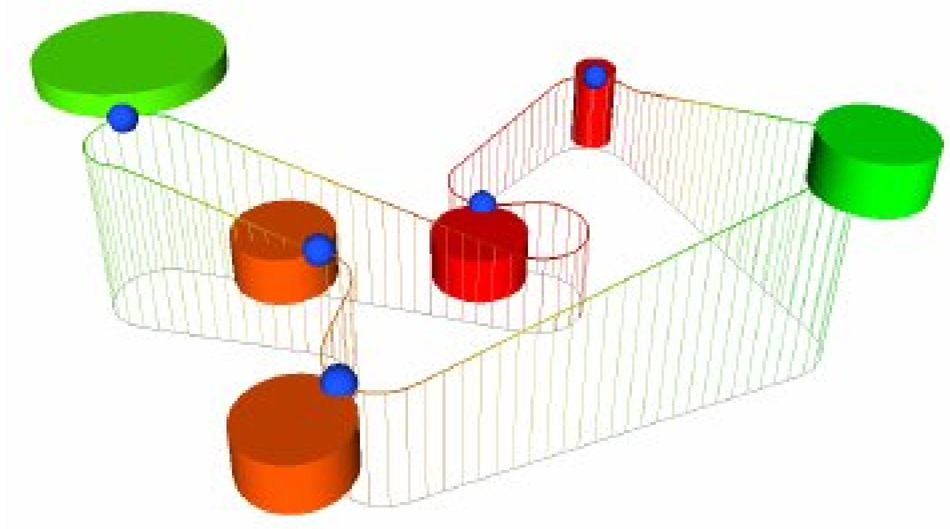
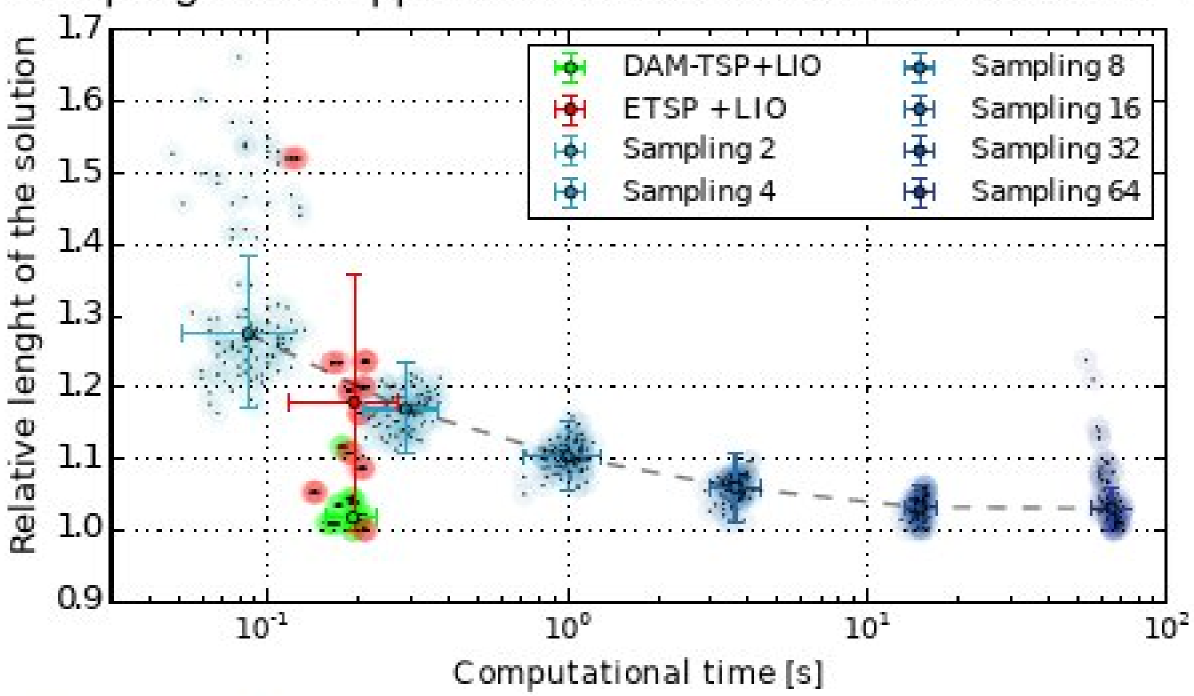


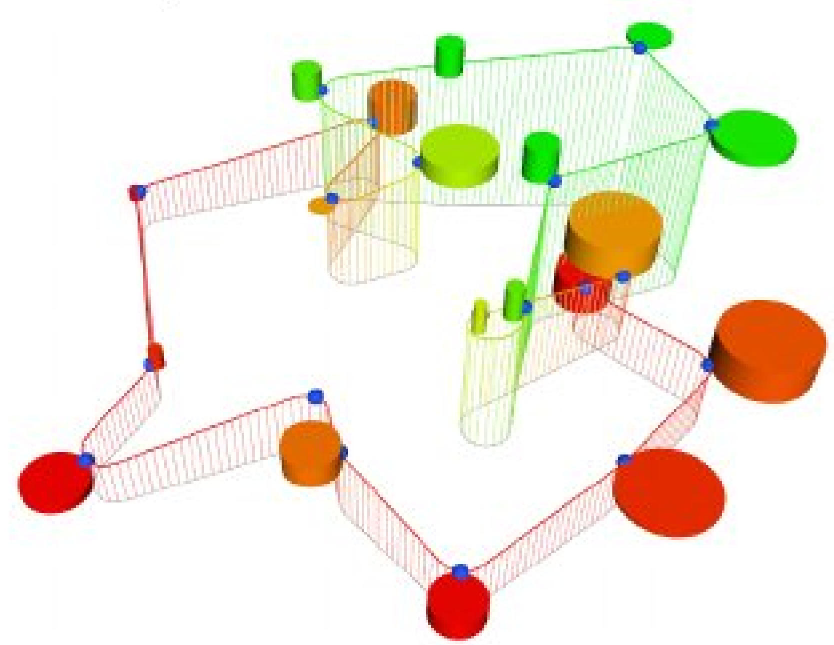
Algorithm 1: LIO-based Solver for 3D-DTSPN

