Trajectory driven point cloud compression techniques for visual SLAM

Luis Angel Contreras-Toledo, PhD

Bio-Robotics Laboratory
National Autonomous University of Mexico

https://goo.gl/KmKYDq @TenshiTeacher

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Motivation

Small devices in large environments require optimal memory footprint; on the other hand, more sophisticated robots performing complex tasks, mapping and navigation are some of multiple processes that run at the same time.

Motivation

From a given point cloud, what information do we have?
What is really necessary to perform a specific task?

Motivation

Given $u_i \sim N(\mu,\sigma)$ and $z_i \sim N(\mu,\sigma)$, at time T we have

$X_T = \{x_0, x_1, x_2, \ldots, x_T\}$
$U_T = \{u_1, u_2, u_3, \ldots, u_T\}$
$Z_T = \{z_1, z_2, z_3, \ldots, z_T\}$

The SLAM problem is then defined as

$p(X_T, m \mid U_T, Z_T)$ – full SLAM

$p(x_t, m \mid U_T, Z_T)$ – online SLAM

Motivation

We aim to introduce the task in the mapping process as a function *f*

$p(X_T,m ¦ f(U_T, Z_T))$ – full SLAM

$p(x_t,m ¦ f(U_T, Z_T))$ – online SLAM

This work aims to present a number of point cloud compression techniques for visual odometry and SLAM, useful for relocalisation.

First, **the travelled trajectory is modelled** from a series of cameras' spatial position and then such trajectory is divided in segments depending on the curvature level.

Then, **multiple map-features subsets are generated** by associating each point in the point cloud to the trajectory segments based on some association rules (in this case, Euclidean distance and camera visibility were used).

Finally, a number of selection criteria are proposed to **compress each subset**; the final compressed point cloud is the union of all compressed subsets.

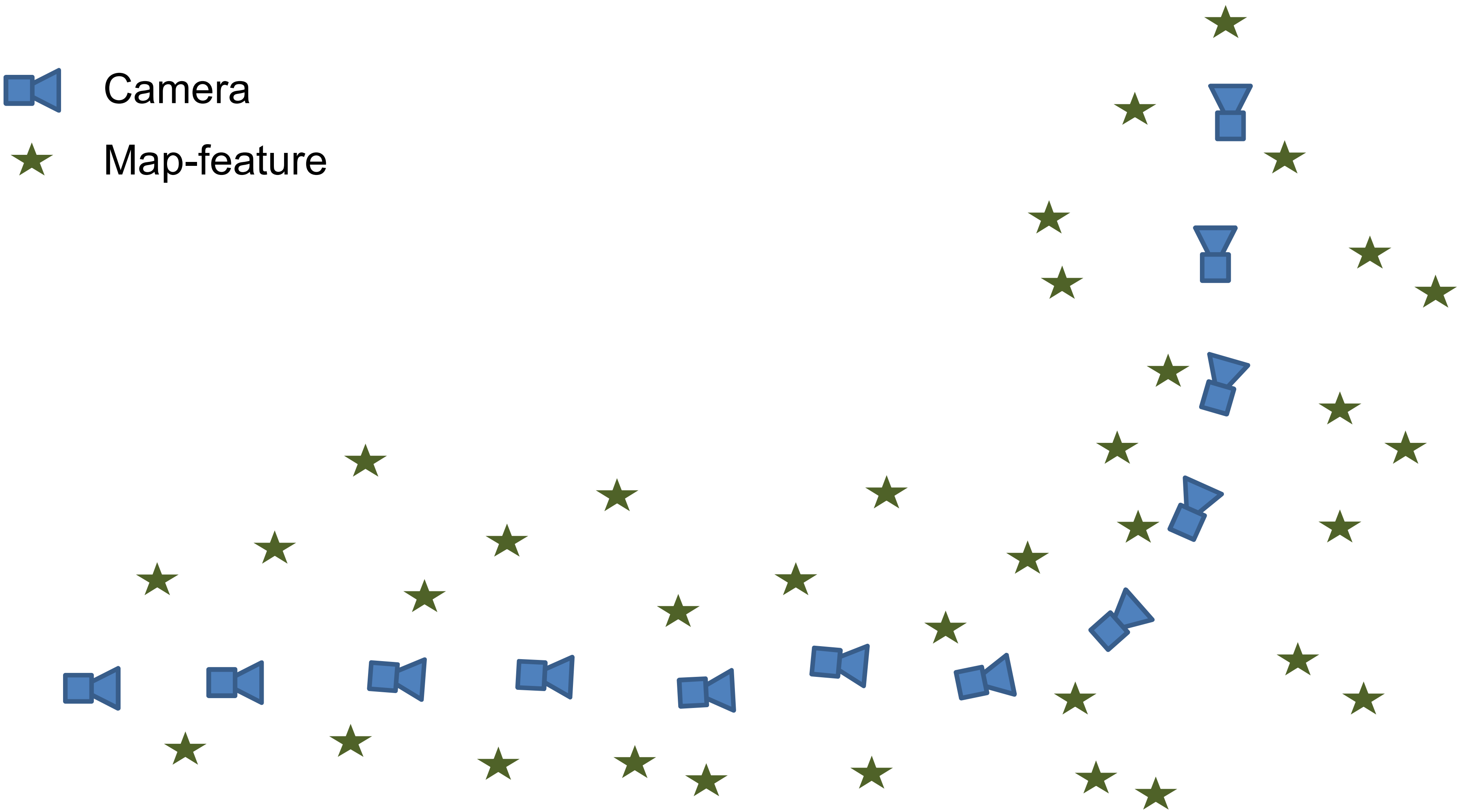
Content

- **Trajectory-driven POint cloud Compression (POCO)**

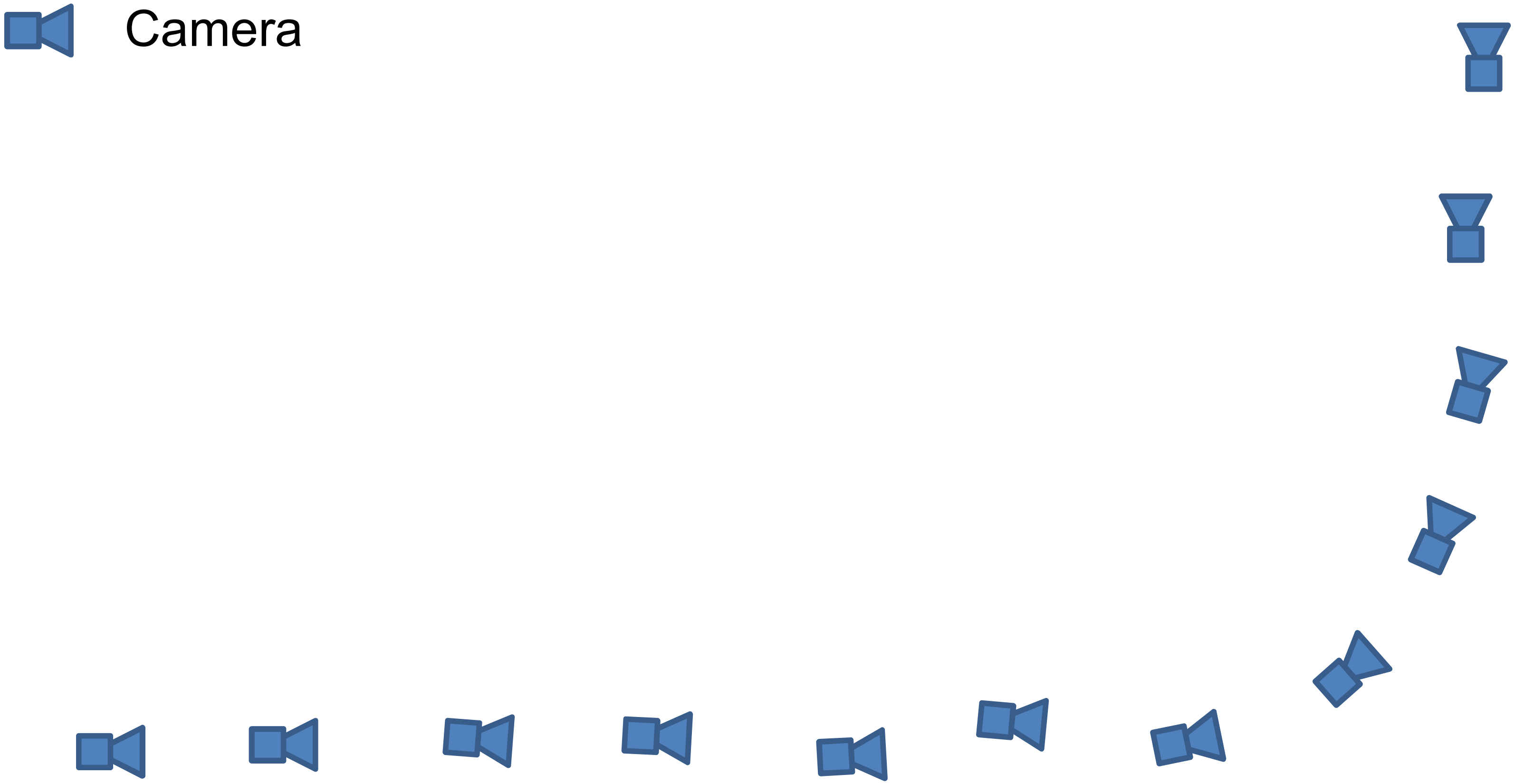
- Online POint cloud COmpression (O-POCO)

