

# Robot Motion Planning II / Multi-Goal Planning

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Lecture 10

A4M36PAH - Planning and Games



## Lecture Goals

- Provide an overview of the existing problem formulations in robotic planning
- Multi-Goal Path Planning a.k.a. robotic Traveling Salesman Problem (TSP)
- Inspection, exploration, and data collection missions
- Challenges in planning for non-holonomic vehicle (Dubins vehicle)
- Example of problem formulations suitable for **robotic data collection planning**

*During the lecture, several problems formulation will be defined. Most of them are variants of the TSP. Each problem aims to address a specific issue related to a particular robotic application.*

**The main goal of the lecture is to make you familiar with the key challenges in the related problems and existing approaches.**

*The goal is not to memorize all the details and definitions!*



## Multi-Goal Planning

Multi-Goal Path Planning

Dubins Planning

Data Collection Planning

Mobile Robotic Exploration (TSP-based)



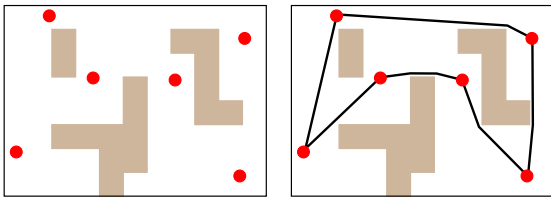
## Multi-Goal Path Planning

### Motivation

Having a set of locations (goals) to be visited, determine the cost efficient path to visit them and return to a starting location.

- Locations where a robotic arm performs some task
- Locations where a mobile robot has to be navigated

*To perform measurements such as scan the environment or read data from sensors.*



Alatartsev et al. (2015) – Robotic Task Sequencing Problem: A Survey



## Traveling Salesman Problem (TSP)

Given a set of cities and the distances between each pair of cities, what is the shortest possible route that visits each city exactly once and returns to the origin city.

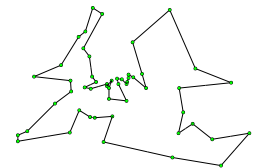
- The TSP can be formulated for a graph  $G(V, E)$ , where  $V$  denotes a set of locations (cities) and  $E$  represents edges connecting two cities with the associated travel cost  $c$  (distance), i.e., for each  $v_i, v_j \in V$  there is an edge  $e_{ij} \in E$ ,  $e_{ij} = (v_i, v_j)$  with the cost  $c_{ij}$ .
- If the associated cost of the edge  $(v_i, v_j)$  is the Euclidean distance  $c_{ij} = |(v_i, v_j)|$ , the problem is called the **Euclidean TSP (ETSP)**.  
*In our case,  $v \in V$  represents a point in  $\mathbb{R}^2$  and solution of the ETSP is a path in the plane.*
- It is known, the TSP is NP-hard (its decision variant) and several algorithms can be found in literature.

*William J. Cook (2012) – In Pursuit of the Traveling Salesman: Mathematics at the Limits of Computation*



## Solutions of the TSP

- Efficient heuristics from the Operational Research have been proposed
- LKH – K. Helsgaun efficient implementation of the Lin-Kernighan heuristic (1998)  
<http://www.akira.ruc.dk/~keld/research/LKH/>
- Concorde – Solver with several heuristic and also optimal solver  
<http://www.math.uwaterloo.ca/tsp/concorde.html>



Problem Berlin52 from the TSPLIB

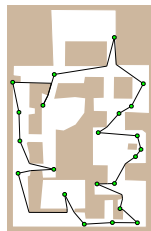
Beside the heuristic and approximations algorithms (such as Christofides 3/2-approximation algorithm), other („soft-computing”) approaches have been proposed, e.g., based on genetic algorithms, and memetic approaches, ant colony optimization (ACO), and **neural networks**.



## Multi-Goal Path Planning (MTP) Problem

Given a map of the environment  $\mathcal{W}$ , mobile robot  $\mathcal{R}$ , and a set of locations, what is the shortest possible **collision free path** that visits each location exactly once and returns to the origin location.

- MTP problem is de facto the TSP with the cost associated to the edges as the length of the *shortest* path connecting the locations
- For  $n$  locations, we need to compute up to  $n^2$  shortest paths (solve  $n^2$  motion planning problems)
- The paths can be found as the shortest path in a graph (roadmap), from which the  $G(V, E)$  for the TSP can be constructed



*Visibility graph as the roadmap for a point robot provides a straight forward solution, but such a shortest path may not be necessarily feasible for more complex robots*



## Multi-Goal Path Planning in Robotic Missions

### Multi-goal path planning

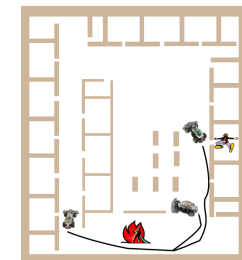
- It builds on a simple path and trajectory planning
- It is a **combinatorial optimization problem** to **determine the sequence** to visit the given locations
- It allows to solve (or improve performance of) more complex problems such as
  - **Inspection planning** - Find the shortest tour to see (inspect) the whole environment
  - **Data collection planning** – Determine a cost efficient path to collect data from the sensor stations (locations)
  - **Robotic exploration** - Create a map of unknown environment as quickly as possible



## Inspection Planning

### Motivations (examples)

- Periodically visit particular locations of the environment to check, e.g., for intruders, and return to the starting locations
- Based on available plans, provide a guideline how to search a building to find possible victims as quickly as possible (search and rescue scenario)