Data: Regions $\mathcal{R}$
Result: Solution represented by $\mathcal{Q}$ and Σ

```
Σ ← getInitialSequence(R);
Q ← getInitialSolution(R, Σ);
while terminal condition do
    Q ← optimizeHeadings(Q, R, Σ);
    Q ← optimizeAlpha(Q, R, Σ);
    Q ← optimizeBeta(Q, R, Σ);
end
return Q, Σ;
```

- Solutions based on LIO (ETSP+LIO), TSP with the travel cost according to Dubins Airplane Model (DAM-TSP+LIO), and sampling-based approach with transformation of the GTSP to the ATSP solved by LKH



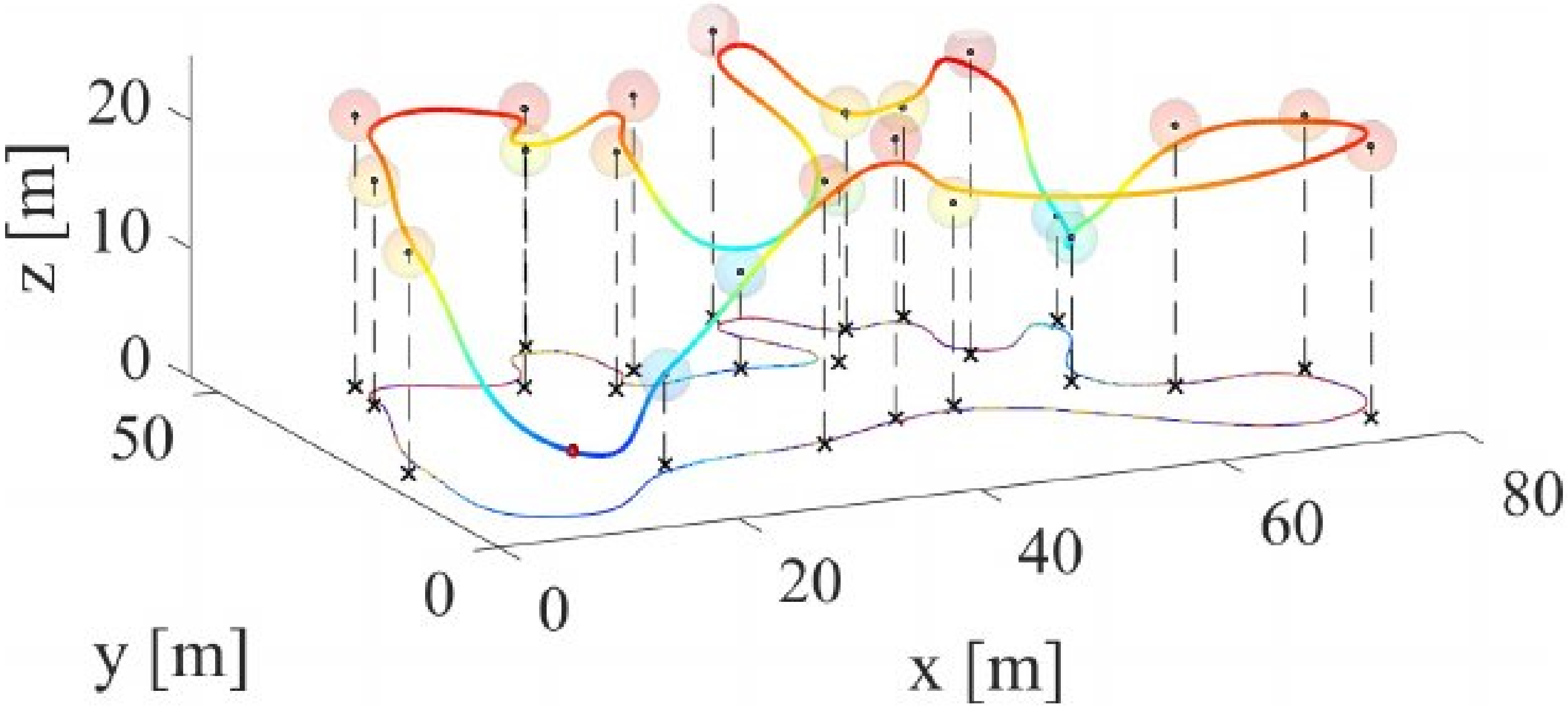


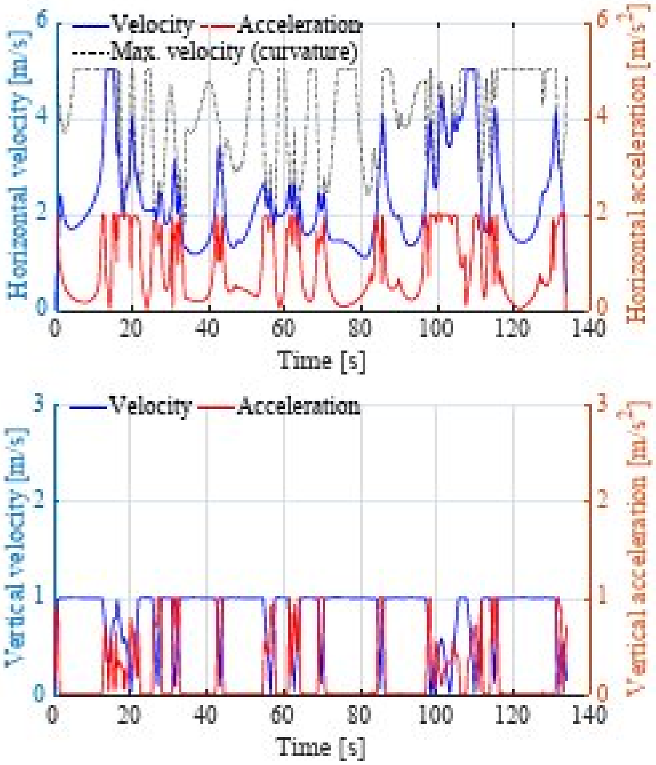
- Váňa and Faigl: *On the Dubins Traveling Salesman Problem with Neighborhoods*. IROS 2015.
- Váňa et al.: *Data collection planning with Dubins airplane model and limited travel budget*. ECMR 2017.
- Váňa and Faigl: *The Dubins Traveling Salesman Problem with Neighborhoods in the Three-Dimensional Space*. ICRA 2018.

Surveillance Planning with Bézier Curves
DTSPN with Parametrization of 3D Smooth Trajectory

- Multi-rotor aerial vehicles can generally move in arbitrary direction
  - DTSPN variant for surveillance planning with 3D trajectory

- Find a 3D smooth trajectory visiting a given set of 3D regions
- Minimizes the **Travel Time Estimation** (TTE)
- Satisfies limited velocity and acceleration of the vehicle