Final Remarks and Future Work

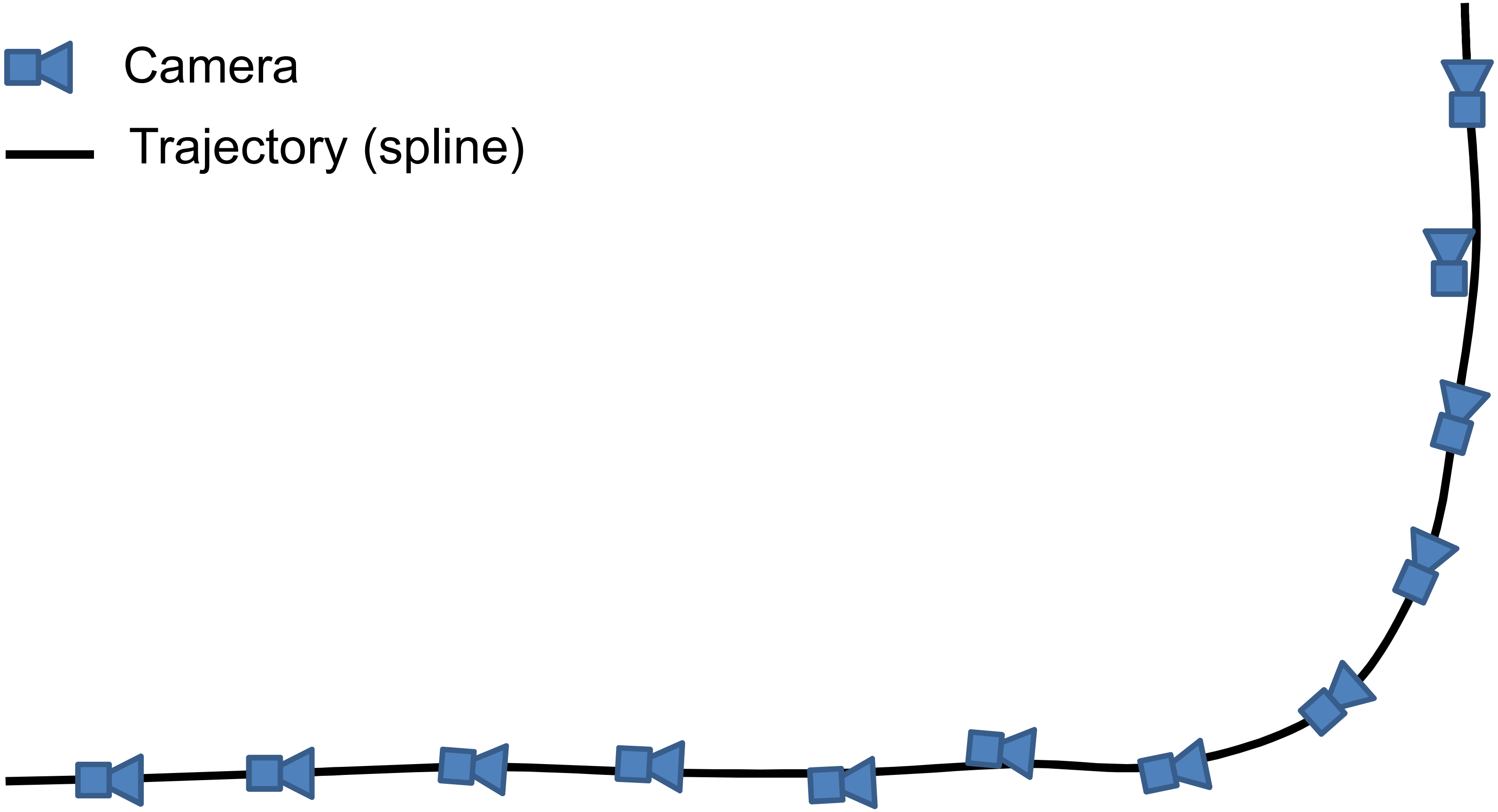
Trajectory modeling



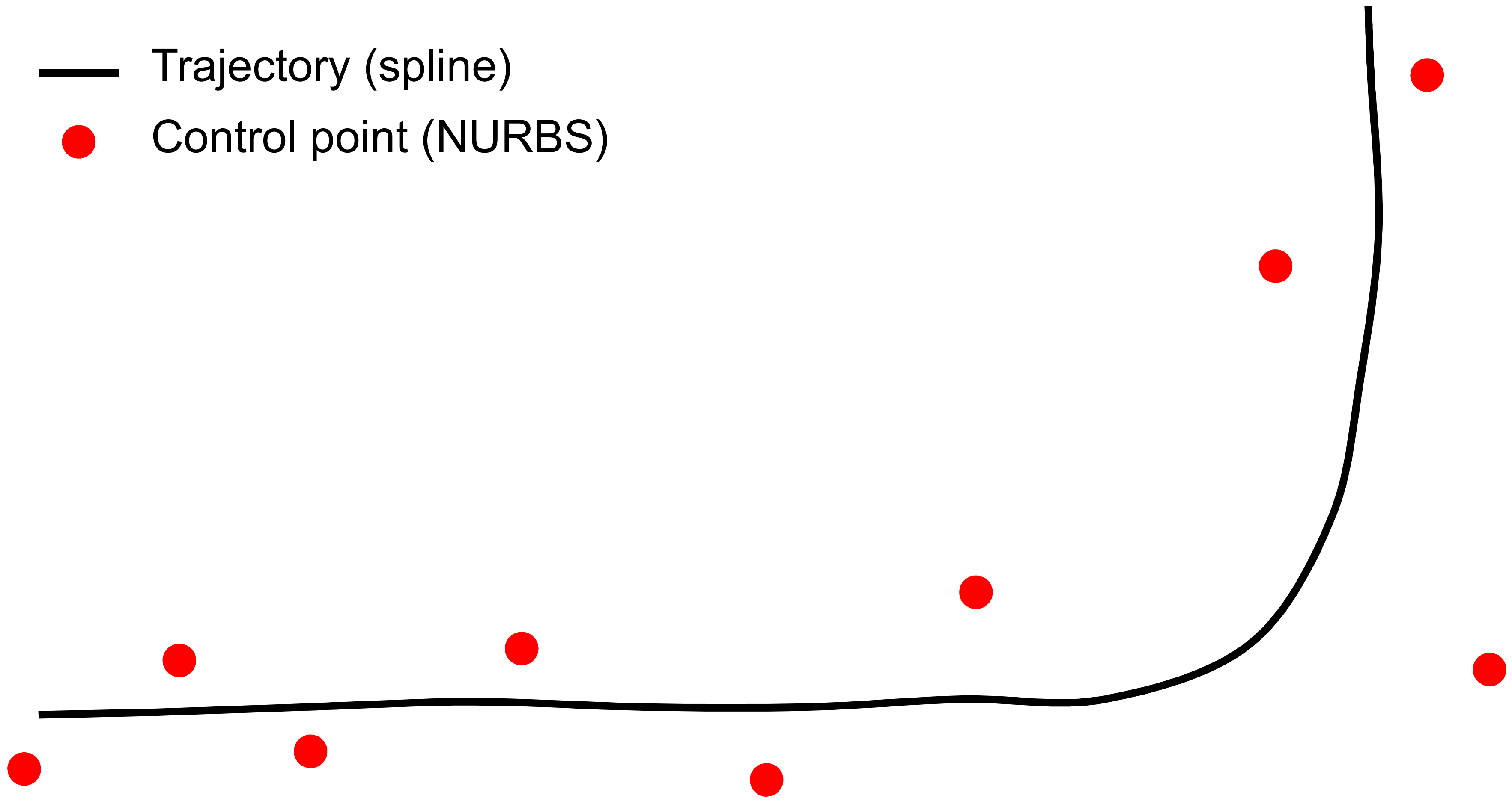
Trajectory modeling



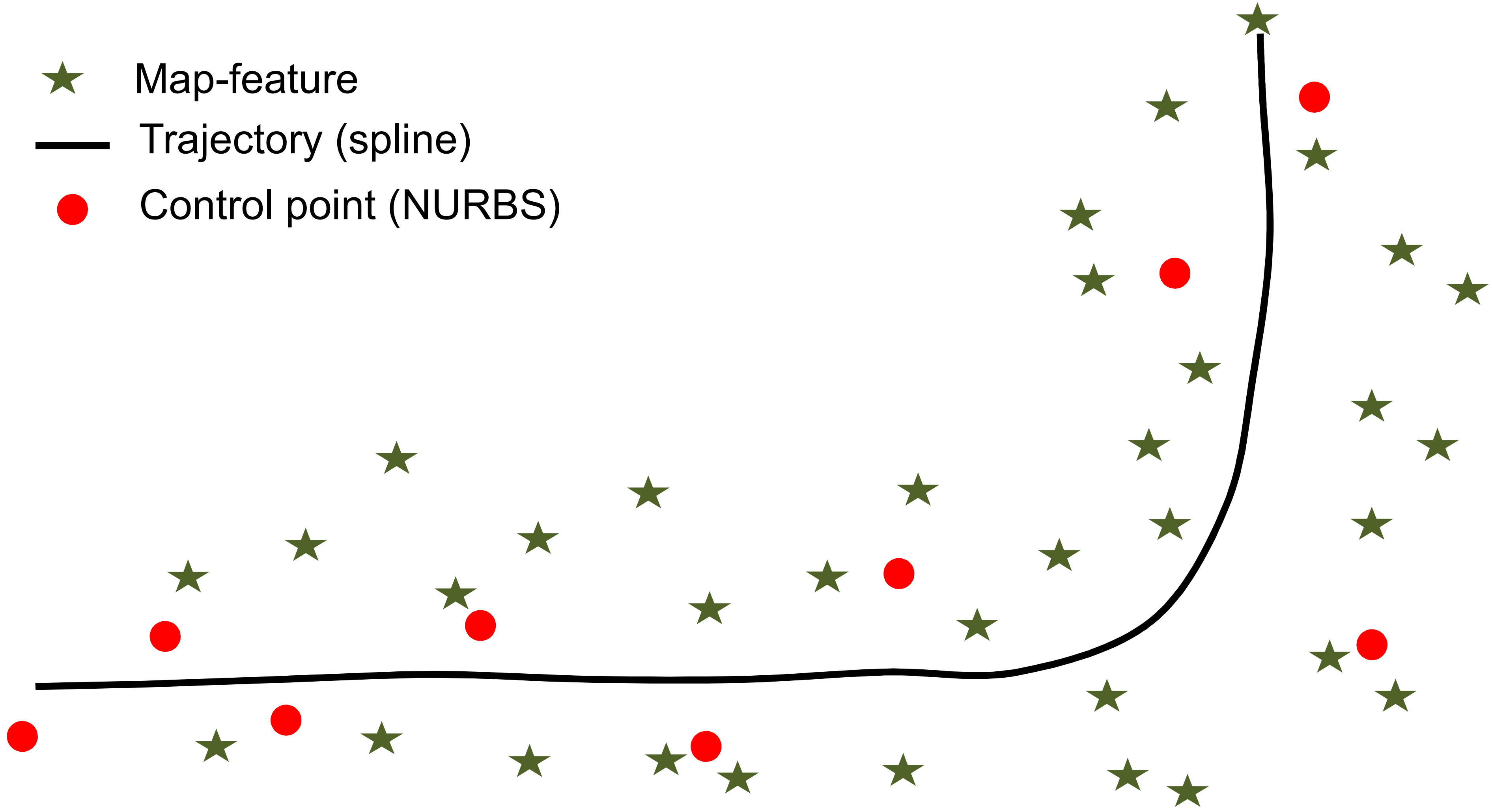
Trajectory modeling



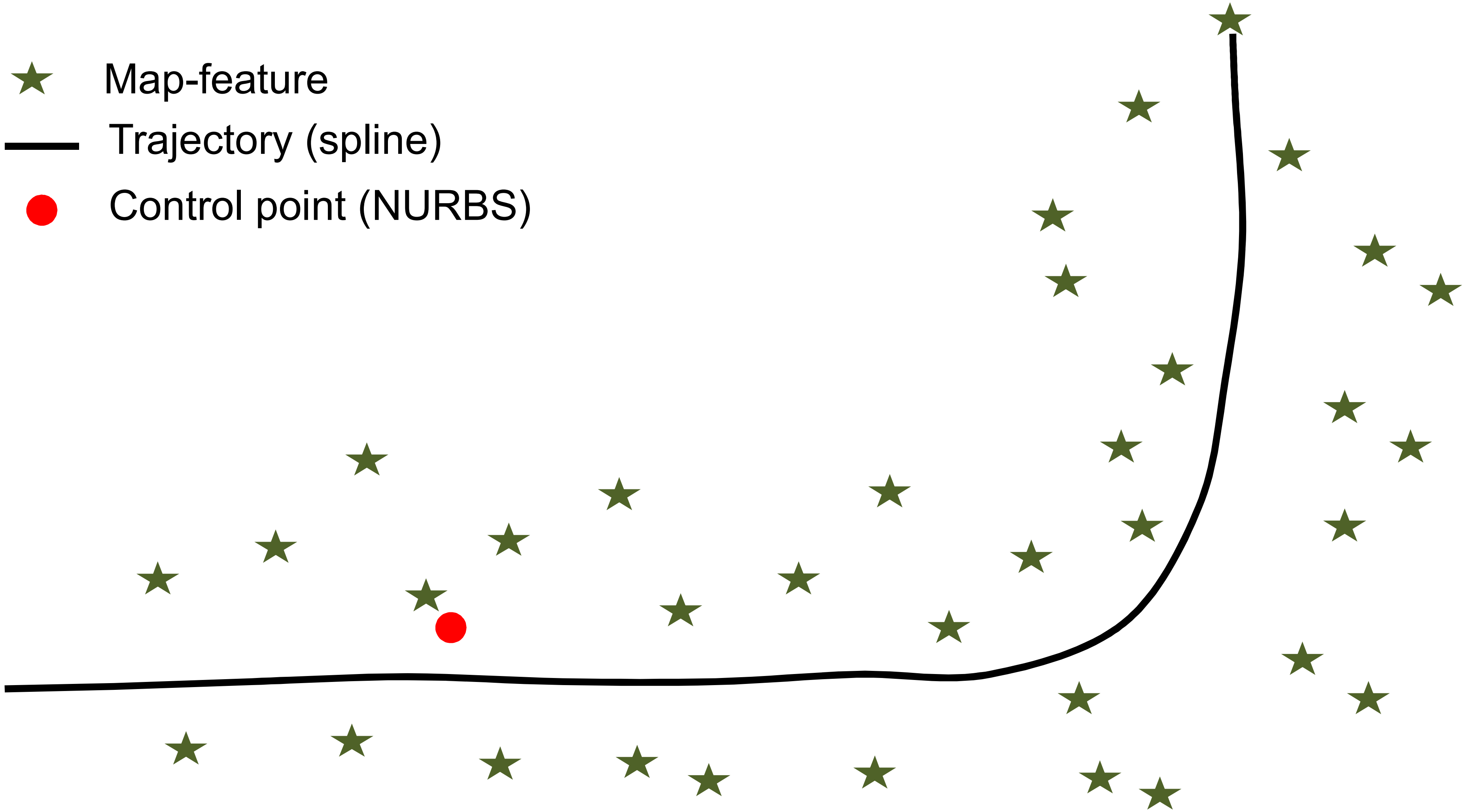
Trajectory modeling



Subset generation by map-feature position.



Subset generation by map-feature position.



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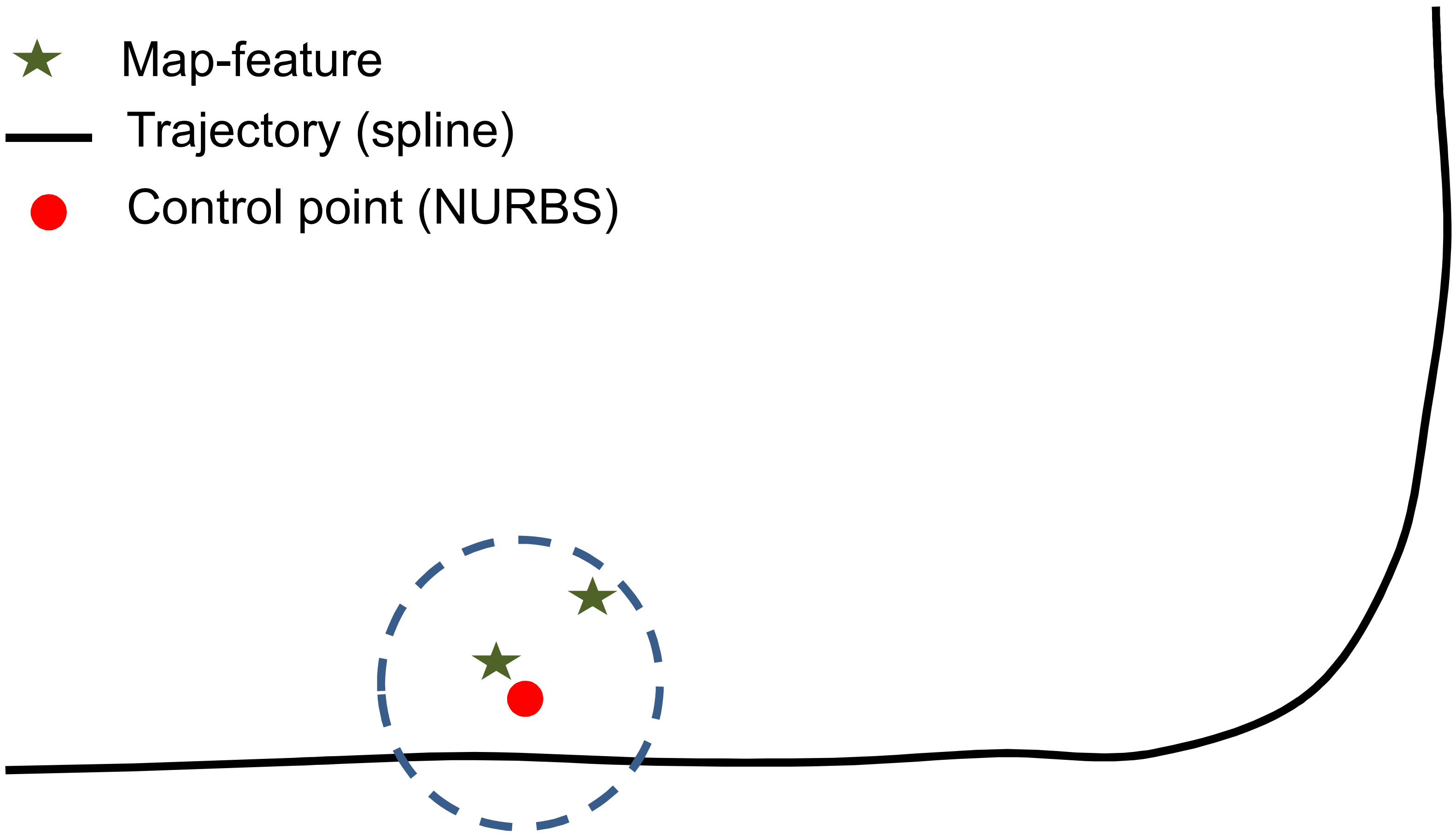
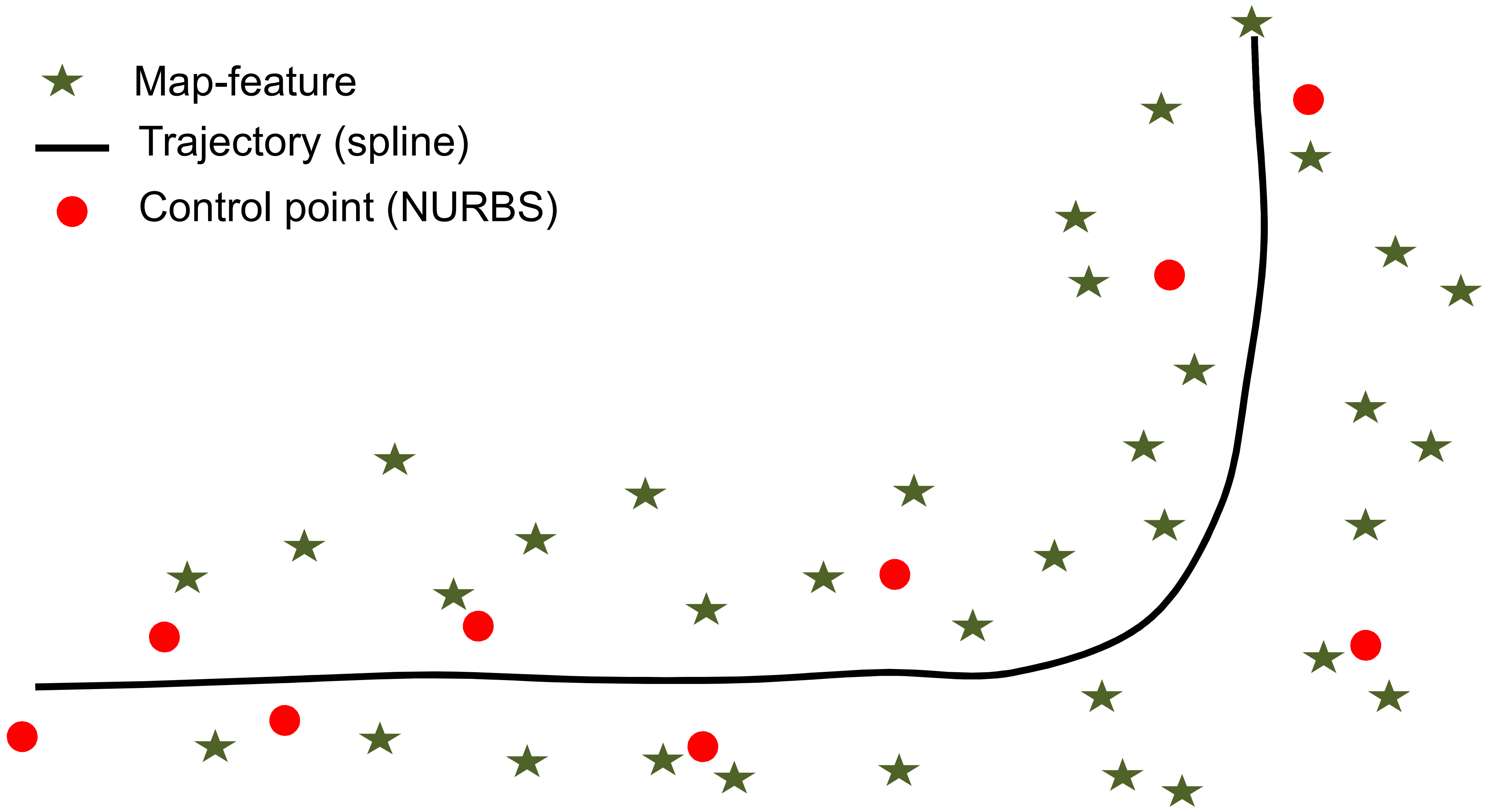


Subset generation by map-feature position.