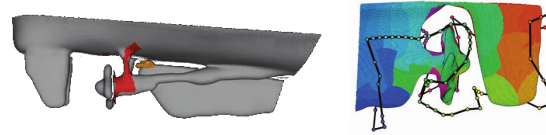
## Inspection Planning – Decoupled Approach

- Determine sensing locations such that the whole environment would be inspected (seen) by visiting them  
*A solution of the Art Gallery Problem*
  - Create a roadmap connecting the sensing location  
*E.g., using visibility graph or randomized sampling based approaches*
  - Find the inspection path visiting all the sensing locations as a solution of the multi-goal path planning  
*De facto solution of the TSP*
- Inspection planning is also called coverage path planning in literature.*



## Example – Inspection Planning with AUV

- Determine shortest inspection path for Autonomous Underwater Vehicle (AUV) to inspect a propeller of the vessel

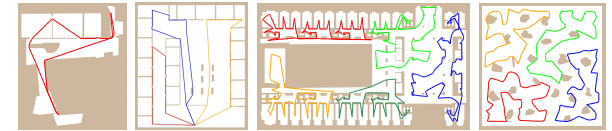


Three-dimensional coverage planning for an underwater inspection robot  
Brendan Englot and Franz S. Hover  
International Journal of Robotic Research, 32(9-10):1048–1073, 2013.



## Inspection Planning – “Continuous Sensing”

- If we do not prescribe a discrete set of sensing locations, we can formulate the problem as the **Watchman route problem**
- Given a map of the environment  $\mathcal{W}$  determine the shortest, closed, and collision free path, from which the whole environment is covered by an omnidirectional sensors with the radius  $\rho$ .



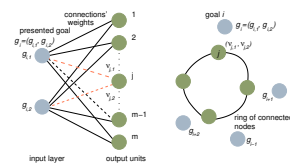
Approximate Solution of the Multiple Watchman Routes Problem with Restricted Visibility Range  
Jan Faigl  
IEEE Transactions on Neural Networks, 21(10):1668–1679, 2010.



## Self-Organizing Maps based Solution of the TSP

Kohonen’s type of unsupervised two-layered neural network

- Neurons’ **weights** represent **nodes**  $\mathcal{N} = \{\nu_1, \dots, \nu_m\}$  in a **plane**.
- Nodes are organized into a **ring**.
- Sensing locations  $\mathcal{S} = \{s_1, \dots, s_n\}$  are presented to the network in a **random** order.
- Nodes **compete** to be winner according to their distance to the presented goal  $s$



$$\nu^* = \operatorname{argmin}_{\nu \in \mathcal{N}} |\mathcal{D}(\nu, s)|$$

- The **winner** and its **neighbouring** nodes are adapted (**moved**) towards the city according to the neighbouring function

$$f(\sigma, d) = \begin{cases} e^{-\frac{d^2}{\sigma^2}} & \text{for } d < m/nr, \\ 0 & \text{otherwise,} \end{cases}$$

- Best matching unit  $\nu$  to the presented prototype  $s$  is determined according to distance function  $|\mathcal{D}(\nu, s)|$
- For the Euclidean TSP,  $\mathcal{D}$  is the Euclidean distance
- However, for problems with obstacles, the multi-goal path planning,  $\mathcal{D}$  should correspond to the length of the shortest, collision free path.

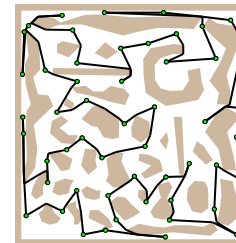


## SOM for the Multi-Goal Path Planning

Unsupervised learning procedure

```

 $\mathcal{N} \leftarrow \text{initialization}(\nu_1, \dots, \nu_m)$ 
repeat
  error  $\leftarrow 0$ 
  foreach  $g \in \Pi(\mathcal{S})$  do
     $\nu^* \leftarrow$ 
    selectWinner  $\operatorname{argmin}_{\nu \in \mathcal{N}} |S(g, \nu)|$ 
    adapt( $S(g, \nu), \mu f(\sigma, l) |S(g, \nu)|$ )
    error  $\leftarrow \max\{\text{error}, |S(g, \nu^*)|\}$ 
   $\sigma \leftarrow (1 - \alpha) \cdot \sigma$ 
until error  $\leq \delta$ 
    
```



- For multi-goal path planning – the **selectWinner** and **adapt** procedures are based on the solution of the path planning problem

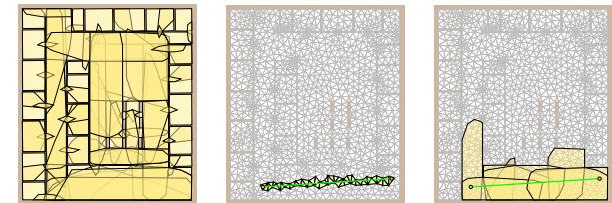
An Application of Self-Organizing Map in the non-Euclidean Traveling Salesman Problem  
Jan Faigl, Miroslav Kulich, Vojtěch Vonásek and Libor Preučil  
Neurocomputing, 74(5):671–679, 2011.



## SOM for the TSP in the Watchman Route Problem

During the unsupervised learning, we can compute **coverage** of  $\mathcal{W}$  from the current **ring** (solution represented by the neurons) and **adapt** the network **towards uncovered parts** of  $\mathcal{W}$

- Convex cover set of  $\mathcal{W}$  created on top of a triangular mesh
- Incident convex polygons with a straight line segment are found by walking in a triangular mesh technique



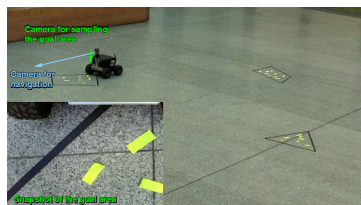
Jan Faigl (2010), TNN



## Multi-Goal Path Planning with Goal Areas

- It may be sufficient to visit a goal region instead of the particular point location

*E.g., to take a sample measurement at each goal*



Not only a sequence of goals visit has to be determined, but also an appropriate sensing location for each goal need to be found.