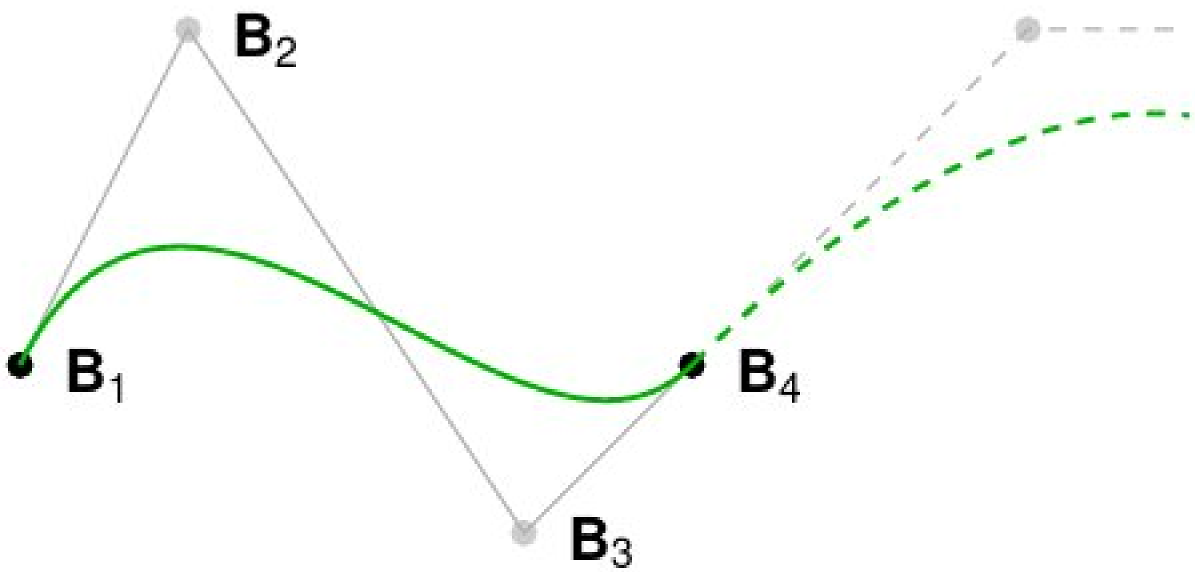


High altitudes changes saturate vertical velocity

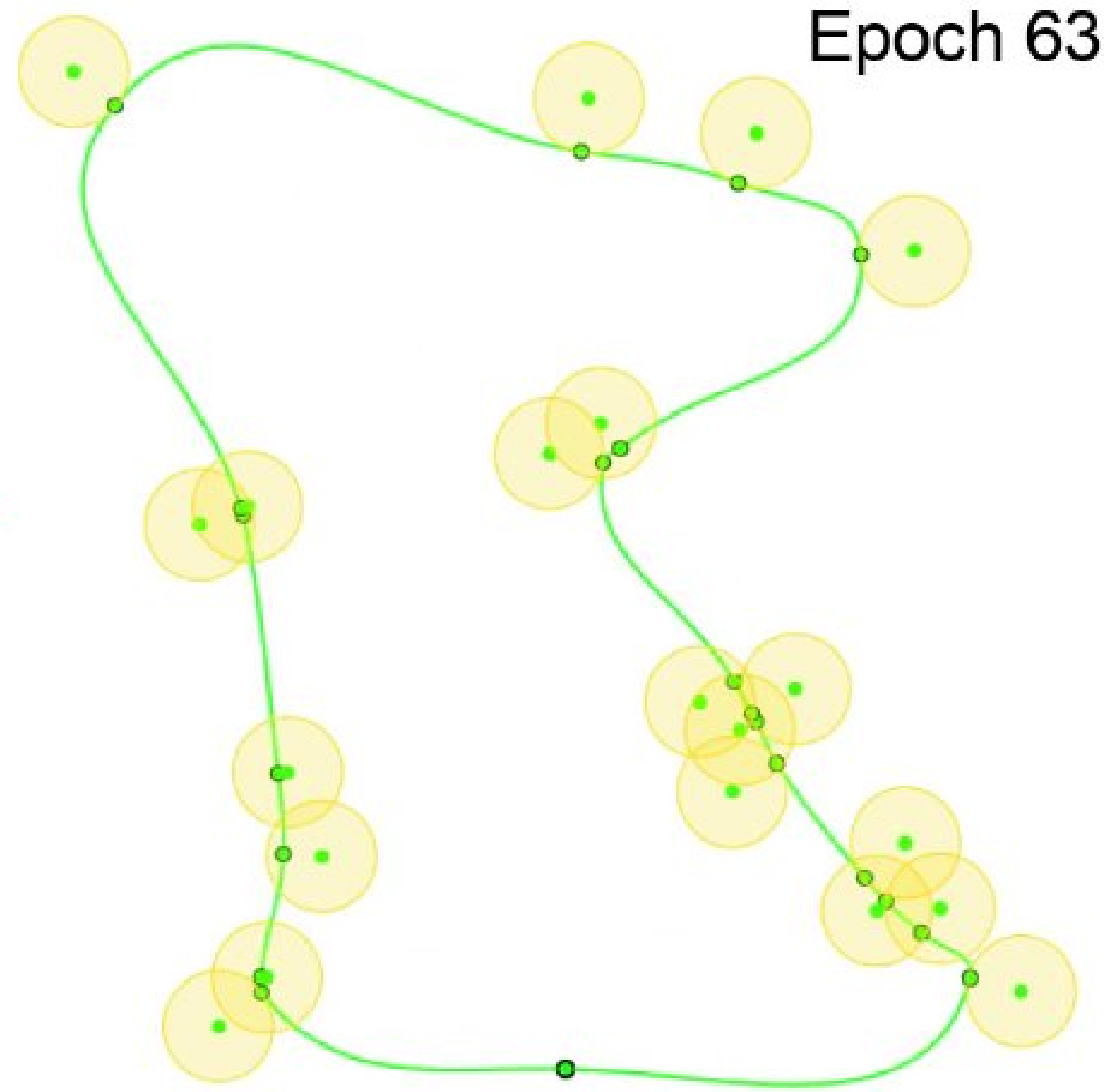
- Faigl and Váňa: *Surveillance Planning With Bézier Curves.* IEEE Robotics and Automation Letters 2018.

Unsupervised Learning using Bézier Curves

- **Benefits of Bézier curves**
  - Flexible and easy to use
  - Start/end direction is given by the first/last two control points