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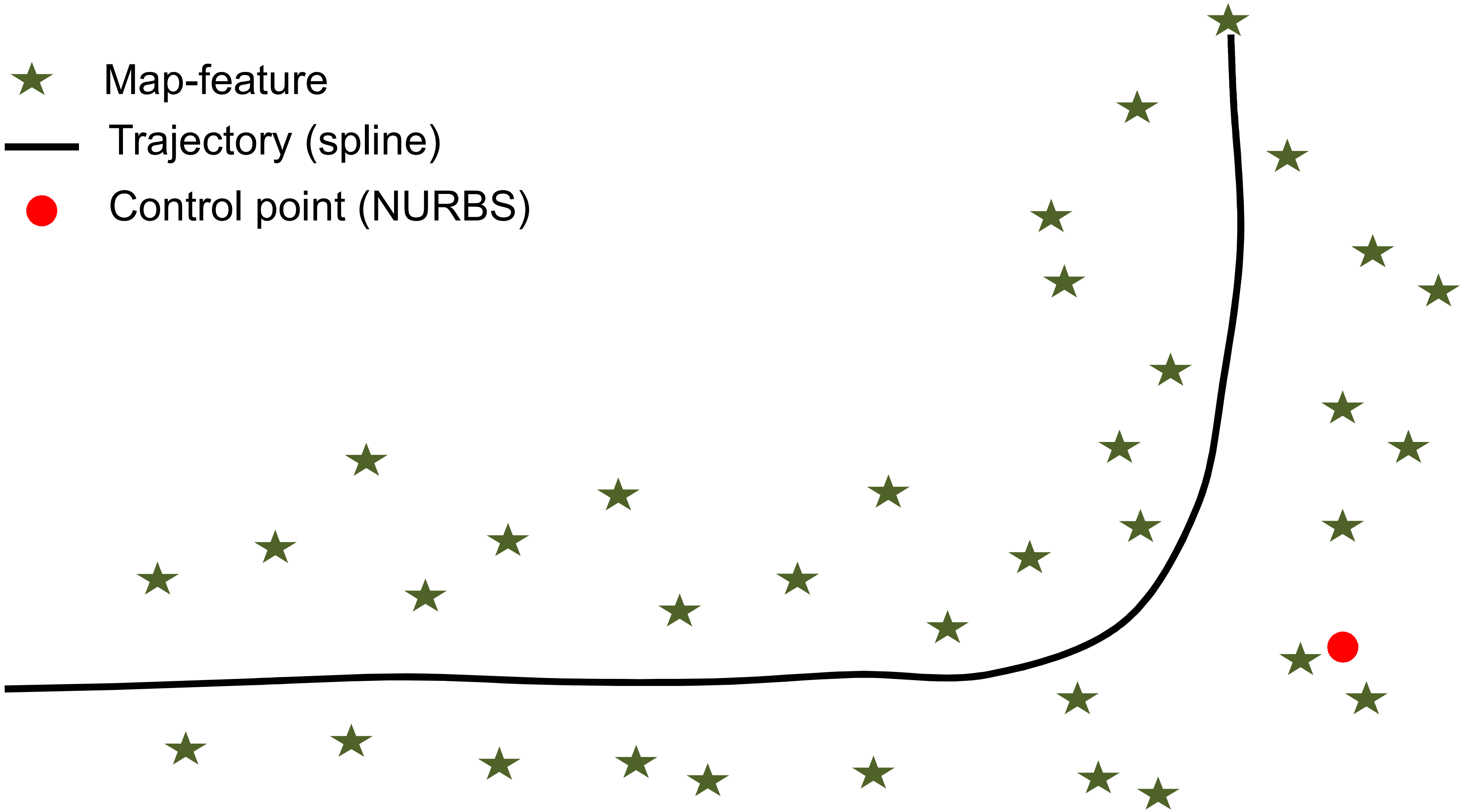
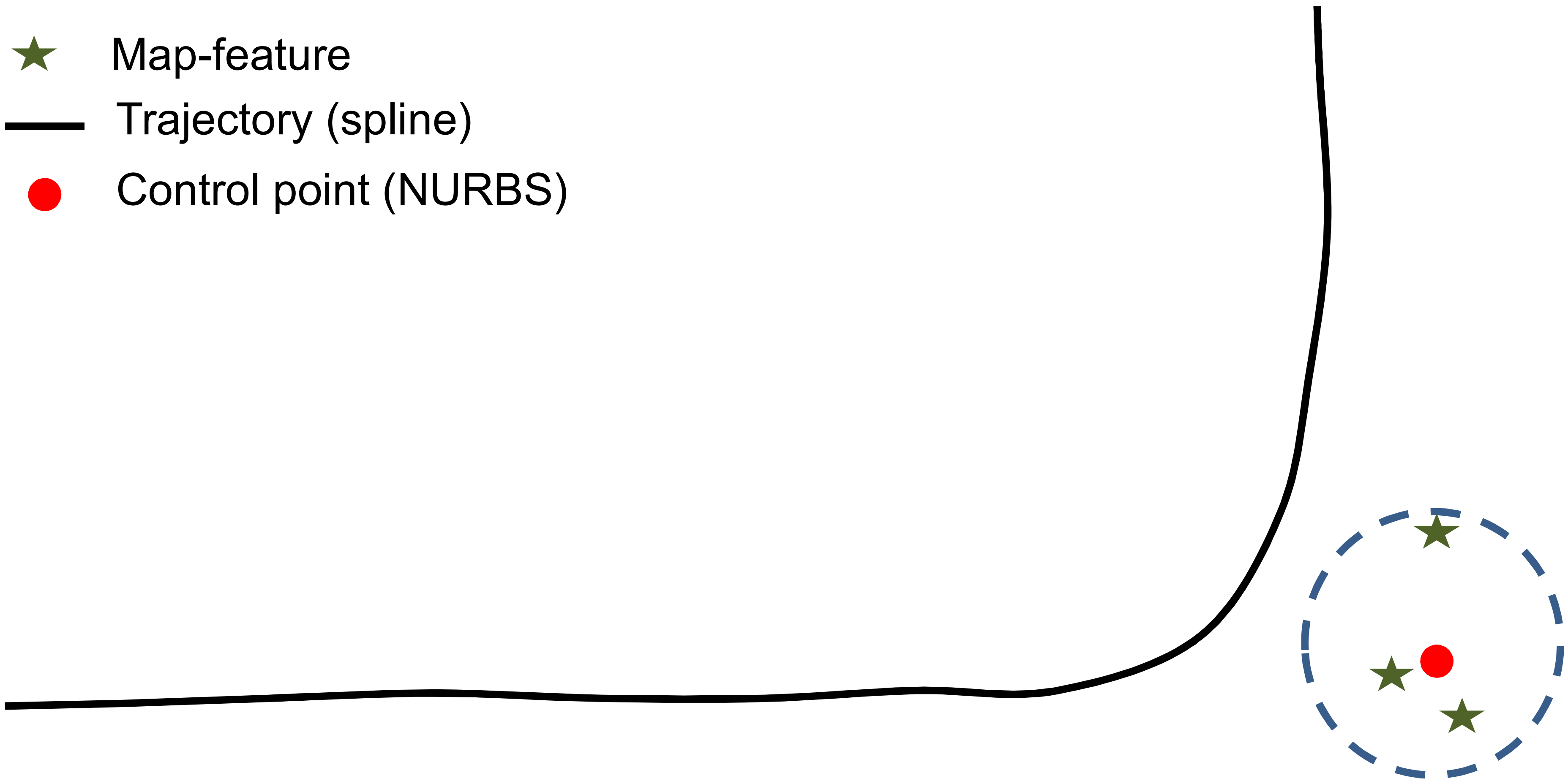
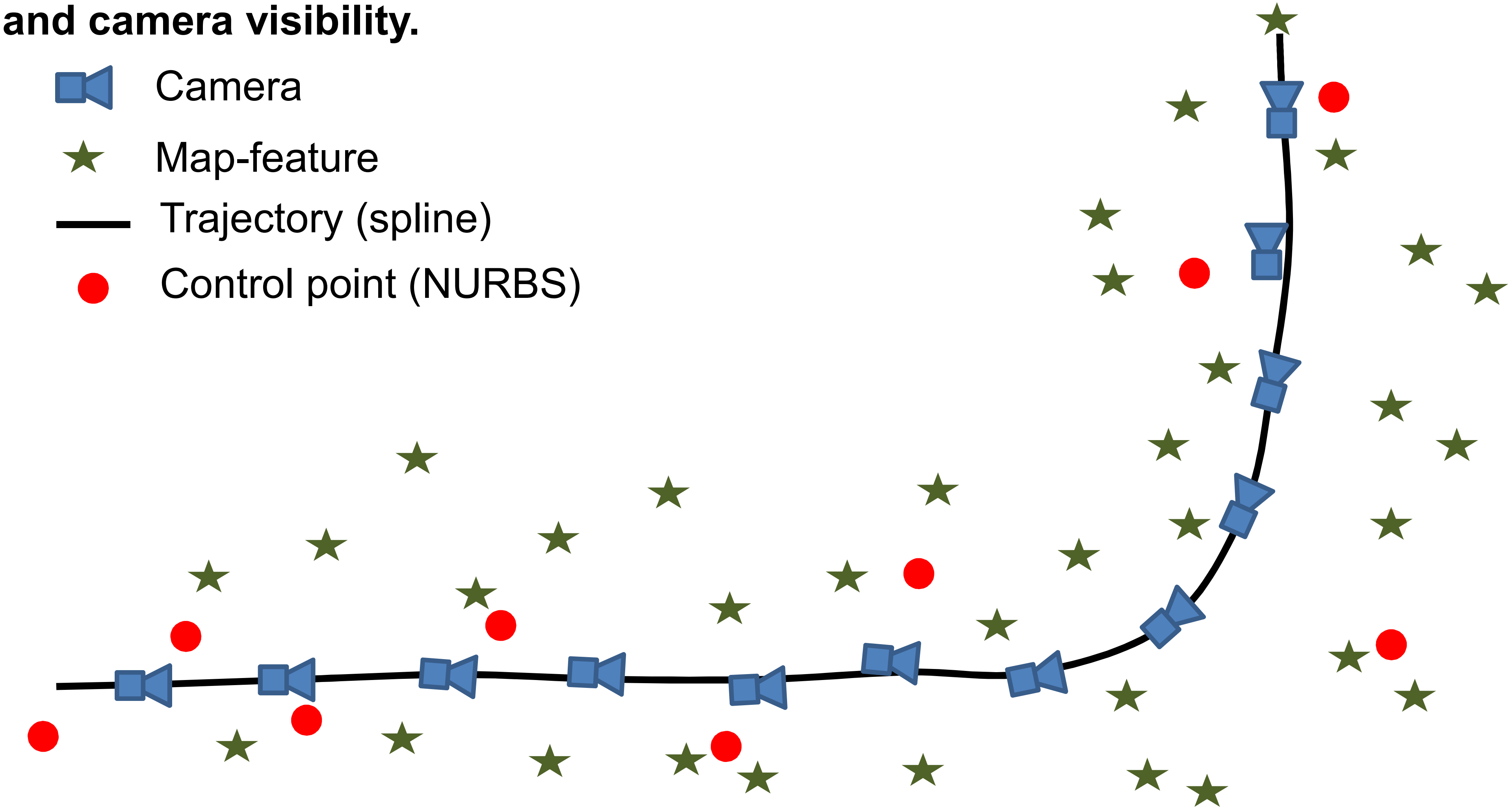


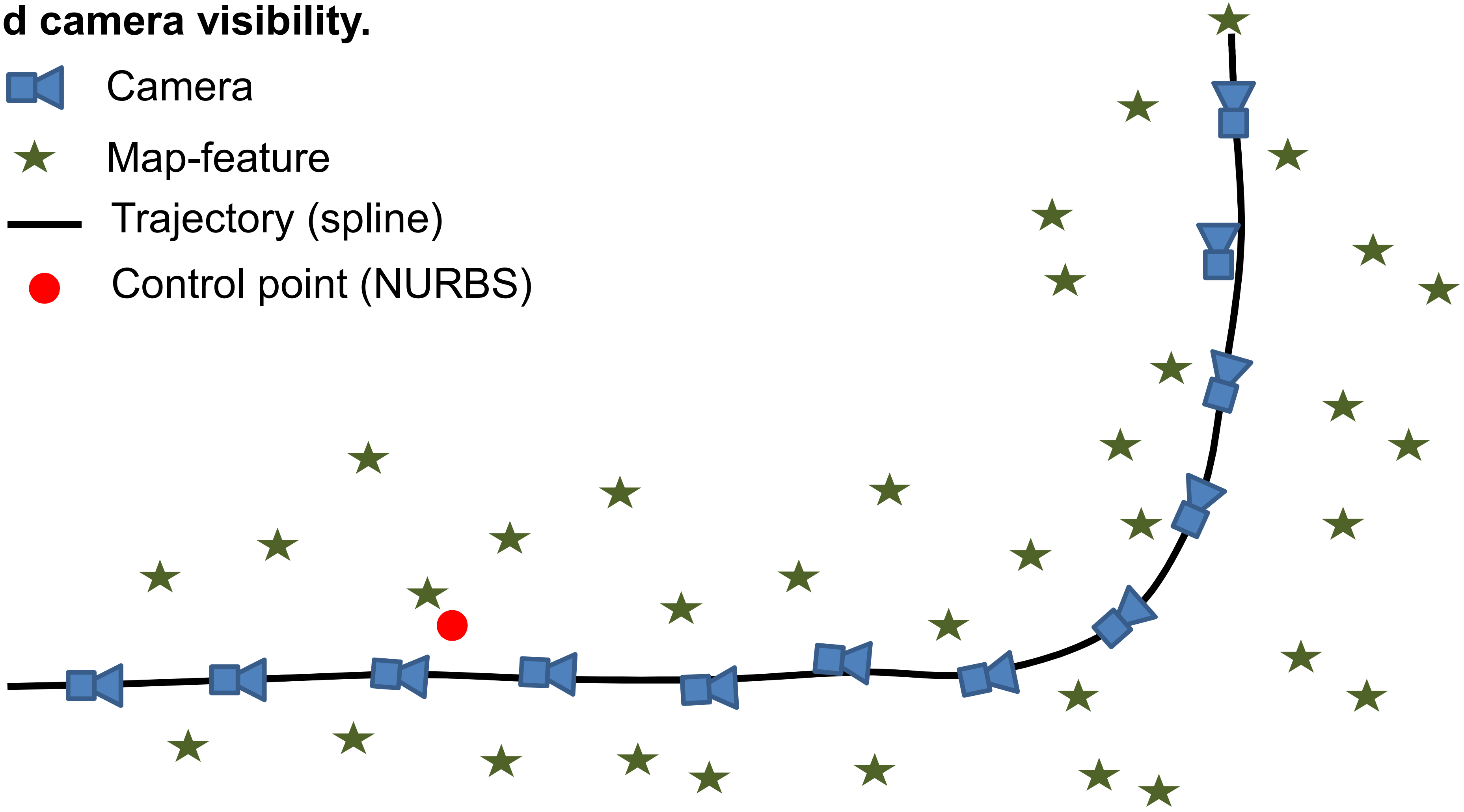
Subset generation by map-feature position.