The problem with goal regions can be considered as a variant of the **Traveling Salesman Problem with Neighborhoods (TSPN)**.



## Traveling Salesman Problem with Neighborhoods

Given a set of  $n$  regions (neighbourhoods), what is the shortest closed path that visits each region.

- The problem is NP-hard and APX-hard, it cannot be approximated to within factor  $2 - \epsilon$ , where  $\epsilon > 0$

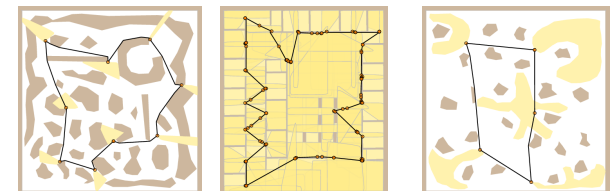
*Safra and Schwartz (2006) – Computational Complexity*

- Approximate algorithms exists for particular problem variants  
*E.g., Disjoint unit disk neighbourhoods*
- Flexibility of SOM for the TSP allows to generalize the unsupervised learning procedure to address the TSPN

- TSPN provides a suitable problem formulation for planning various inspection and data collection missions**



## SOM-based Solution of the Traveling Salesman Problem with Neighborhoods (TSPN)



Polygonal Goals  
 $n=9, T=0.32$  s

Convex Cover Set  
 $n=106, T=5.1$  s

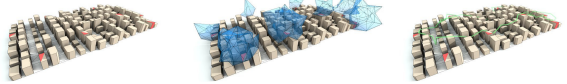
Non-Convex Goals  
 $n=5, T=0.1$  s

Visiting Convex Regions in a Polygonal Map,  
Jan Faigl, Vojtěch Vonásek and Libor Preučil  
Robotics and Autonomous Systems, 61(10):1070–1083, 2013.



### Example – TSPN for Inspection Planning with UAV

- Determine a cost efficient trajectory from which a given set of target regions is covered
- For each target region a subspace  $S \subset \mathbb{R}^3$  from which the target can be covered is determined *S represents the neighbourhood*
- The PRM motion planning algorithm is utilized to construct a motion planning roadmap (a graph)
- SOM based solution of the TSP with a graph input is generalized to the TSPN



Janoušek and Faigl, (2013) – ICRA

### Problem Statement – MGMP Problem

- The working environment  $\mathcal{W} \subset \mathbb{R}^3$  is represented as a set of obstacles  $\mathcal{O} \subset \mathcal{W}$  and the robot configuration space  $\mathcal{C}$  describes all possible configurations of the robot in  $\mathcal{W}$
- For  $q \in \mathcal{C}$ , the robot body  $\mathcal{A}(q)$  at  $q$  is collision free if  $\mathcal{A}(q) \cap \mathcal{O} = \emptyset$  and all collision free configurations are denoted as  $\mathcal{C}_{free}$
- Set of  $n$  goal locations is  $\mathcal{G} = \{g_1, \dots, g_n\}$ ,  $g_i \in \mathcal{C}_{free}$
- Collision free path from  $q_{start}$  to  $q_{goal}$  is  $\kappa : [0, 1] \rightarrow \mathcal{C}_{free}$  with  $\kappa(0) = q_{start}$  and  $d(\kappa(1), q_{end}) < \epsilon$ , for an admissible distance  $\epsilon$
- Multi-goal path  $\tau$  is **admissible** if  $\tau : [0, 1] \rightarrow \mathcal{C}_{free}$ ,  $\tau(0) = \tau(1)$  and there are  $n$  points such that  $0 \leq t_1 \leq t_2 \leq \dots \leq t_n$ ,  $d(\tau(t_i), v_i) < \epsilon$ , and  $\bigcup_{1 \leq i \leq n} v_i = \mathcal{G}$
- **The problem is to find path  $\tau^*$  for a cost function  $c$  such that  $c(\tau^*) = \min\{c(\tau) \mid \tau \text{ is admissible multi-goal path}\}$**



### Optimal Maneuvers for Dubins Vehicle

- For two states  $q_1 \in SE(2)$  and  $q_2 \in SE(2)$  in the environment **without obstacles**  $\mathcal{W} = \mathbb{R}^2$  the optimal paths can be characterized as one of two main types
  - CCC type: LRL, RLR;
  - CSC type: RLR, LSL, LSR, RSL, RSR;
 where S – straight line arc, C – circular arc oriented to left (L) or right (R) *L. E. Dubins (1957) – American Journal of Mathematics*
- The optimal paths are called **Dubins maneuvers**:
  - Constant velocity:  $v(t) = v$  and turning radius  $\rho$
  - 6 types of trajectories connecting any configuration in  $\mathbb{R}^2 \times S^1$  *without obstacles*
  - The control  $u$  is according to C and S type one of the three possible values  $u \in \{-1, 0, 1\}$



### Example – TSPN for Planning with Localization Uncertainty

- Selection of waypoints from the neighbourhood of each location
- P3AT ground mobile robot in an outdoor environment



Real overall error at the goals decreased from 0.89 m → 0.58 m (about 35%)