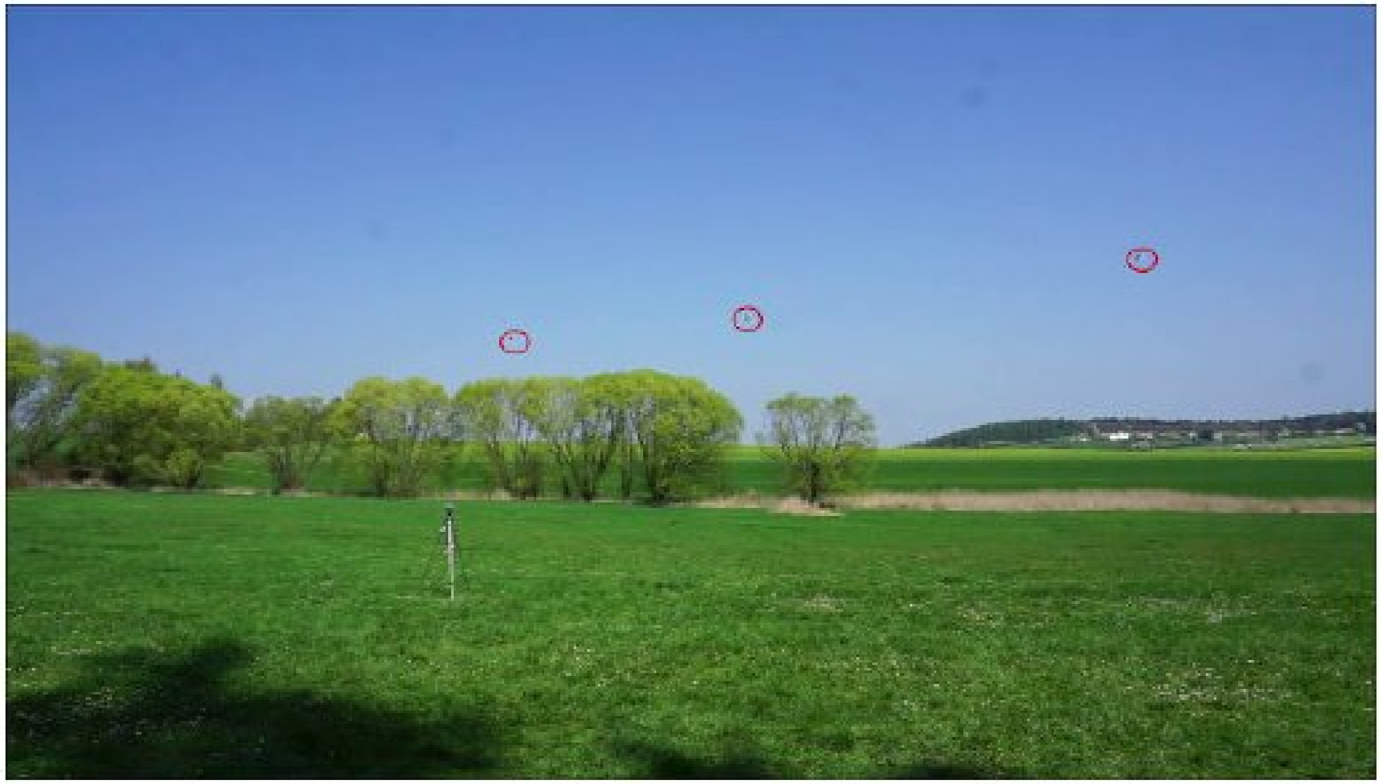
Example of a cubic Bézier curve

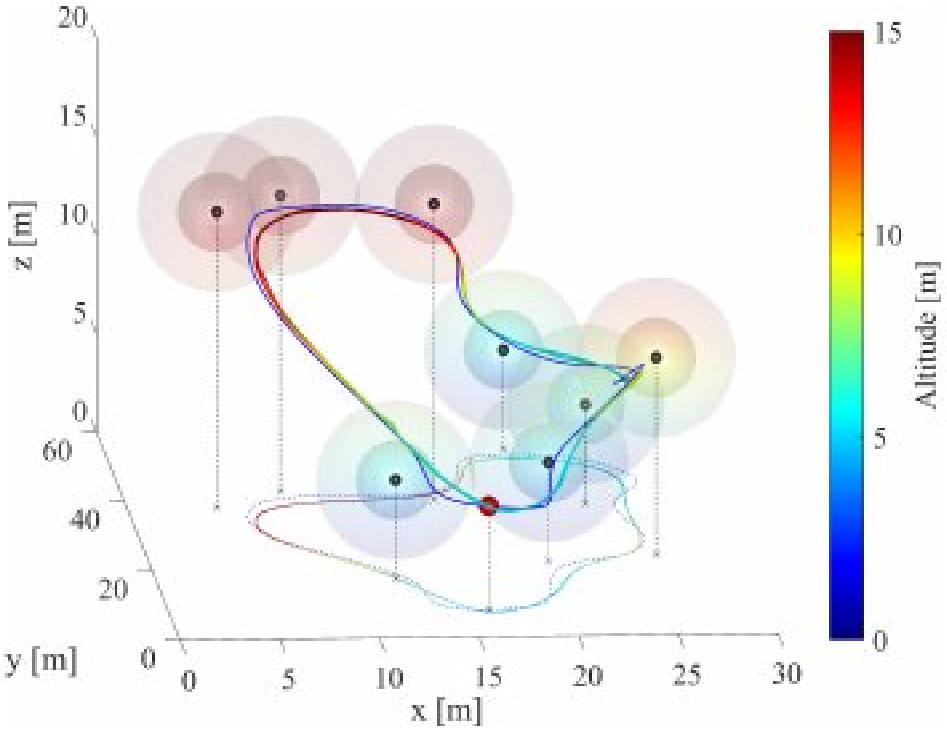


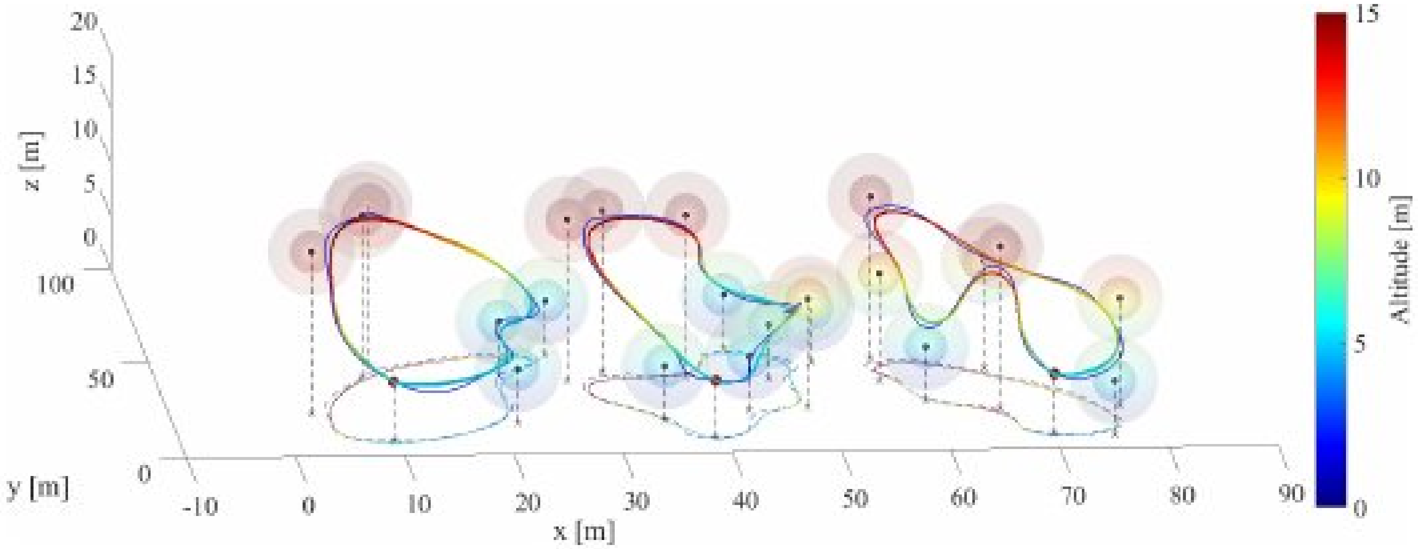
$$\mathbf{X}(\tau) = \mathbf{B}_0(1-\tau)^3 + 3\mathbf{B}_1\tau(1-\tau)^2 + 3\mathbf{B}_2\tau^2(1-\tau) + \mathbf{B}_3\tau^3$$

- Faigl and Váňa: *Surveillance Planning With Bézier Curves.* IEEE Robotics and Automation Letters 2018.