Subset generation by single camera position and camera visibility.



Subset generation by single camera position and camera visibility.



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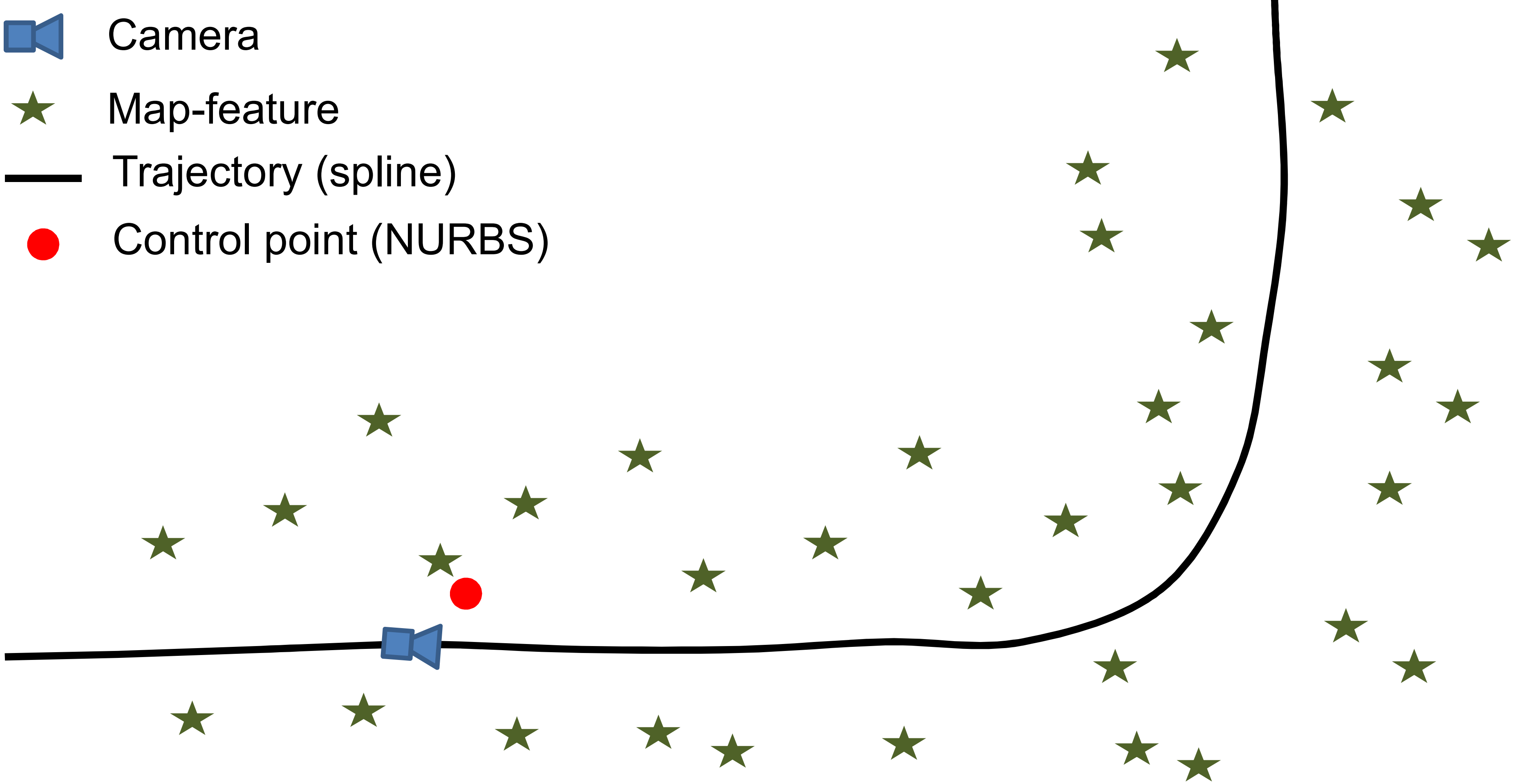
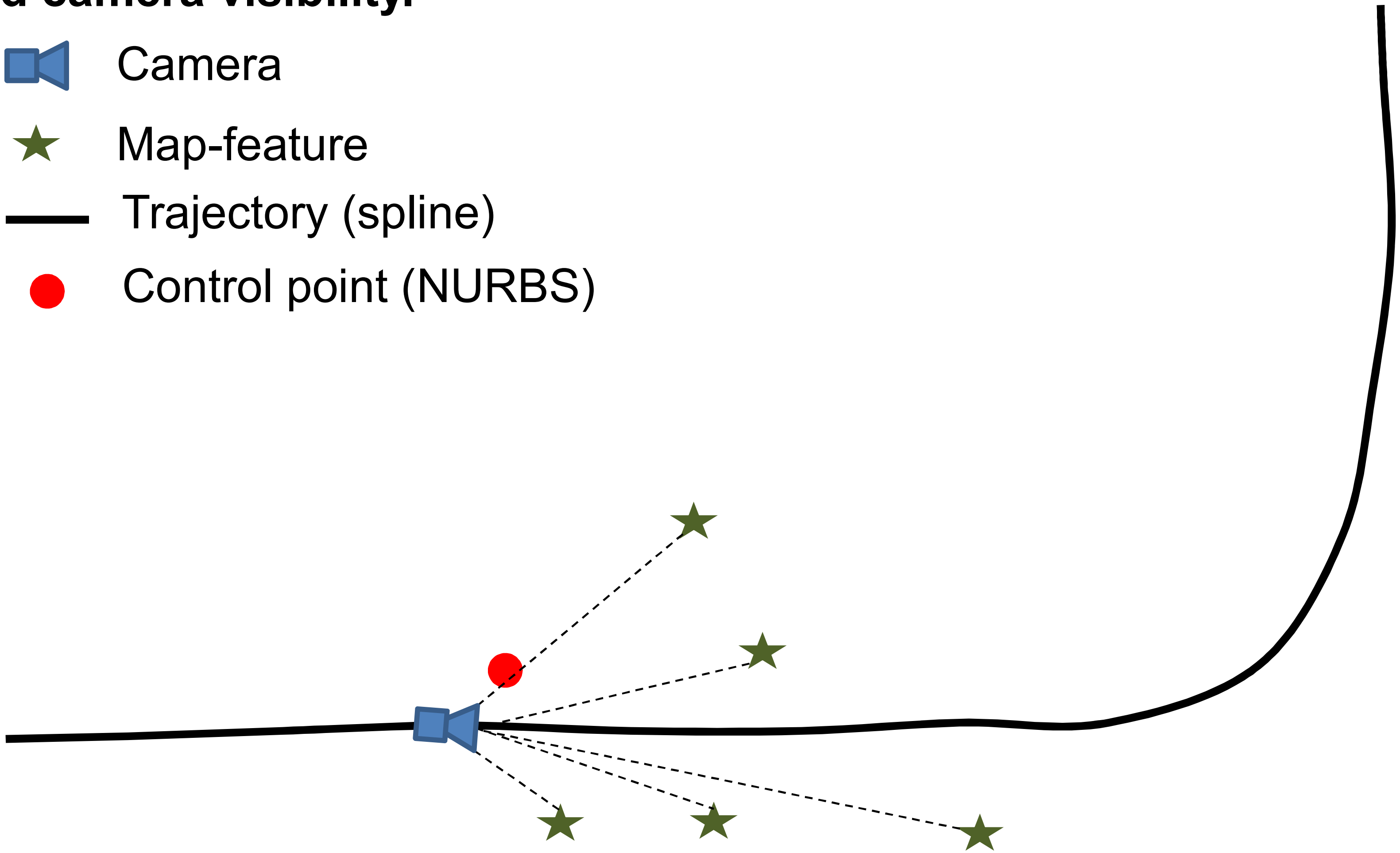
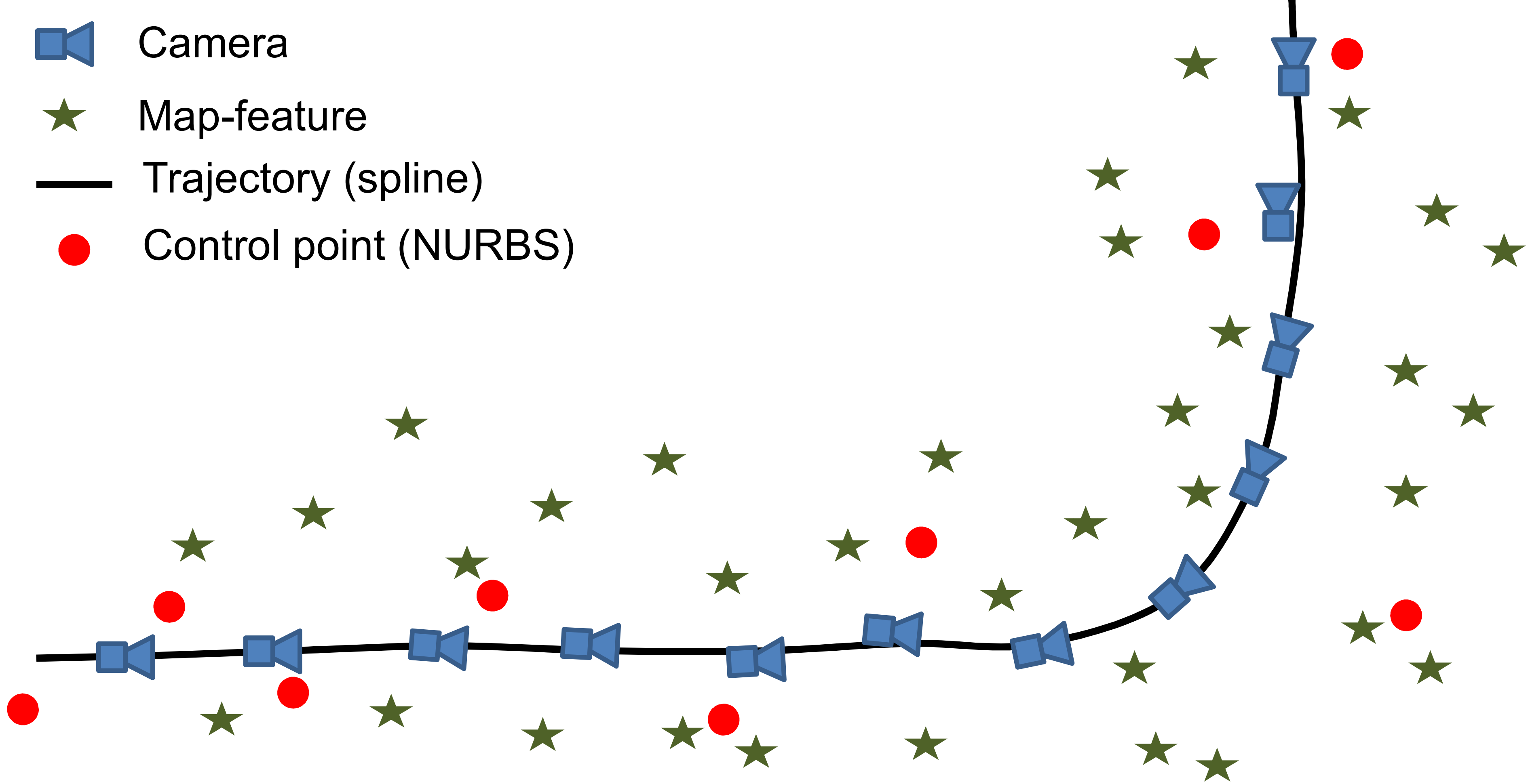


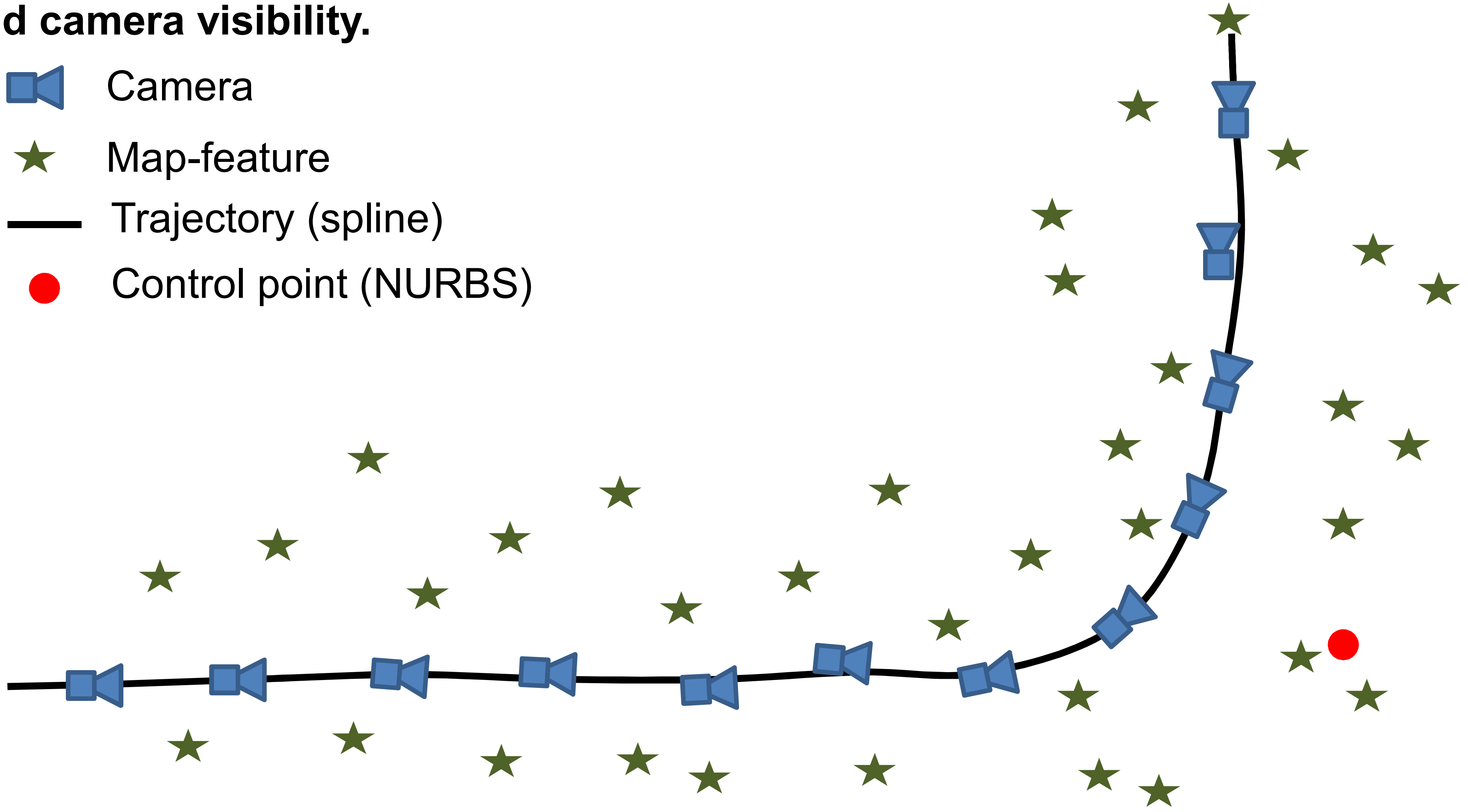
Subset generation by single camera position and camera visibility.