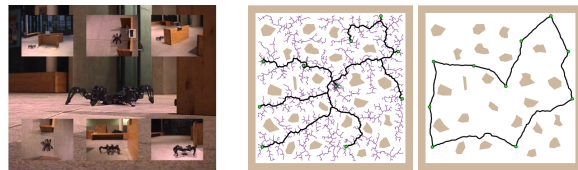
- Decrease localization error at the target locations (indoor)



Improved success of the locations' visits 83% → 95%  
Faigl et al., (2012) – ICRA

### MGMP – Examples of Solutions

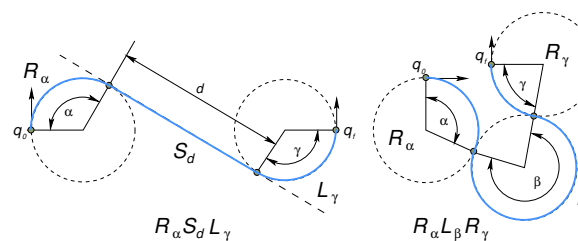
- We aim to avoid explicit determination of all paths connecting two locations  $g_i, g_j \in \mathcal{G}$
- Various approaches can be found in literature, e.g.,
  - Considering Euclidean distance as approximation in solution of the TSP as the Minimum Spanning Tree (MST) *Saha et al. (2006), IJRR*
  - Steering RRG roadmap expansion by unsupervised learning of SOM for the TSP *Faigl (2016), WSOM*



### Parametrization of Dubins Maneuvers

- Parametrization of each trajectory phase:
 
$$\{L_\alpha R_\beta L_\gamma, R_\alpha L_\beta R_\gamma, L_\alpha S_d L_\gamma, L_\alpha S_d R_\gamma, R_\alpha S_d L_\gamma, R_\alpha S_d R_\gamma\}$$
 for  $\alpha \in [0, 2\pi)$ ,  $\beta \in (\pi, 2\pi)$ ,  $d \geq 0$ 

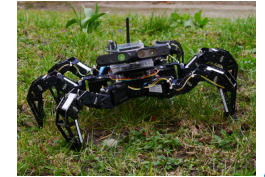
*Notice the prescribed orientation at  $q_0$  and  $q_f$ .*



### Multi-Goal Motion Planning

- In the previous cases, we consider existing roadmap or relatively "simple" collision free (shortest) paths in the polygonal domain
- However, determination of the collision free path in a high dimensional configuration space ( $\mathcal{C}$ -space) can be a challenging problem itself
- Therefore, we can generalize the MTP to multi-goal **motion** planning (MGMP) considering motion (trajectory) planners in  $\mathcal{C}$ -space.
- An example of MGMP can be

Plan a cost efficient trajectory for hexapod walking robot to visit a set of target locations.



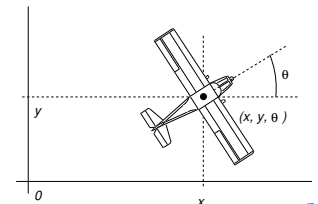
### Dubins Vehicle

- Non-holonomic vehicle such as car-like or aircraft can be modeled as the Dubins vehicle
  - Constant forward velocity
  - Limited minimal turning radius  $\rho$
  - Vehicle state is represented by a triplet  $q = (x, y, \theta)$ , where  $(x, y) \in \mathbb{R}^2$ ,  $\theta \in S^2$  and thus,  $q \in SE(2)$

The vehicle motion can be described by the equation:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = v \begin{bmatrix} \cos \theta \\ \sin \theta \\ \frac{u}{\rho} \end{bmatrix}, \quad |u| \leq 1,$$

where  $u$  is the control input.



### Planning with Dubins vehicle

- The optimal path connecting two configurations can be found analytically *E.g., for UAVs that usually operates in environment without obstacles*
- The Dubins maneuvers can be used in randomized-sampling based motion planners, such as RRT, in the control based sampling
- We can consider the model of Dubins vehicle in the multi-goal path planning
  - Surveillance, inspection or monitoring missions to periodically visits given target locations (areas)
- **Dubins Traveling Salesman Problem DTSP**

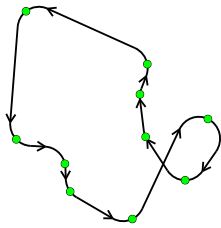
Given a set of locations, what is the shortest Dubins path that visits each location exactly once and returns to the origin location.





## Dubins Traveling Salesman Problem (DTSP)

- Let have Dubins vehicle with minimal turning radius  $\rho$
- Let the given set of  $n$  target locations be  $G = \{g_1, \dots, g_n\}$
- Let  $\Sigma = (\sigma_1, \dots, \sigma_n)$  be a permutation of  $\{1, \dots, n\}$
- Let  $\mathcal{P}$  be projection form  $SE(2)$  to  $\mathbb{R}^2$  such that  $\mathcal{P}(q_i) = (x_i, y_i)$ ,  $q_i \in SE(2)$  and  $g_i = (x_i, y_i)$ .



- DTSP is a problem to determine the minimum length tour that visits every location  $g_i \in G$  while satisfying motion constraints of the Dubins vehicle



## DTSP – Optimization Criterion

- DTSP is an optimization problem over all permutations  $\Sigma$  and headings  $\Theta = \{\theta_{\sigma_1}, \dots, \theta_{\sigma_n}\}$  for the states  $(q_{\sigma_1}, \dots, q_{\sigma_n})$  such that  $q_{\sigma_i} = (g_{\sigma_i}, \theta_{\sigma_i})$

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

$$\text{subject to } q_i = (g_i, \theta_i) \quad i = 1, \dots, n \quad (2)$$

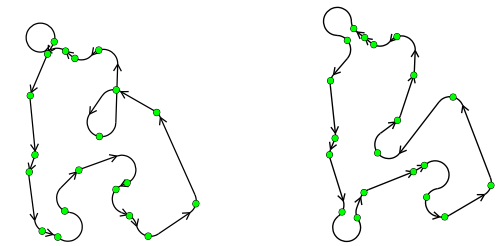
- $\mathcal{L}(q_{\sigma_i}, q_{\sigma_j})$  is the length of the shortest possible Dubins maneuver connecting the states  $q_{\sigma_i}$  and  $q_{\sigma_j}$ .