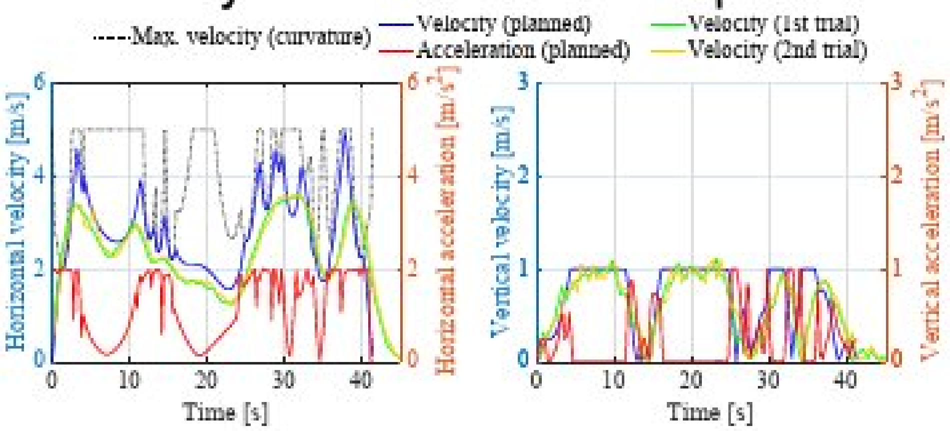
Surveillance Planning with Bézier Curves
Real Experimental Results







Velocity and acceleration profiles



- Faigl and Váňa: *Surveillance Planning With Bézier Curves*. IEEE Robotics and Automation Letters 2018.

Data Collection Planning with Limited Travel Budget
Dubins Orienteering Problem (with Neighborhoods)

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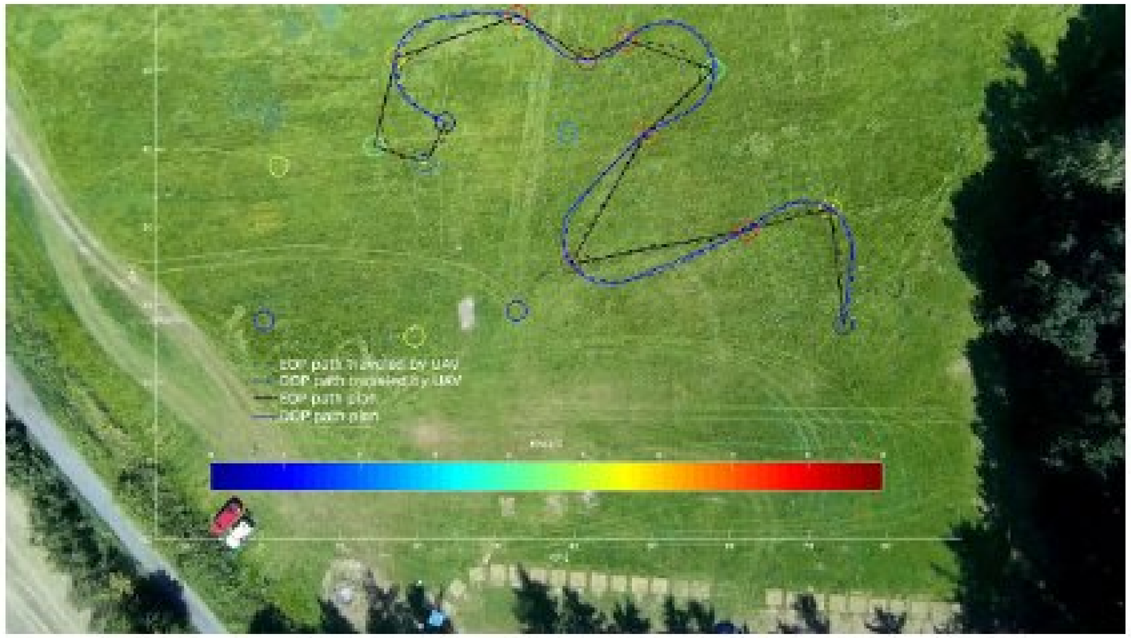
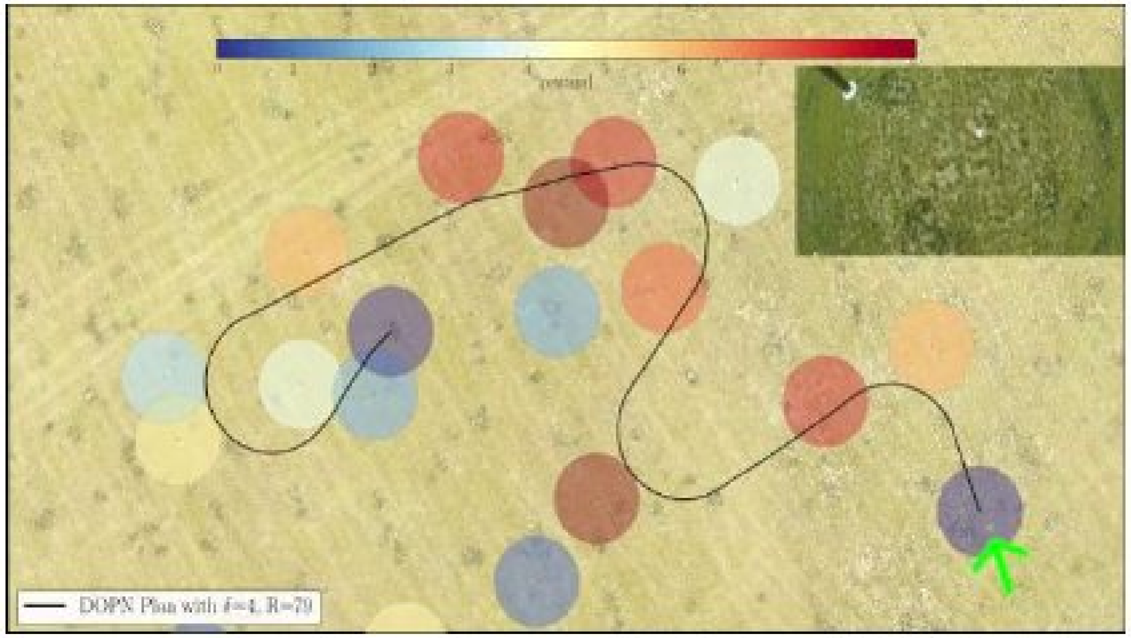
- Visit the most important targets because of limited travel budget
- The problem can be formulated as the **Dubins Orienteering Problem** (**DOP**)
- It can be solved using sampling-based methods, e.g., with Variable Neighborhood Search (VNS) combinatorial metaheuristic