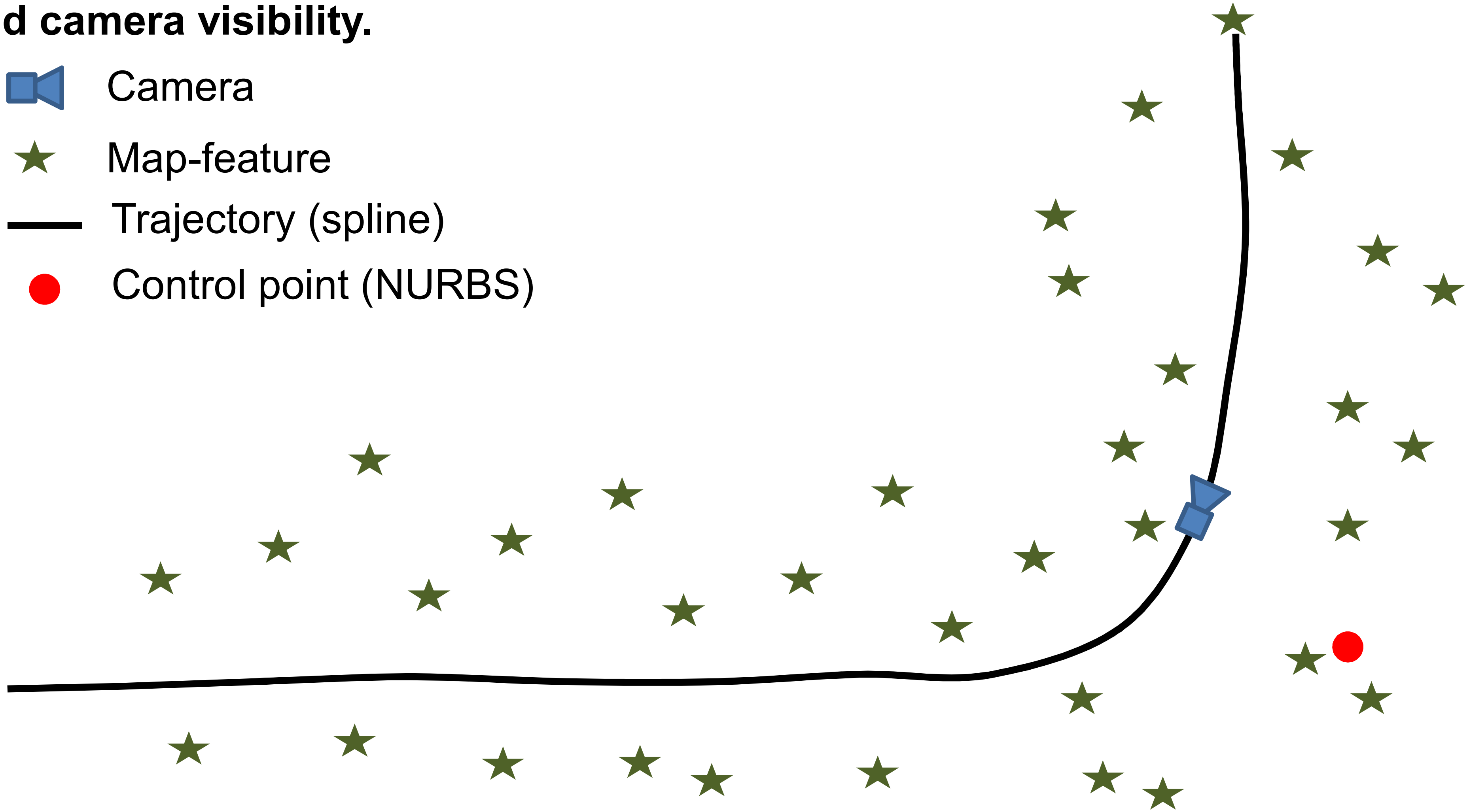
Subset generation by single camera position and camera visibility.



Subset generation by single camera position and camera visibility.



Subset generation by single camera position and camera visibility.



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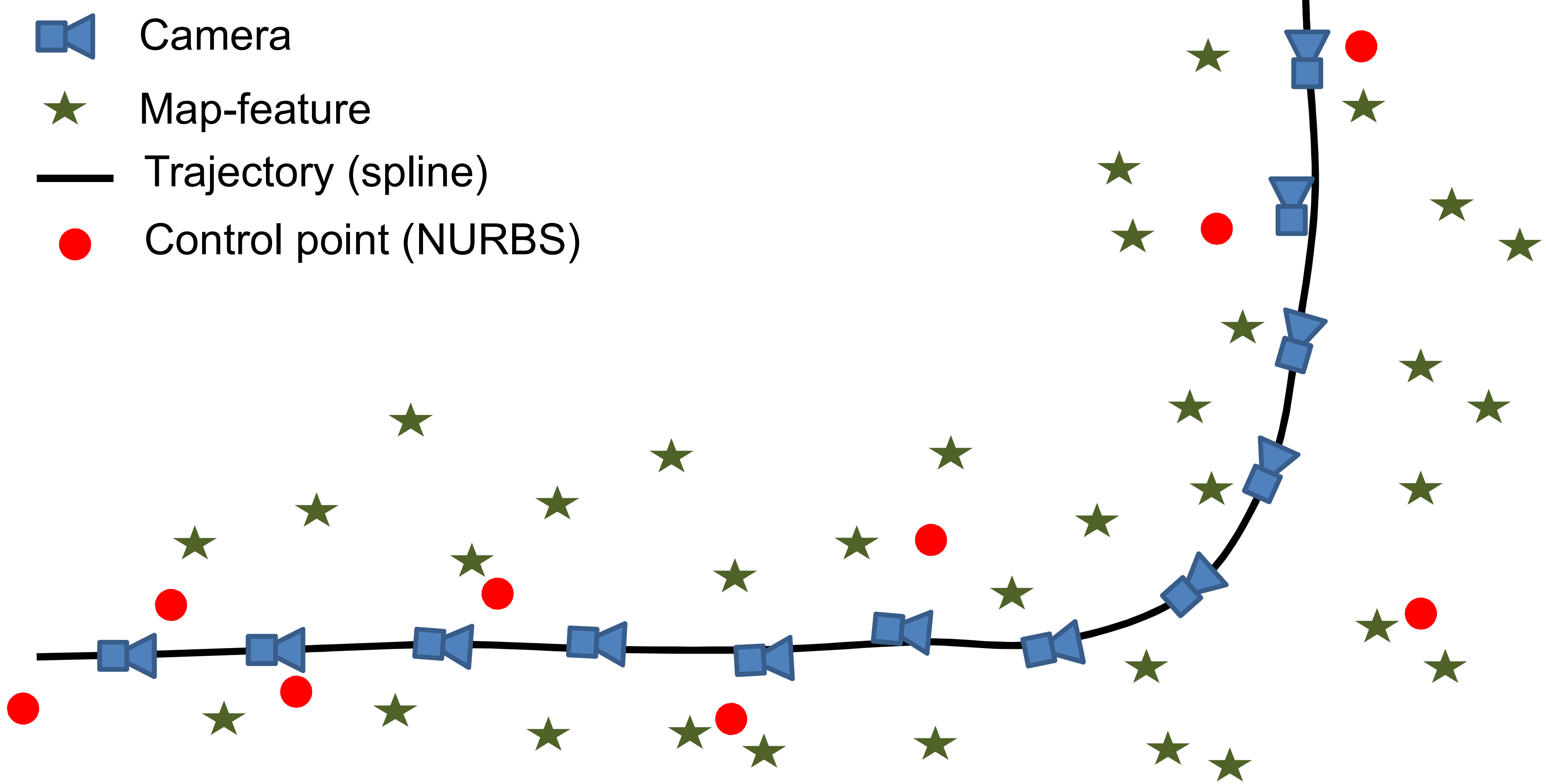
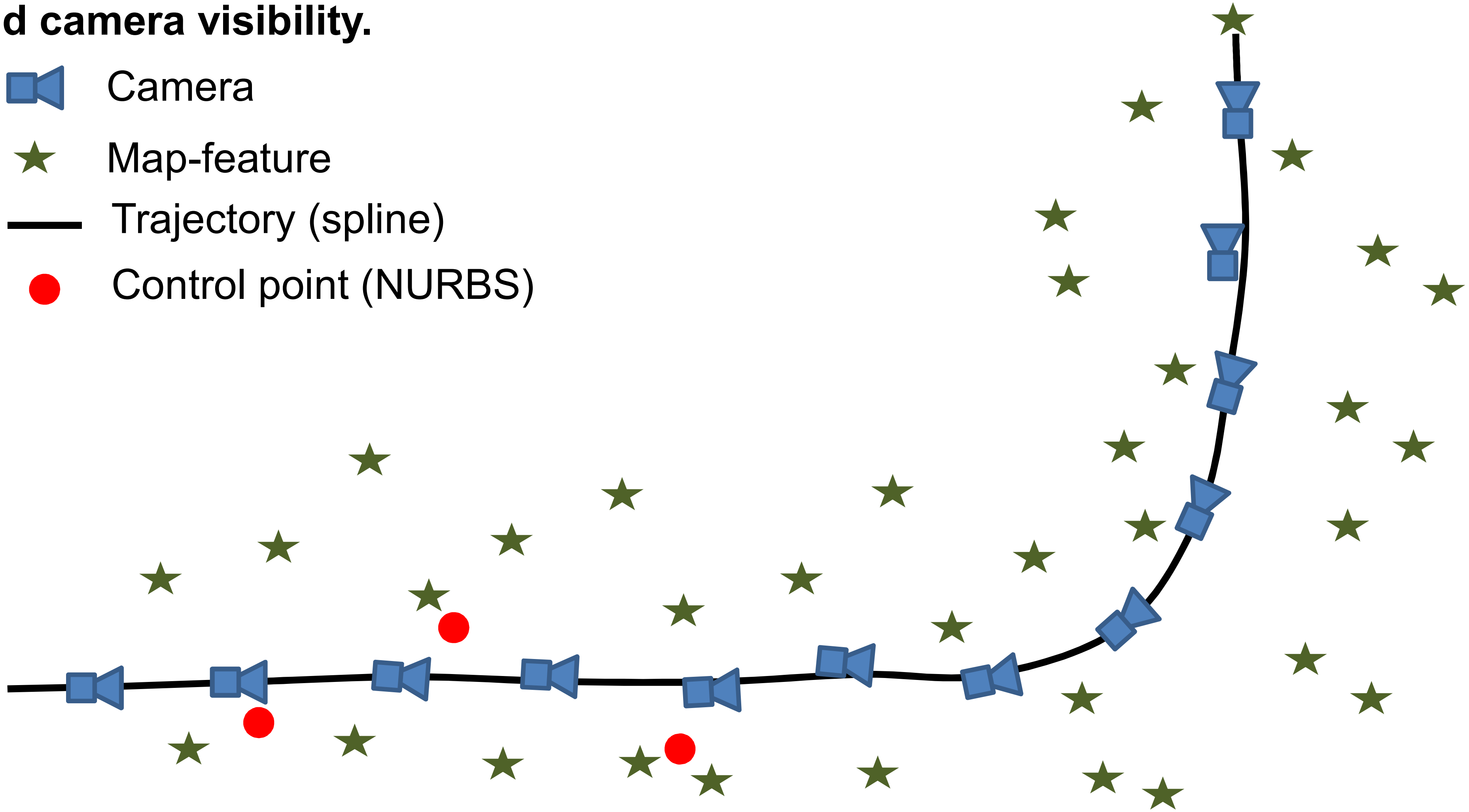
Subset generation by single camera position and camera visibility.

Subset generation by trajectory segmentation and camera visibility.



Subset generation by trajectory segmentation and camera visibility.



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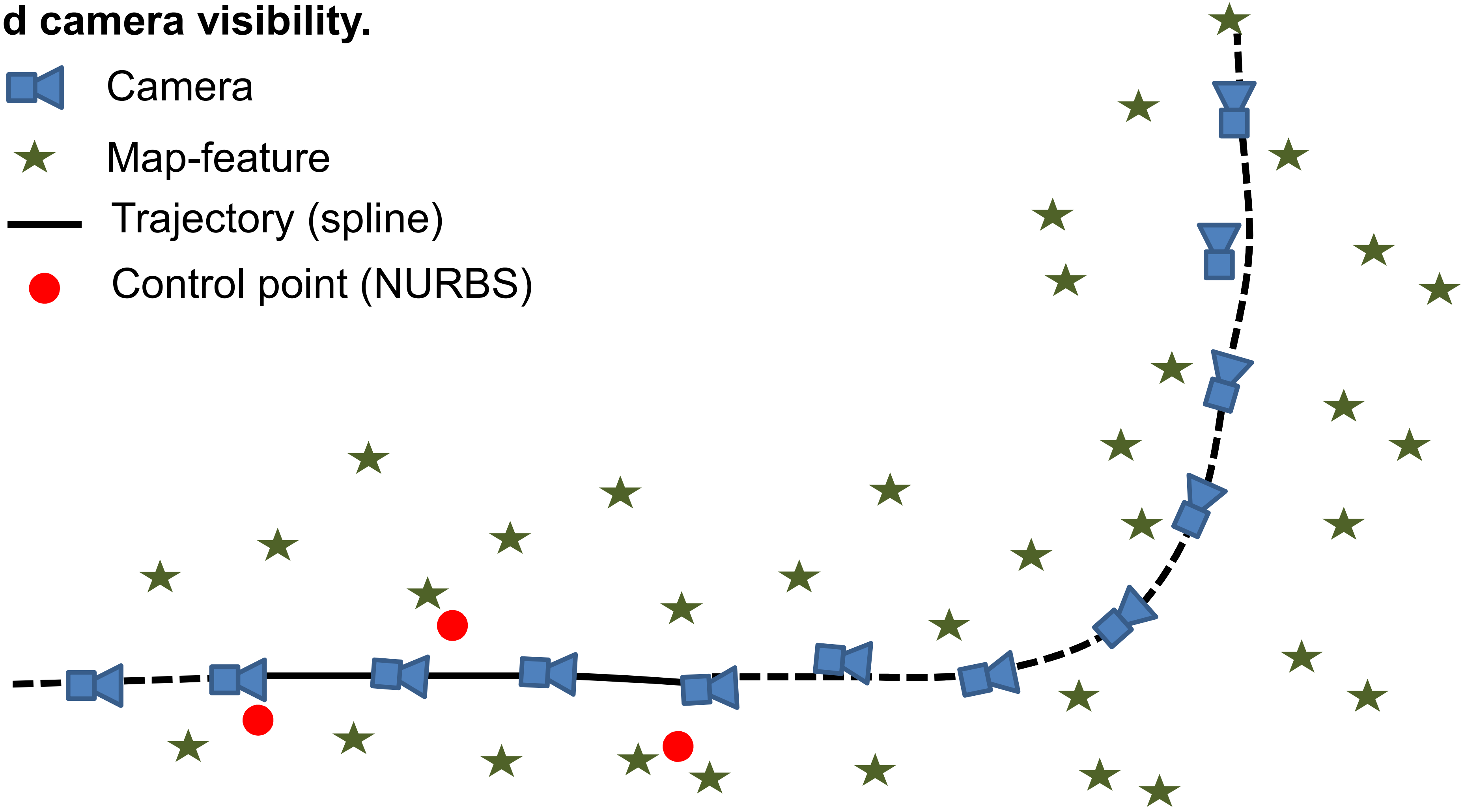