## Challenges of the Dubins Traveling Salesman Problem

- The key difficulty of the DTSP is that the path length mutually depends on
  - Order of the visits to the locations
  - Headings at the target locations

We need the sequence to determine headings, but headings may influence the sequence



## Algorithms for the DTSP

Two fundamental approaches can be found in literature

- Considering a sequence of the visits is given
  - E.g., found by a solution of the Euclidean TSP
- Sampling the headings at the locations into discrete sets of values and considering the problem as the variant of the Generalized TSP
  - Sampling based approaches

Besides, further approaches are

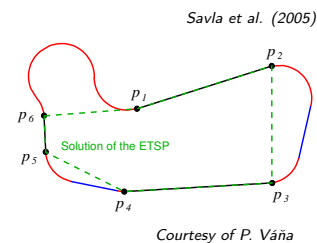
- Approximation algorithms; optimal solutions for restricted variants
- Soft-computing technique such as genetic and memetic technique or neural networks



## DTSP – Alternating Algorithm

Alternating Algorithm (AA) provides a solution of the DTSP for an even number of targets  $n$

- Solve the related Euclidean TSP
  - Relaxed motion constraints
- Establish headings for even edges using straight line segments
- Determine optimal maneuvers for odd edges



AA is heuristic algorithm which solutions can be bounded by  $L_{TSP} \kappa \lceil n/2 \rceil \pi \rho$ , where  $L_{TSP}$  is the length of the optimal solution of the ETSP and  $\kappa < 2.658$ .



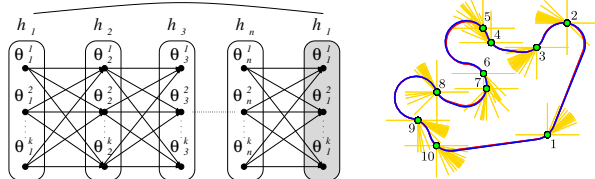
## DTSP with the Given Sequence of the Visits to the Targets

- If the sequence of the visits  $\Sigma$  to the target locations is given
  - the problem is to determine the optimal heading at each location
  - We call the problem as the **Dubins Touring Problem (DTP)**
    - Váňa and Faigl (2016)
- Let for each location  $g_i \in G$  sample possible heading to  $k$  values, i.e., for each  $g_i$  the set of headings be  $h_i = \{\theta_1^i, \dots, \theta_k^i\}$ .
- Since  $\Sigma$  is given, we can construct a graph connecting two consecutive locations in the sequence by all possible headings
- For such a graph and particular headings  $\{h_1, \dots, h_n\}$ , we can find an optimal headings and thus, the optimal solution of the DTP.



## DTSP as a Solution of the DTP

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



- Better solution of the DTP can be found for more samples
- Better solution of the DTP will also improve the DTSP, but only for the given sequence

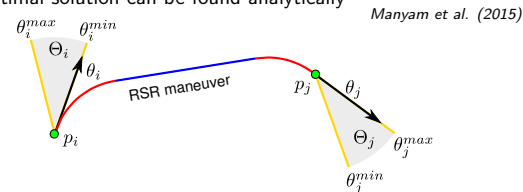
Two questions arise for a practical solution of the DTP

- How to sample the headings? Since more samples makes finding solution more demanding
  - We need it sample the headings in a "smart" way.
- What is the solution quality? Is there a tight lower bound?



## Dubins Interval Problem

- Dubins Interval Problem (DIP) is a generalization of Dubins maneuvers to the shortest path connecting two points  $p_i$  and  $p_j$
- In the DIP, an leaving interval  $\Theta_i$  at  $p_i$  and arrival interval  $\Theta_j$  at  $p_j$  are allowed
- The optimal solution can be found analytically

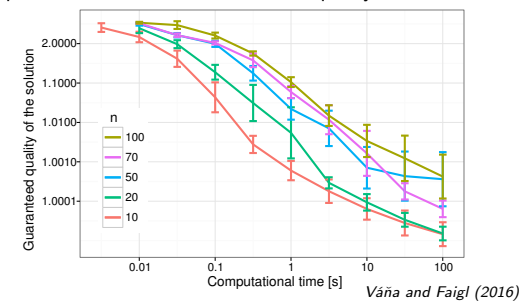


- Solution of the DIP is a tight lower bound for the DTP
  - Manyam and Rathinam (2015)
- Solution of the DIP is not a feasible solution of the DTP
  - Notice, for  $\Theta_i = \Theta_j = \langle 0, 2\pi \rangle$  the optimal maneuver for DIP is straight line segment



## The DIP-based Sampling of Headings in the DTP

- A similar graph as for DTP can be used for heading intervals
- The solution of the DIP is a lower bound of the DTP
- It can be used to inform how to splitting heading intervals
- The ratio between the lower bound and feasible solution of the DTP provides estimation of the solution quality



## DTSP – Sampling-based Approach

- Sampled heading values can be directly utilized to find the sequence as a solution of the **Generalized Traveling Salesman Problem (GTSP)**

*Also called Set TSP or Covering Salesman Problem*

*Notice For Dubins vehicle, it is the Generalized Asymmetric TSP (GATSP)*

The problem is to determine a shortest tour in a graph that visits all specified subsets of the graph's vertices.