- Pěnička, Faigl, Váňa and Saska: *Dubins Orienteering Problem*. IEEE Robotics and Automation Letters 2017.

- Similarly the **Dubins Orienteering Problem with Neighborhoods** (**DOPN**) can be formulated and solved
- We need to sample the waypoint locations and headings as in DTSPN



- Pěnička, Faigl, Saska and Váňa: *Dubins Orienteering Problem with Neighborhoods*. ICUAS 2017.

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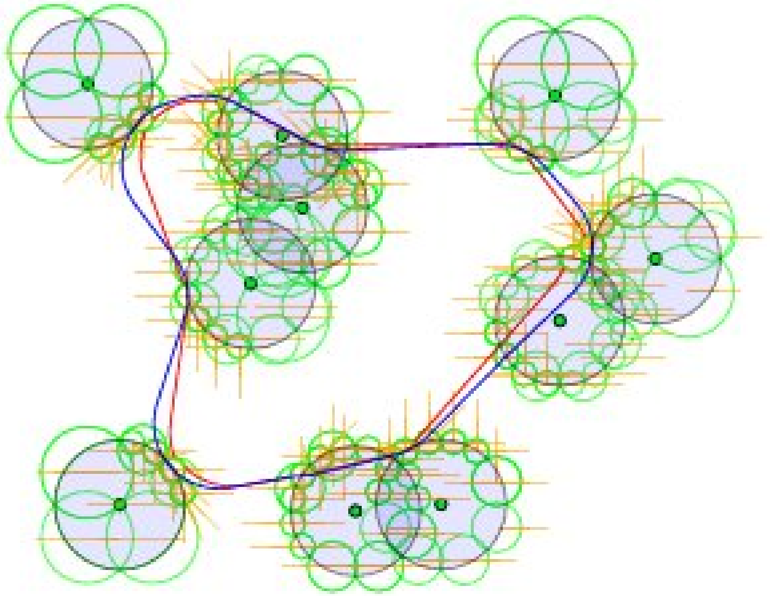
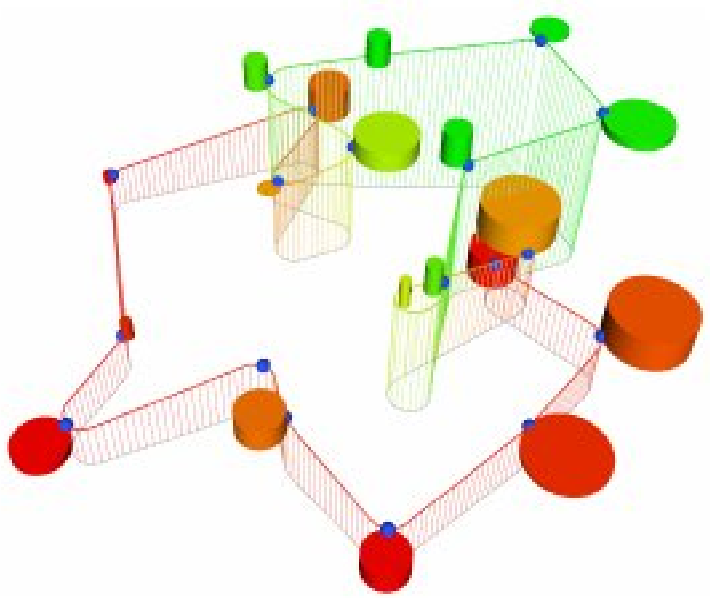
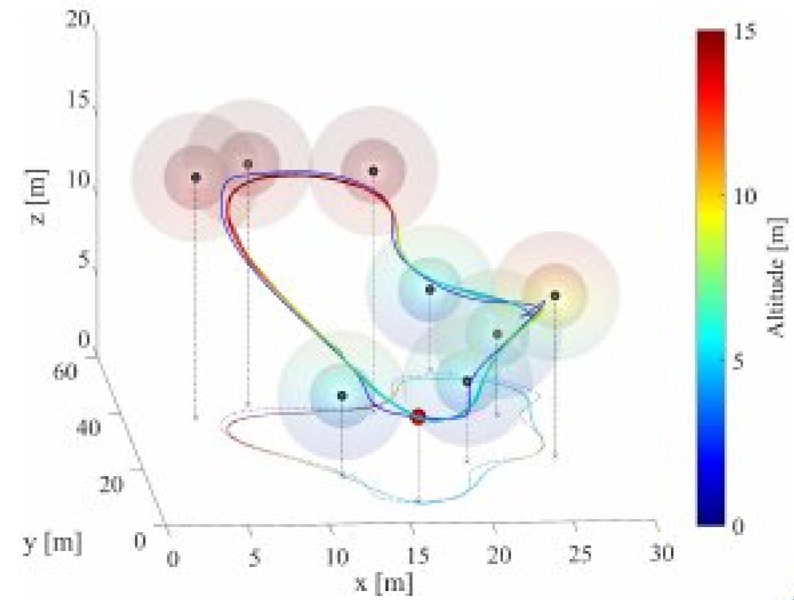
Summary