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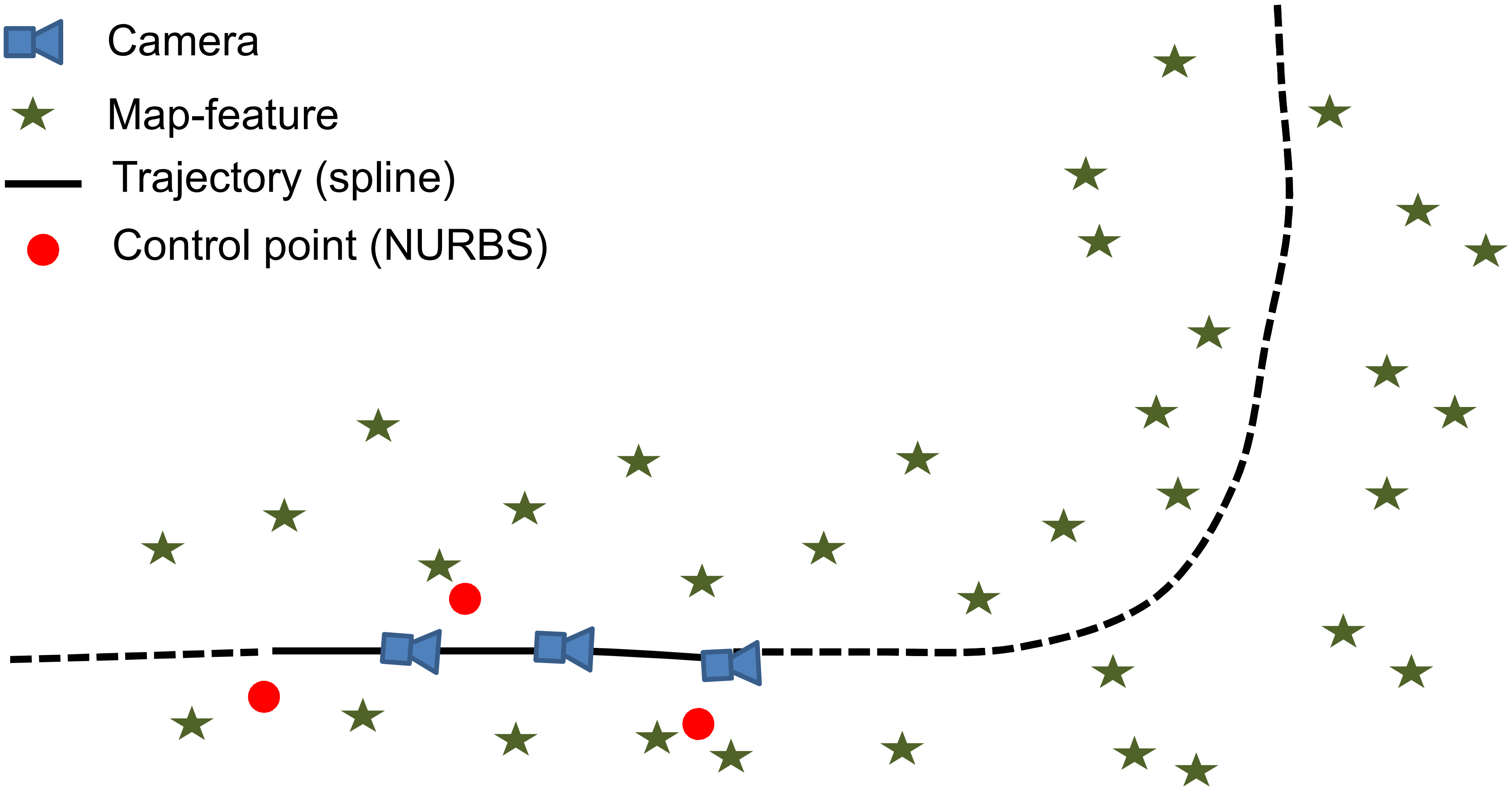

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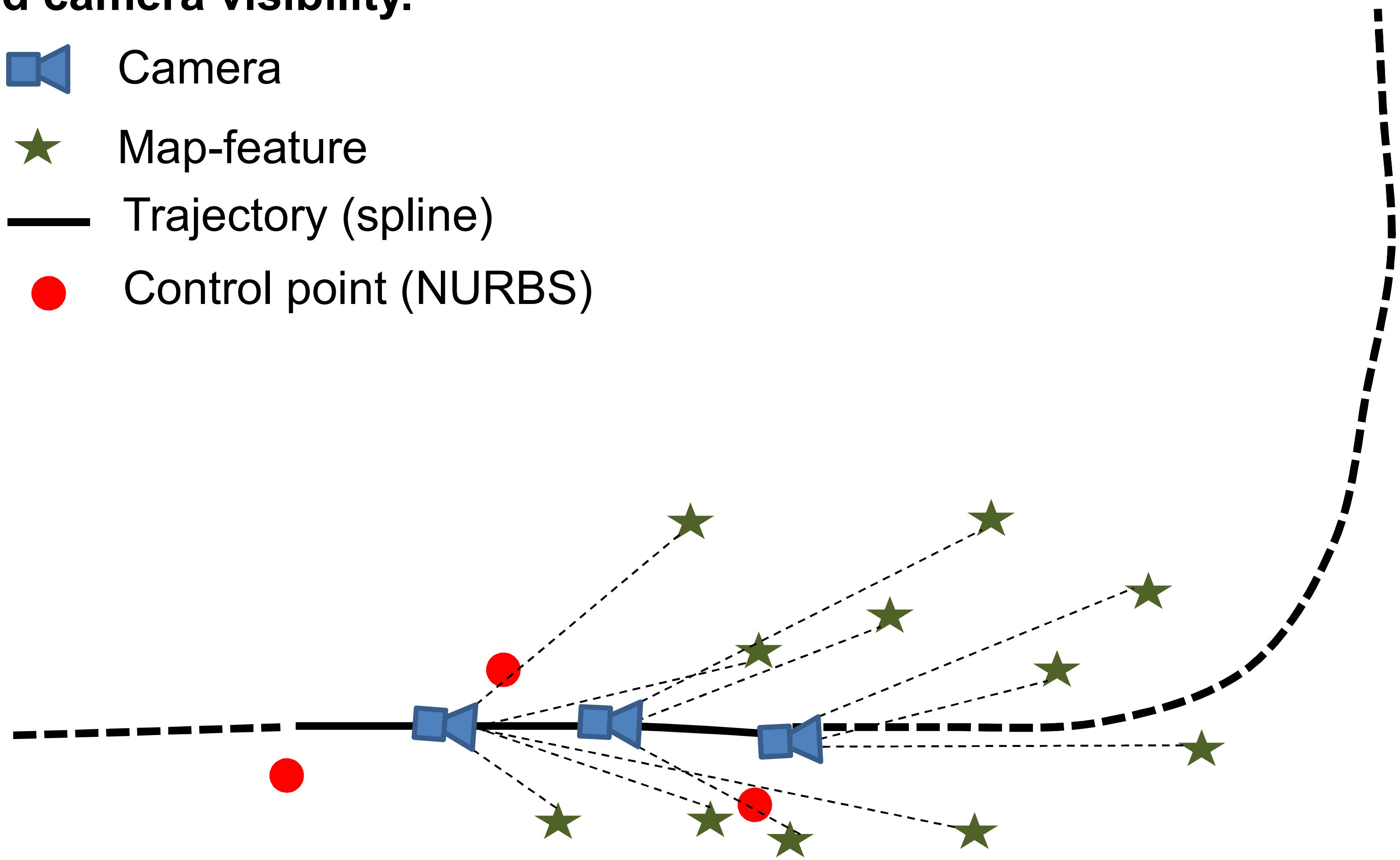

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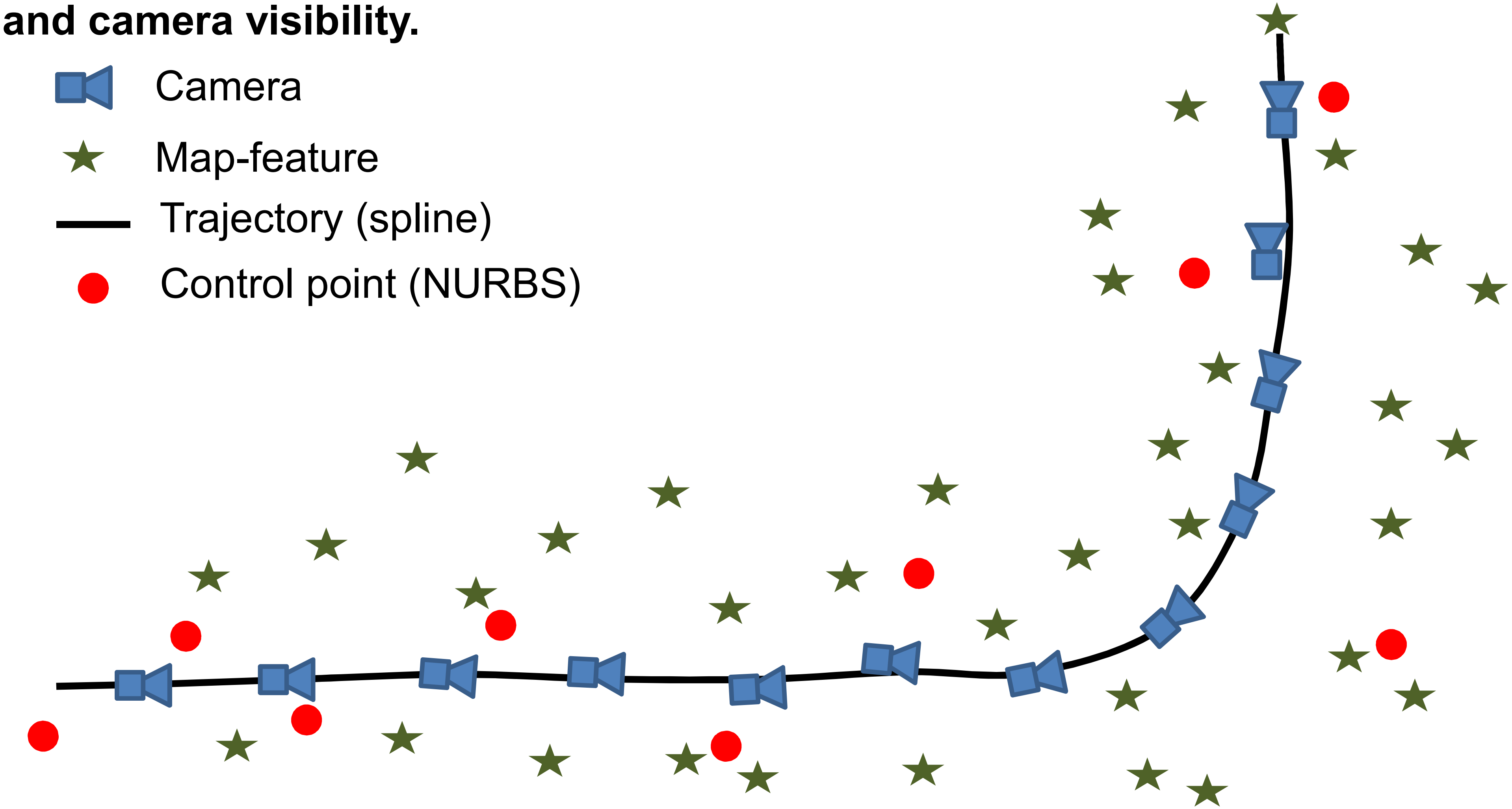

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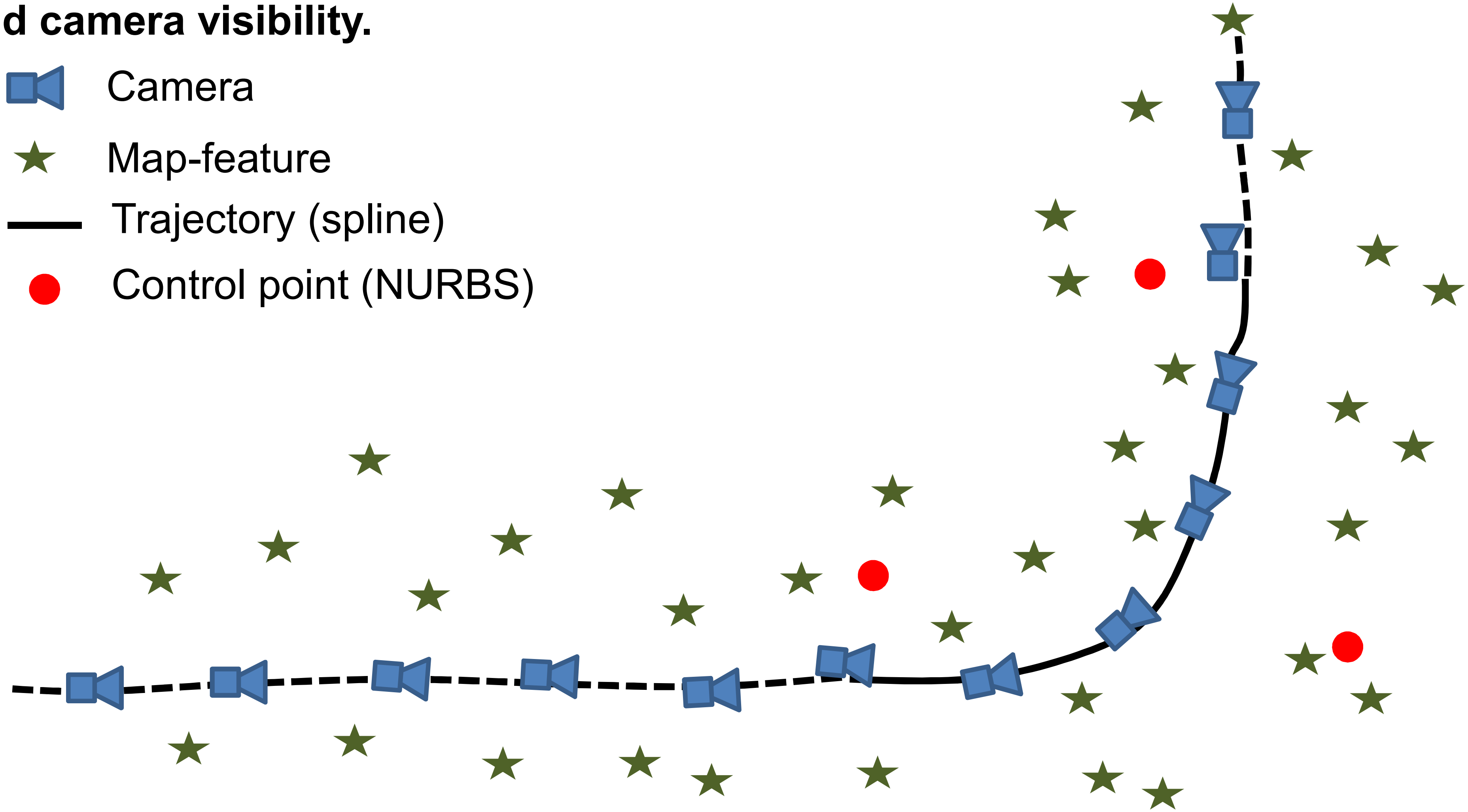