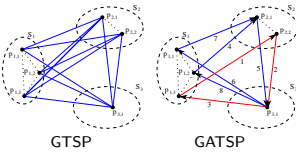
*The TSP is a special case of the GTSP when each subset to be visited consists just a single vertex.*

- GATSP → ATSP

*Noon and Bean (1991)*

- ATSP can be solved by LKH
- ATSP → TSP, which can be solved optimally

*E.g., by Concorde*



## Dubins Traveling Salesman Problem with Neighborhoods

- In surveillance planning, it may be required to visit a set of target regions  $G = \{R_1, \dots, R_n\}$  by the Dubins vehicle
- Then, for each target region  $R_i$ , we have to determine a particular point of the visit  $p_i \in R_i$  and DTSP becomes the **Dubins Traveling Salesman Problem with Neighborhoods (DTSPN)**

*In addition to  $\Sigma$  and headings  $\Theta$ , locations  $P$  have to be determined.*



## DTSPN – Optimization Criterion

- DTSPN is an optimization problem over all permutations  $\Sigma$ , headings  $\Theta = \{\theta_{\sigma_1}, \dots, \theta_{\sigma_n}\}$  and points  $P = (p_{\sigma_1}, \dots, p_{\sigma_n})$  for the states  $(q_{\sigma_1}, \dots, q_{\sigma_n})$  such that  $q_{\sigma_i} = (p_{\sigma_i}, \theta_{\sigma_i})$  and  $p_{\sigma_i} \in R_{\sigma_i}$ :

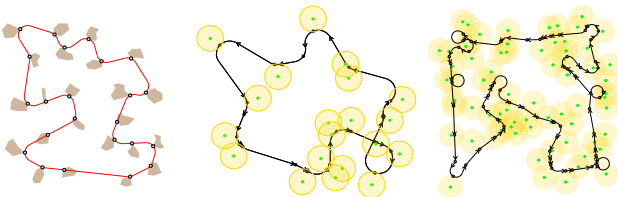
$$\text{minimize}_{\Sigma, \Theta, P} \sum_{i=1}^{n-1} \mathcal{L}(q_{\sigma_i}, q_{\sigma_{i+1}}) + \mathcal{L}(q_{\sigma_n}, q_{\sigma_1}) \quad (3)$$

$$\text{subject to } q_i = (p_i, \theta_i), p_i \in R_i, i = 1, \dots, n \quad (4)$$

- $\mathcal{L}(q_{\sigma_i}, q_{\sigma_j})$  is the length of the shortest possible Dubins maneuver connecting the states  $q_{\sigma_i}$  and  $q_{\sigma_j}$ .



## DTSPN – Examples of Solution



*Vaña and Faigl (2015), (IROS)  
Faigl and Vaña (2016)*

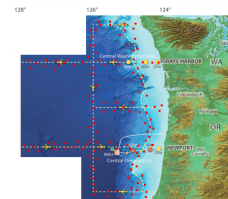


## Autonomous Data Collection

- Having a set of sensors (sampling stations), we aim to determine a cost efficient path to retrieve data from the individual sensors

*E.g., Sampling stations on the ocean floor*

- The planning problem is a variant of the **Traveling Sampling Problem**



Two practical aspects of the data collection can be identified

- Data from particular sensors may be of different importance
- Data from the sensor can be retrieved using wireless communication

*These two aspects can be considered in Prize-Collecting Traveling Salesman Problem (PC-TSP) and Orienteering Problem (OP) and their extensions with neighborhoods.*



## Prize-Collecting Traveling Salesman Problem with Neighborhoods (PC-TSPN)

- Let  $n$  sensors be located in  $\mathbb{R}^2$  at the locations  $S = \{s_1, \dots, s_n\}$
- Each sensor has associated penalty  $\zeta(s_i) \geq 0$  characterizing additional cost if the data are not retrieved from  $s_i$
- Let the data collecting vehicle operates in  $\mathbb{R}^2$  with the motion cost  $c(p_1, p_2)$  for all pairs of points  $p_1, p_2 \in \mathbb{R}^2$
- The data from  $s_i$  can be retrieved within  $\delta$  distance from  $s_i$



## PC-TSPN – Optimization Criterion

The **PC-TSPN** is a problem to

- Determine a set of unique locations**  $G = \{g_1, \dots, g_k\}$ ,  $k \leq n$ ,  $g_i \in \mathbb{R}^2$ , at which data readings are performed
- Find a cost efficient tour**  $T$  visiting  $G$  such that the total cost  $C(T)$  of  $T$  is minimal

$$C(T) = \sum_{(g_i, g_{i+1}) \in T} c(g_i, g_{i+1}) + \sum_{s \in S \setminus S_T} \zeta(s), \quad (5)$$

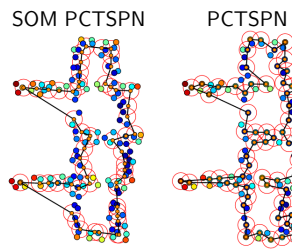
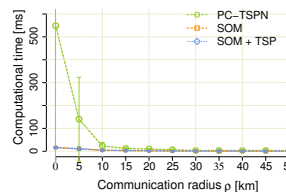
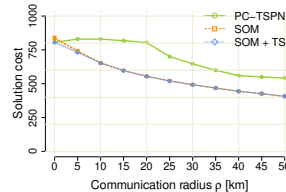
where  $S_T \subseteq S$  are sensors such that for each  $s_i \in S_T$  there is  $g_{l_j}$  on  $T = (g_1, \dots, g_{k-1}, g_k)$  and  $g_{l_j} \in G$  for which  $|(s_i, g_{l_j})| \leq \delta$ .