- Surveillance planning with curvature-constrained trajectory
  - Dubins Traveling Salesman Problem (with Neighborhoods) – DTSPN
  - Informed sampling-based methods based on
  - **Tight lower bound for the DTSPN based on the GDIP**
  - 3D data collection planning with **Dubins Airplane Model**
  - Fast unsupervised learning based methods for DTSPN
  - **Surveillance planning with Bézier curves**
  - **Dubins Orienteering Problem (with Neighborhoods)**

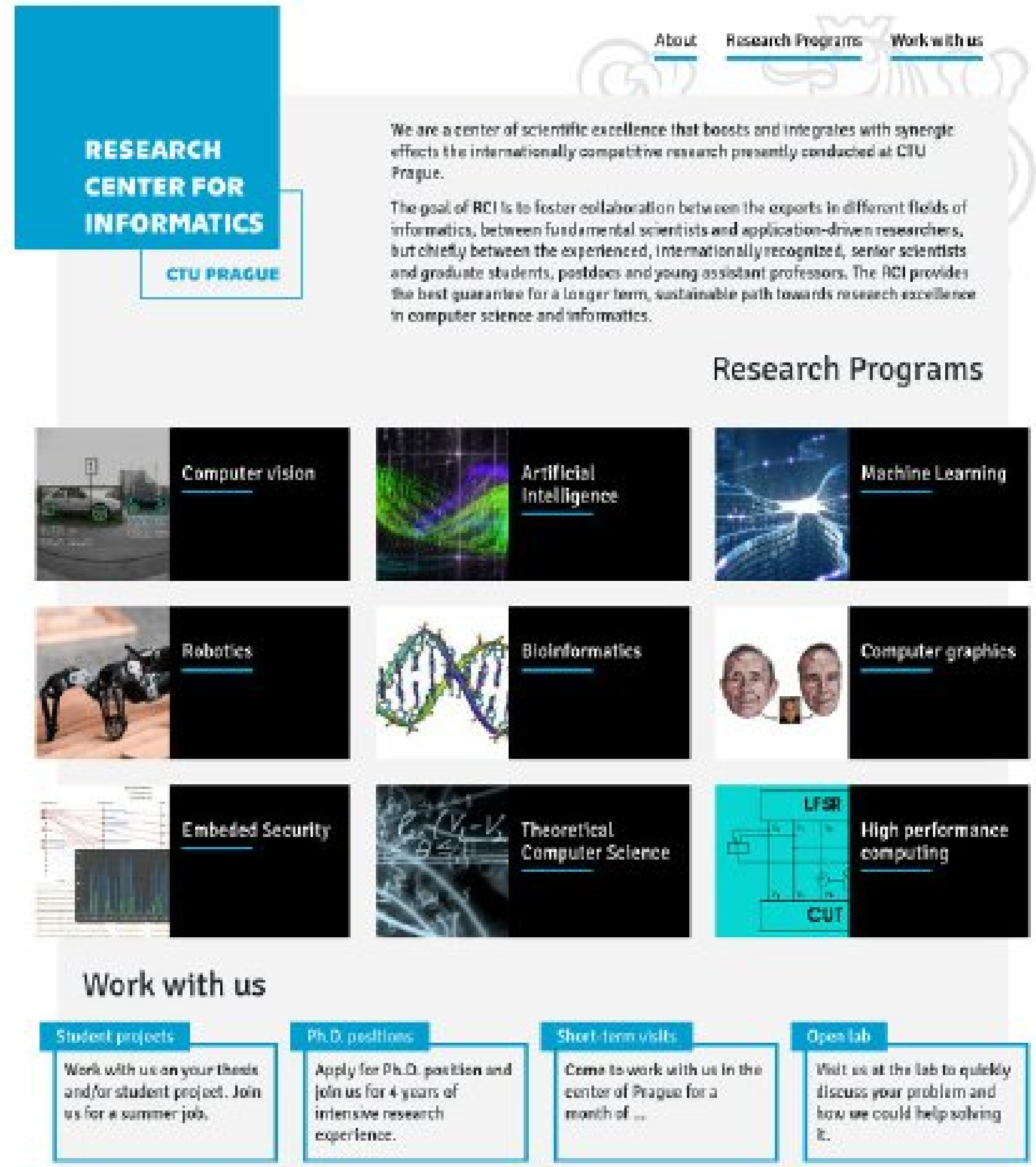






People Behind the Scene

- The presented work are mostly results of my colleagues from the **Computational Robotics Laboratory** and **Multi-Robot Systems Group**



- Work with us within the **Research Center for Informatics** – **http://rci.cvut.cz**

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