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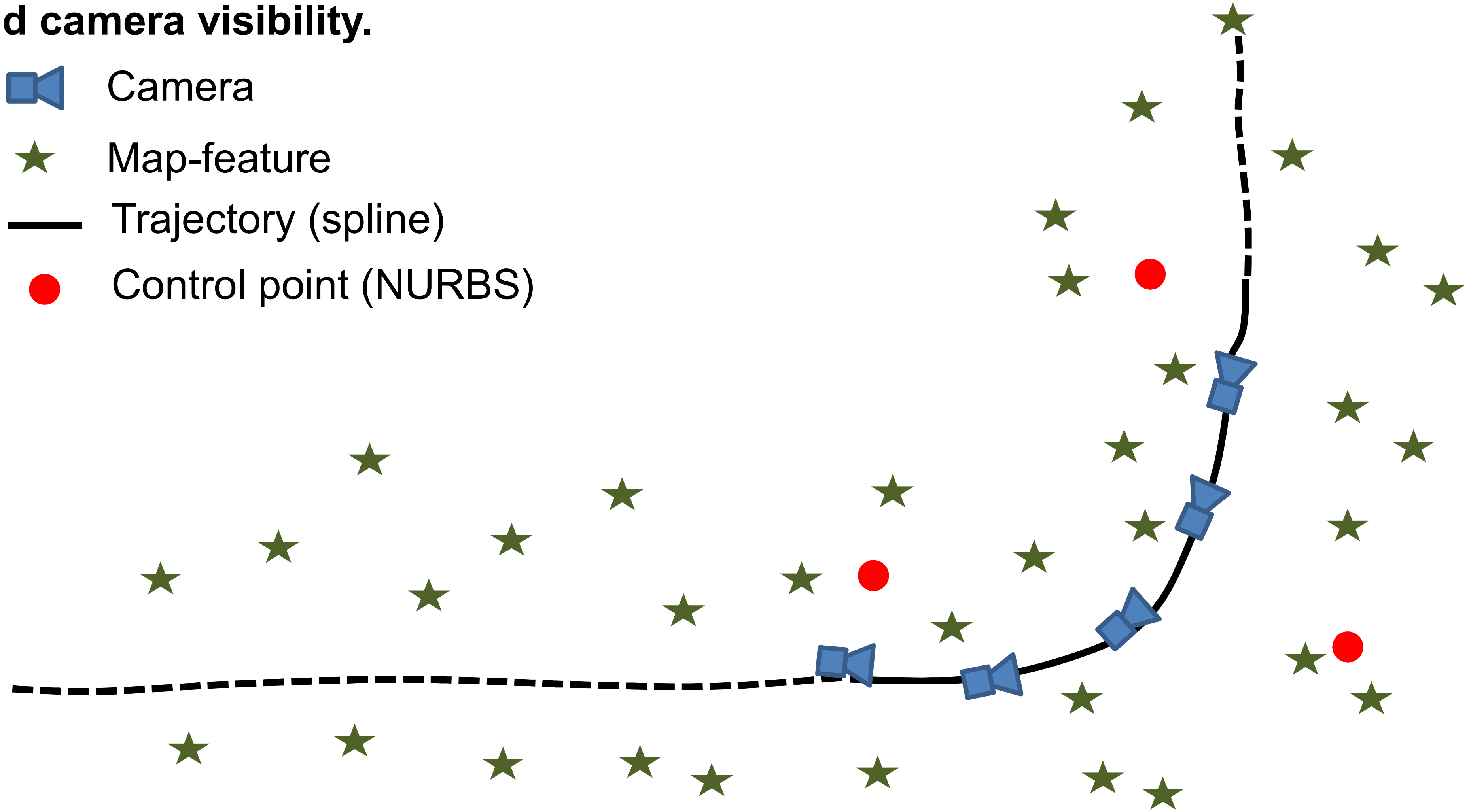

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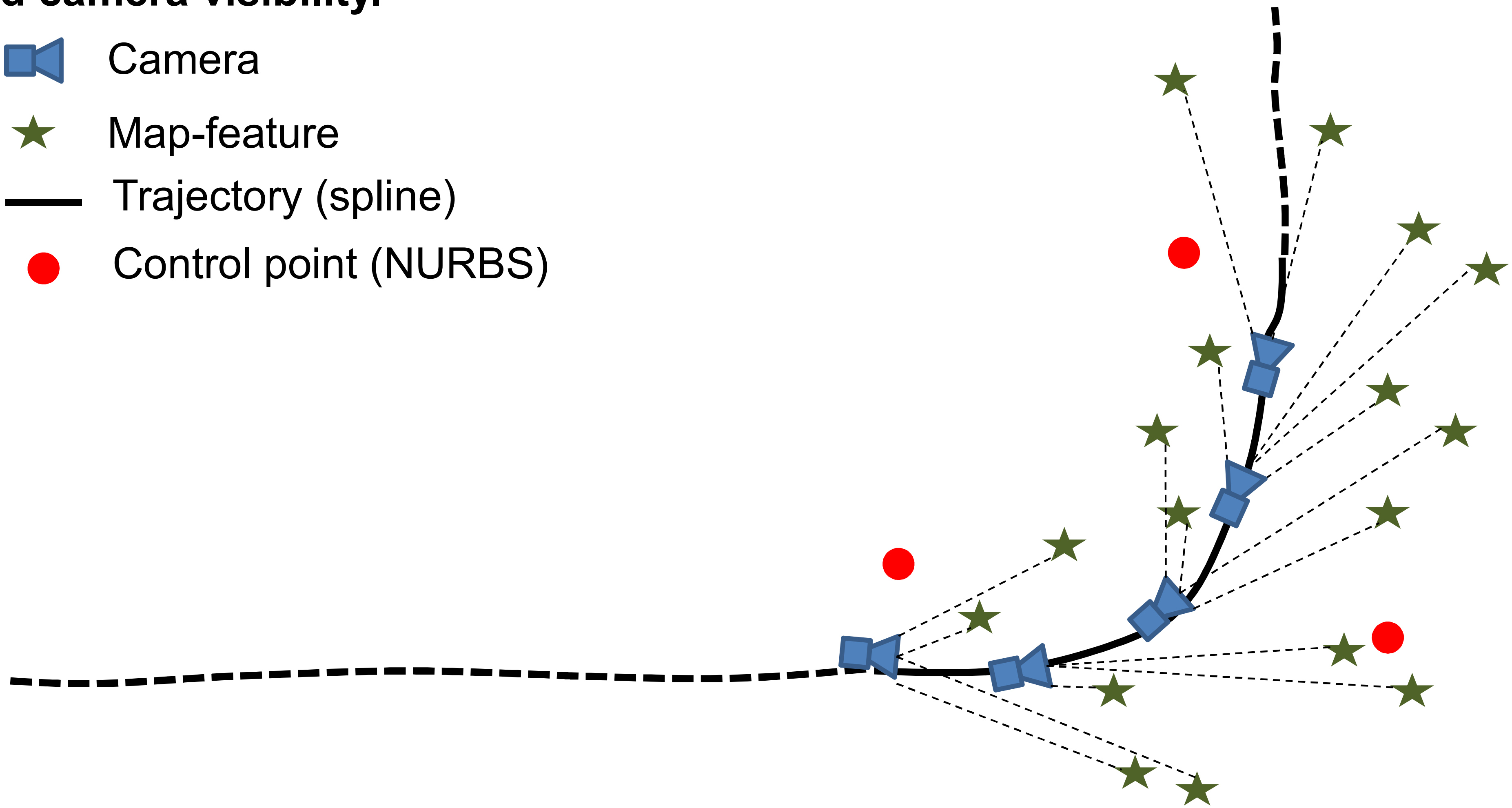

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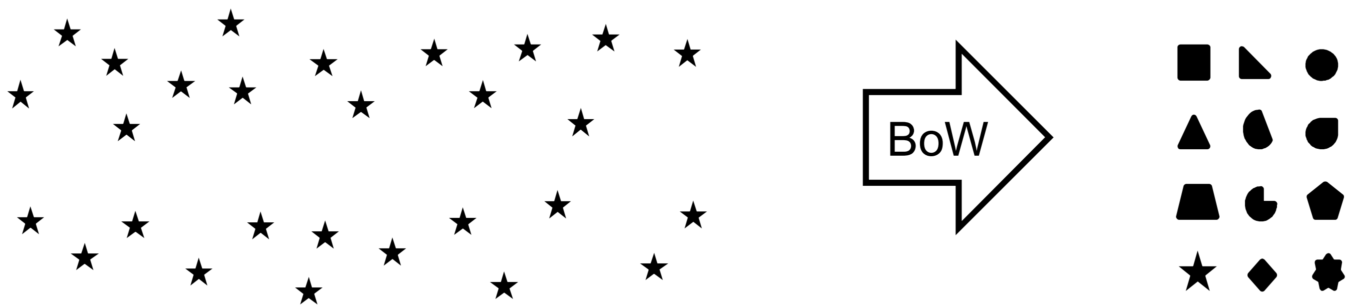
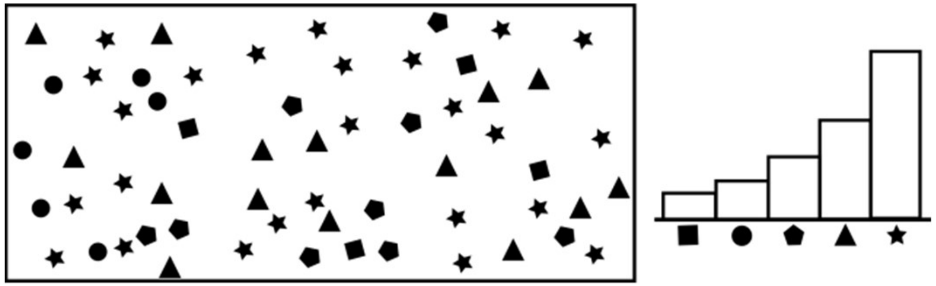
Point Cloud compression

Bag of Words generation (from the complete point cloud)

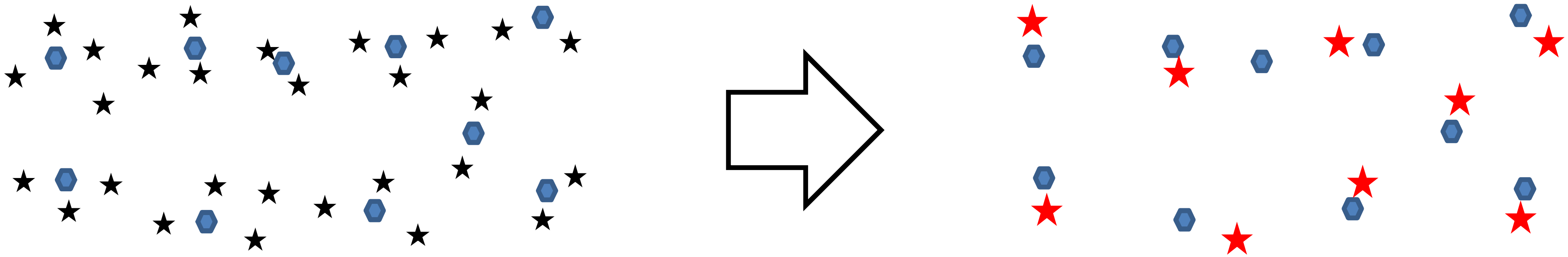


Map-feature selection (from a given subset) by word count:

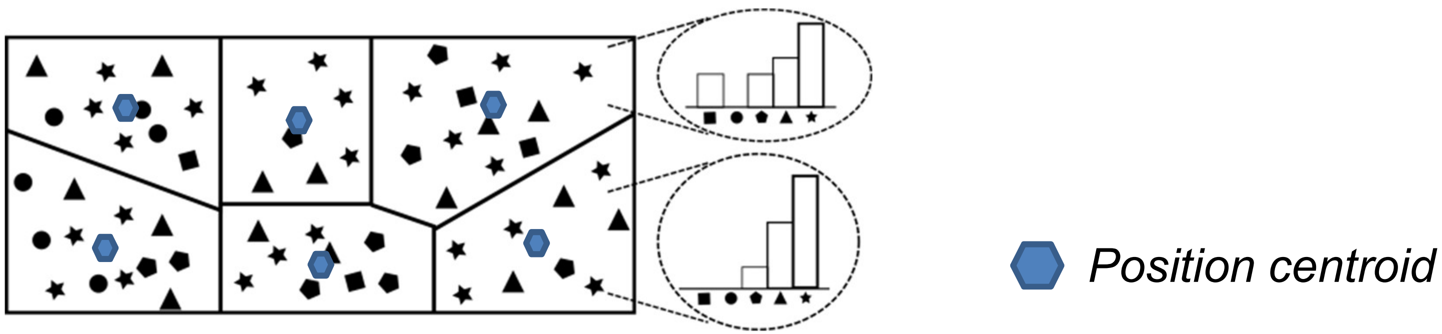


Point Cloud compression

Map-feature selection (from a given subset) by position clustering:



Map-feature selection (from a given subset) by position clustering and word count:



Trajectory-driven POint cloud COmpression (POCO)

Outline:

1. Subsets generation from the complete point cloud.
2. Individual subset compression.

	Criteria	Options		
Subsetting	3D points	Visibility		3D position
	Camera	Single		Multiple
Compression	Descriptor clustering	Low-band	Mid-band	Sparsity
Baselines	key-frame	key-point density	Frame rate	Camera distance
	Random	percentage sampling		
	Point-sampled geometry	k-means clustering		

Spatial and visual relevant point's selection criteria.

Trajectory-driven POint cloud COmpression (POCO)

Proposed compression methods:

Evaluated compression methods, CM01-11 are trajectory-driven, while CM12-16 are baselines.

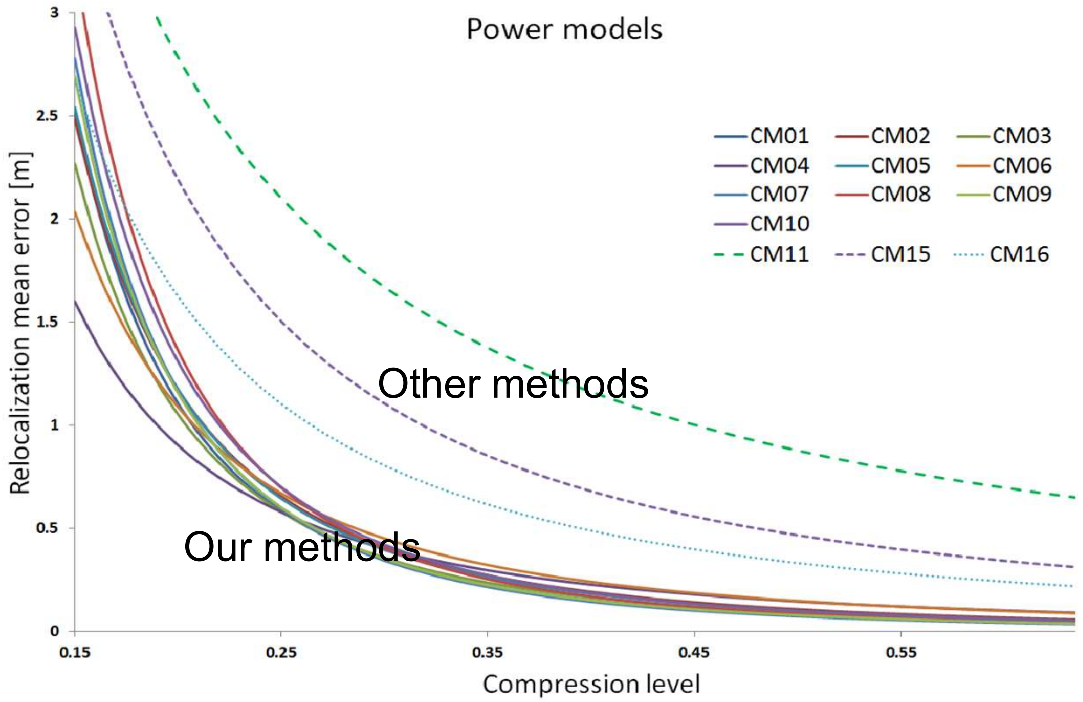
	CM01	CM02	CM03	CM04	CM05	CM06	CM07	CM08	CM09	CM10	CM11	CM12	CM13	CM14	CM15	CM16
3D point visibility	X	X	X	X	X	X	X	X	X	X						
3D point pose											X					
Single camera	X		X		X		X		X							
Multiple camera		X		X		X		X		X						
Low-band descriptor	X	X					X	X			X					
Mid-band descriptor			X	X					X	X						
Sparsely located features					X	X	X	X	X	X						
key-frame key-point density												X				
key-frame frame rate													X			
key-frame camera distance														X		
Random sampling															X	
Point-sampled geometry																X

e.g.

CM04: 3D point visivility + Multiple cameras + Mid-band descriptor

Trajectory-driven POint cloud COmpression (POCO)

The parameters that we considered were: x_1, the *compression method*; x_2, the *number of control points*; x_3, the *number of descriptor clusters*; and x_4, the *compression level*.