- PC-TSPN includes other variants of the TSP
  - for  $\delta = 0$  it is the PC-TSP
  - for  $\zeta(s_i) = 0$  and  $\delta \geq 0$  it is the TSPN
  - for  $\zeta(s_i) = 0$  and  $\delta = 0$  it is the ordinary TSP



## PC-TSPN – Example of Solution

Ocean Observatories Initiative (OOI) scenario



*Faigl and Hollinger (2014) – IROS*



## Orienteeing Problem

- The **Orienteeing Problem (OP)** originates from the orienteeing outdoor sport
- The problem is to collect as many rewards as possible within the given travel budget

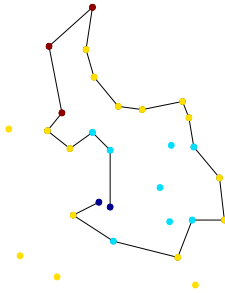
- It is similar to the PC-TSP, but the tour length must not exceed the prescribed maximize tour length  $T_{max}$
- In OP, the starting and termination locations are prescribed, and they can be different

*The solution may not be a closed tour as in the TSP*



## Orienteering Problem – Specification

- Let the given set of  $n$  sensors be located in  $\mathbb{R}^2$  with the locations  $S = \{s_1, \dots, s_n\}$ ,  $s_i \in \mathbb{R}^2$
- Each sensor  $s_i$  has an associated score  $c_i$  characterizing the reward if data from  $s_i$  are collected
- The vehicle is operating in  $\mathbb{R}^2$  and the travel cost is the Euclidean distance
- The starting and termination locations are prescribed
- We aim to determine a subset of  $k$  locations  $S_k \subseteq S$  that maximizes the sum of the collected rewards while the travel cost to visit them is below  $T_{max}$ .



## Orienteering Problem – Optimization Criterion

- Let  $\Sigma = (\sigma_1, \dots, \sigma_k)$  be a permutation of  $k$  sensor labels,  $1 \leq \sigma_i \leq n$  and  $\sigma_i \neq \sigma_j$  for  $i \neq j$
- $\Sigma$  defines a tour  $T = (s_{\sigma_1}, \dots, s_{\sigma_k})$  visiting the selected sensors  $S_k$
- Let the start and end points of the tour be  $\sigma_1 = 1$  and  $\sigma_k = n$
- The **Orienteering problem (OP)** is to determine the number of sensors  $k$ , the subset of sensors  $S_k$ , and their sequence  $\Sigma$  such that

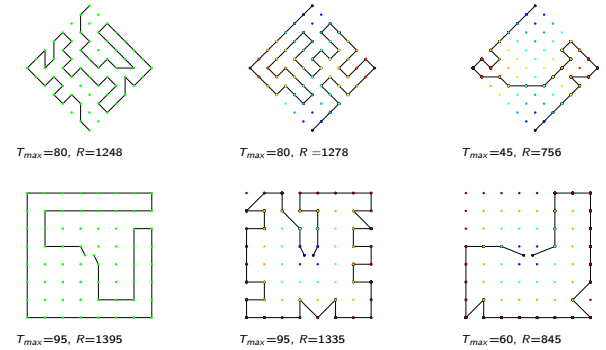
$$\begin{aligned} & \text{maximize}_{k, S_k, \Sigma} && R = \sum_{i=1}^k c_{\sigma_i} \\ & \text{subject to} && \sum_{i=2}^k |(s_{\sigma_{i-1}}, s_{\sigma_i})| \leq T_{max} \text{ and} \\ & && s_{\sigma_1} = s_1, s_{\sigma_k} = s_n \end{aligned} \quad (6)$$

The OP combines the problem of determining the most valuable locations  $S_k$  with finding the shortest tour  $T$  visiting the locations  $S_k$ . It is NP-hard, since for  $s_1 = s_n$  and particular  $S_k$  it becomes the TSP.

## Orienteering Problem – Example of Solutions

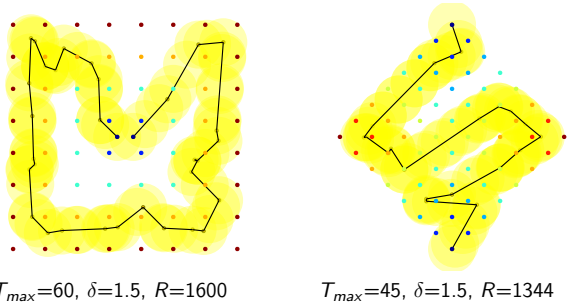
- Heuristic algorithms have been proposed

E.g., Ramesh et al. (1991), Chao et al. (1996)



## Orienteering Problem with Neighborhoods

- Similarly to the TSP with Neighborhoods and PC-TSPN we can formulate the **Orienteering Problem with Neighborhoods**.

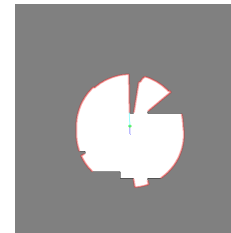


$T_{max}=60, \delta=1.5, R=1600$

$T_{max}=45, \delta=1.5, R=1344$

## Mobile Robot Exploration

- Create a map of the environment
- Frontier-based approach**   
 Yamauchi (1997)
- Occupancy grid**   
 Moravec and Elfes (1985)
- Laser scanner sensor
- Next-best-view approach**   
 Select the next robot goal



Performance metric:

Time to create the map of the whole environment

search and rescue mission

## Multi-Robot Exploration Strategy

- A set of  $m$  robots at positions  $R = \{r_1, r_2, \dots, r_m\}$
- At time  $t$ , let a set of  $n$  goal candidates be  $G(t) = \{g_1, \dots, g_n\}$



e.g., frontiers

- The exploration strategy (at the planning step  $t$ ):

Select a goal  $g \in G(t)$  for each robot  $r \in R$  that will minimize the required time to explore the environment.

The problem is formulated as the **task-allocation problem**

$$(\langle r_1, g_{r_1} \rangle, \dots, \langle r_m, g_{r_m} \rangle) = \text{assign}(R, G(t), \mathcal{M}),$$

where  $\mathcal{M}$  is the current map

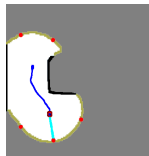
We consider only the distance cost for the assignment

## Distance Cost Variants

### Simple robot–goal distance

- Evaluate all goals using the robot–goal distance   
 a length of the path from the robot position to the goal candidate
- Greedy goal selection

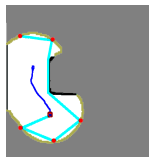
Select the closest goal candidate



### TSP distance cost

- On Distance Utility in the Exploration Task   
 Miroslav Kulich, Jan Faigl and Libor Preucil   
 ICRA, 2011, 4455-4460.

- Consider visitations of all goals   
 Solve the associated traveling salesman problem (TSP)



- A length of the tour visiting all goals

- Goal representatives

TSP distance cost improves performance about 10-30%

## Multi-Robot Exploration – Problem Definition

A problem of creating a grid map of the unknown environment by a set of  $m$  robots  $R = \{r_1, r_2, \dots, r_m\}$ .

Exploration is an iterative procedure:

- Collect new sensor measurements
- Determine a set of goal candidates   
  $G(t) = \{g_1, g_2, \dots, g_n\}$    
 e.g., frontiers
- At time step  $t$ , select next goal for each robot as the **task-allocation problem**   
  $(\langle r_1, g_{r_1} \rangle, \dots, \langle r_m, g_{r_m} \rangle) = \text{assign}(R, G(t), \mathcal{M}(t))$    
 using the distance cost function
- Navigate robots towards goal
- If  $|G(t)| > 0$  go to Step 1; otherwise terminate



## Proposed Multiple Traveling Salesman Approach

- Consider the task-allocation problem as the **Multiple Traveling Salesman Problem (MTSP)**

- MTSP heuristic (*cluster–first, route–second*)

- Cluster the goal candidates  $G$  to  $m$  clusters   
  $C = \{C_1, \dots, C_m\}, C_i \subseteq G$    
 using K-means

- For each robot  $r_i \in R, i \in \{1, \dots, m\}$  select the next goal  $g_i$  from  $C_i$  using the TSP distance cost

Kulich et al., ICRA (2011)

- Solve the TSP on the set  $C_i \cup \{r_i\}$

the tour starts at  $r_i$

- The next robot goal  $g_i$  is the first goal of the found TSP tour

Goal Assignment using Distance Cost in Multi-Robot Exploration   
 Jan Faigl, Miroslav Kulich and Libor Preucil   
 IROS, 2012, 3741–3741.

## Comparison – Goal Assignment Strategies

### 1. Greedy Assignment

*Yamauchi B, Robotics and Autonomous Systems 29, 1999*

- Randomized greedy selection of the closest goal candidate

### 2. Iterative Assignment

*Werger B, Mataric M, Distributed Autonomous Robotic Systems 4, 2001*

- Centralized variant of the broadcast of local eligibility algorithm (BLE)

### 3. Hungarian Assignment

- Optimal solution of the task-allocation problem for assignment of  $n$  goals and  $m$  robots in  $O(n^3)$

*Stachniss C, C implementation of the Hungarian method, 2004*

### 4. MTSP Assignment

- (cluster-first, route-second), the TSP distance cost

*In all strategies, we use the identical selection of the goal candidates from the frontiers.*



## Summary

- Introduction to multi-goal path planning
- Overview of Dubins planning and DTSP
- Data collection planning
- Overview of multi-robot exploration based on the TSP

*Robotic TSP*



## Statistical Evaluation of the Exploration Strategies

- Evaluation for the number of robots  $m$  and sensor range  $\rho$

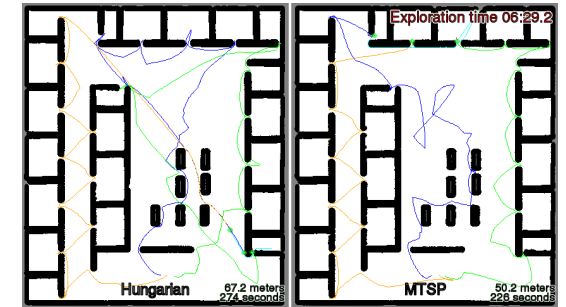
$\rho$	$m$	Iterative	Hungarian	MTSP
		vs Greedy	vs Iterative	vs Hungarian
3.0	3	+	=	+
3.0	5	+	=	+
3.0	7	+	=	+
3.0	10	+	+	-
4.0	3	+	=	+
4.0	5	+	=	=
4.0	7	+	=	+
4.0	10	+	+	-
5.0	3	+	=	+
5.0	5	+	=	+
5.0	7	+	=	+
5.0	10	+	+	-

Total number of trials 14 280



## Performance of the MTSP vs Hungarian Algorithm

- Replanning as quickly as possible;  $m = 3, \rho = 3 m$



The MTSP assignment provides better performance