CM04: 3D point visibility + Multiple camera + Mid-band descriptor

CM06: 3D point visibility + Multiple camera + Sparsely located features

CM09: 3D point visibility + Single camera + Mid-band descriptor + Sparsely located features

Note: CM12-14 – key-frames, CM15 – Random, CM16 – Geometry

Trajectory-driven POint cloud COmpression (POCO)*

Estimated coefficients' p-value scores for the regression model from individual compression methods.

	CM01	CM02	CM03	CM04	CM05	CM06	CM07	CM08	CM09	CM10	CM11
x_2	0.0287	0.009	0.0001	0.0051	0.0001	0.0001	0.9855	0.528	0.427	0.0357	0.415
x_3	0.0142	0.1985	0.0269	0.04179	0.5837	0.7007	0.00268	0.0007	0.0006	0.0002	0.966
x_4	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
x_5	0.8756	0.588	0.3998	0.6702	0.8719	0.9782	0.1413	0.0762	0.0715	0.6396	0.431

*x*1, *compression method*;
x2, number of control points;
x3, number of descriptor clusters;
*x*4, *compression level*.
x5, *descriptor to position factor*.

*L. Contreras and W. Mayol-Cuevas, "Trajectory-driven point cloud compression techniques for visual SLAM.," in IROS, IEEE, 2015.

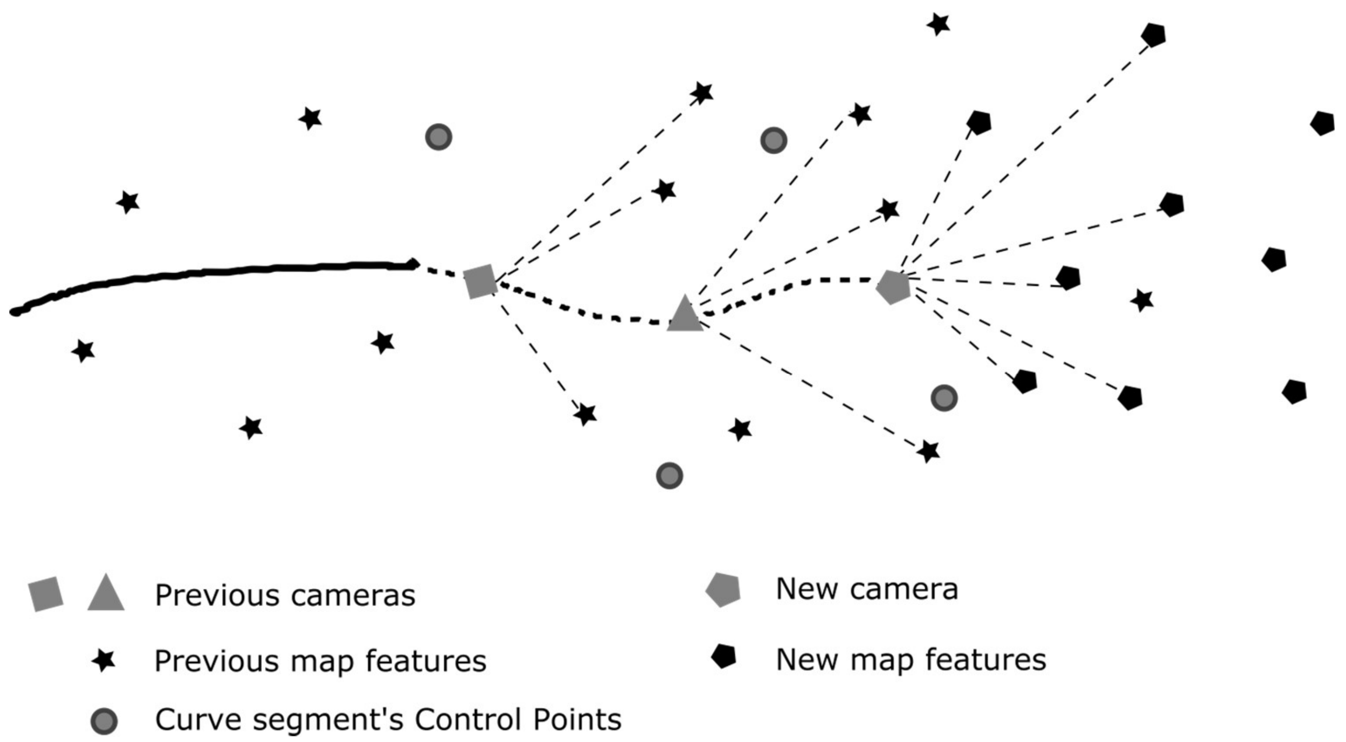
Content

- Trajectory-driven POint cloud Compression
- **Online POint cloud COmpression (O-POCO)**

Final Remarks and Future Work

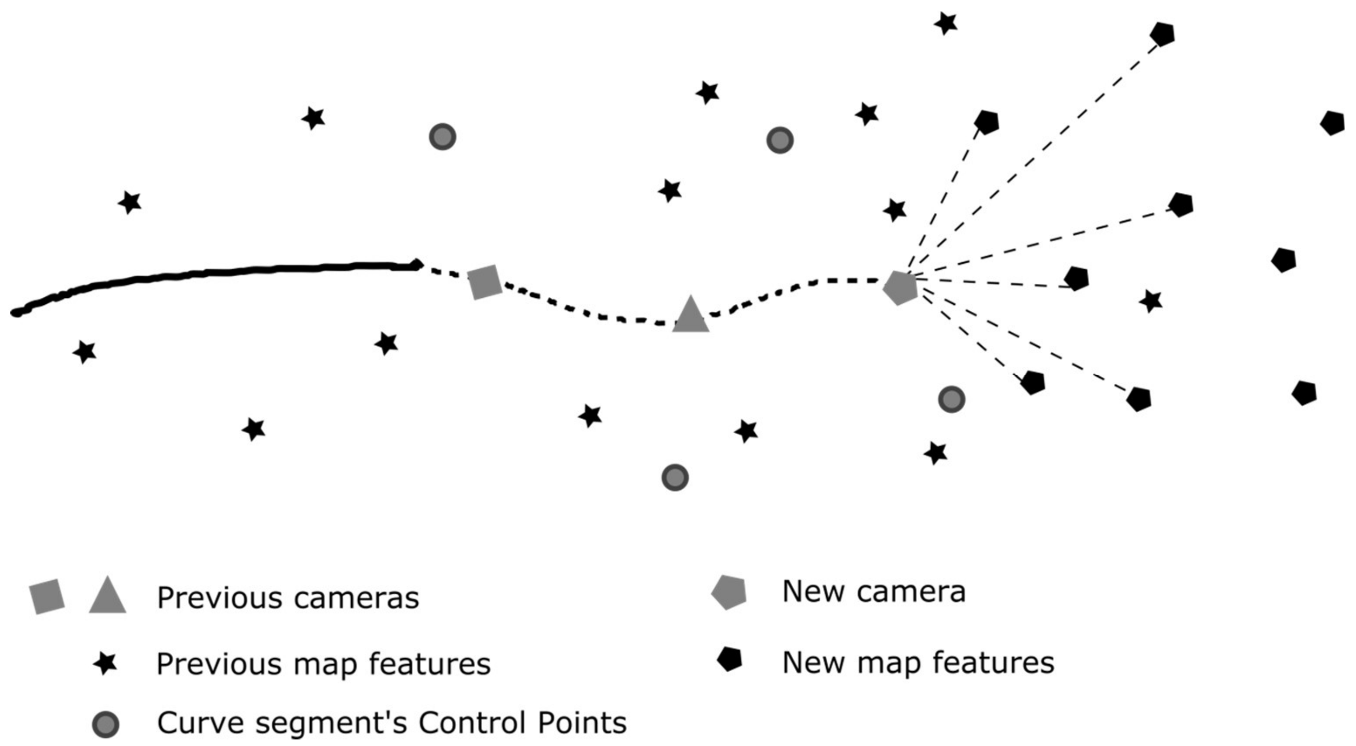
Online POint cloud COmpression (O-POCO)

A windowed version of the compression techniques is applied where, for each new camera, a partial point cloud is generated with the current frame and the points associated to the previous *k-1* cameras, and compress this point cloud, adding to the map the new selected.

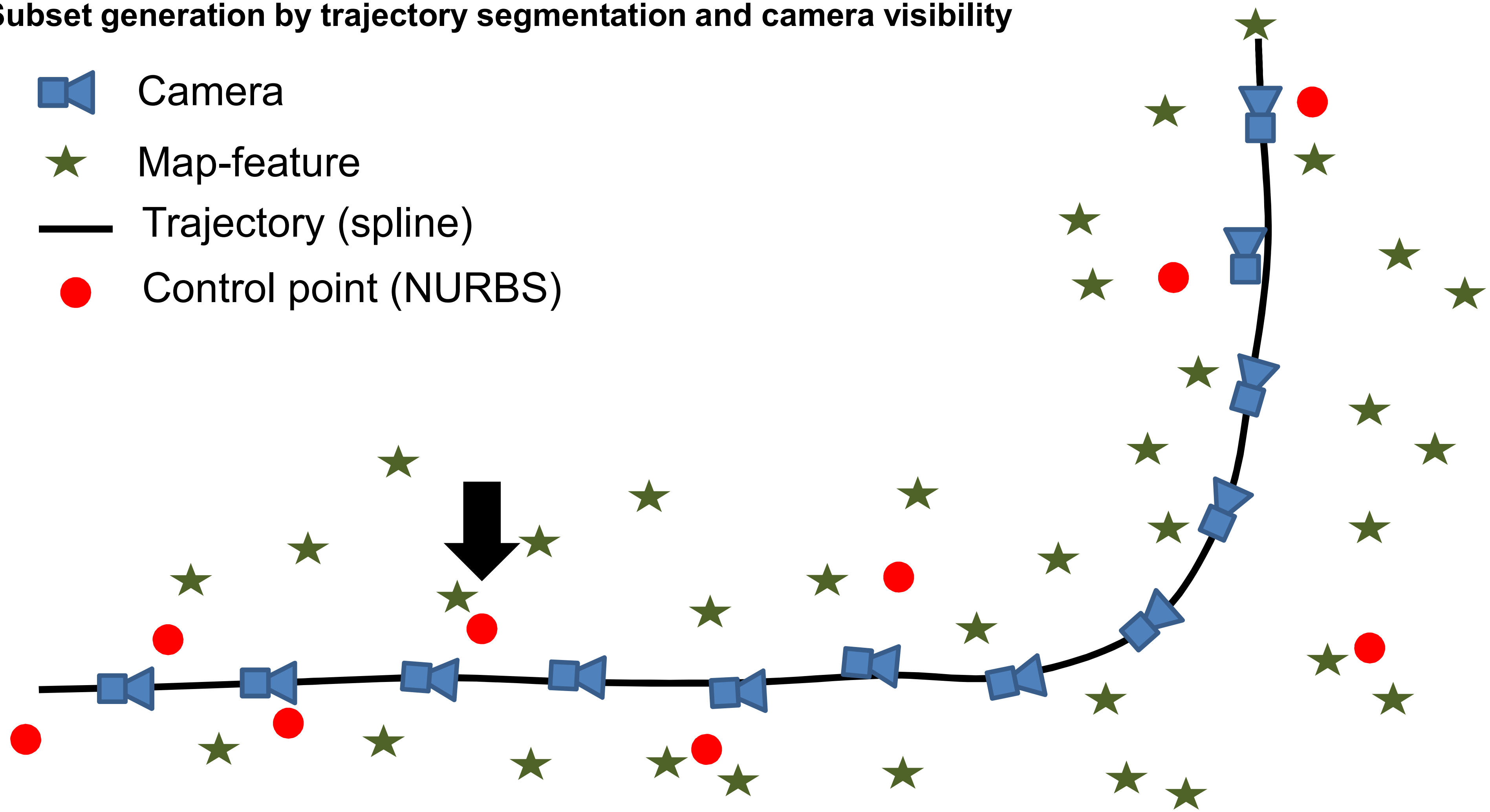


Online POint cloud COmpression (O-POCO)

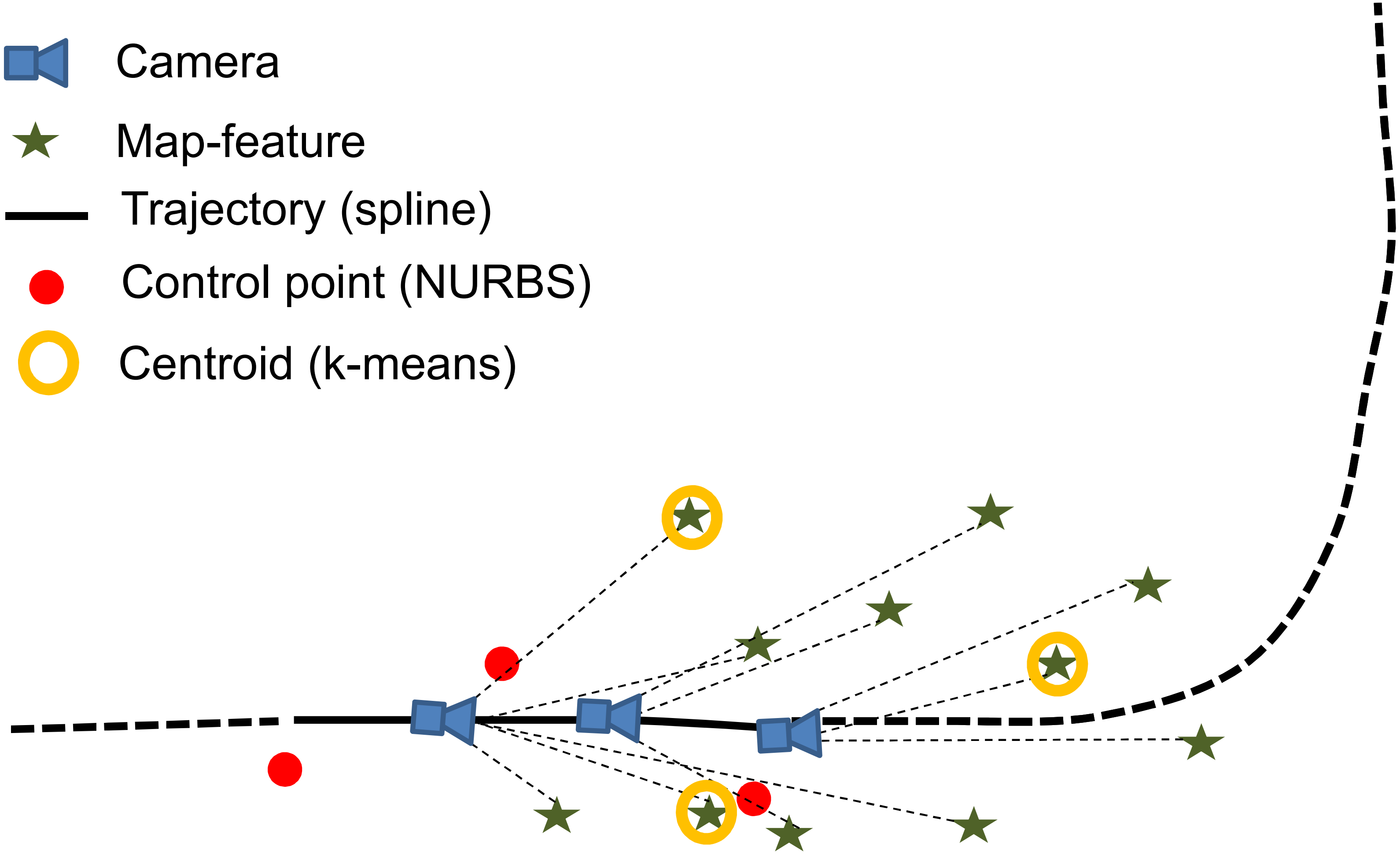
A alternative online compression method consists in using only the camera *k* (and its frame), and the previous *k*-1 cameras without considering their associated points (*key-frame* compression).



Online POint cloud COmpression (O-POCO)
Subset generation by trajectory segmentation and camera visibility

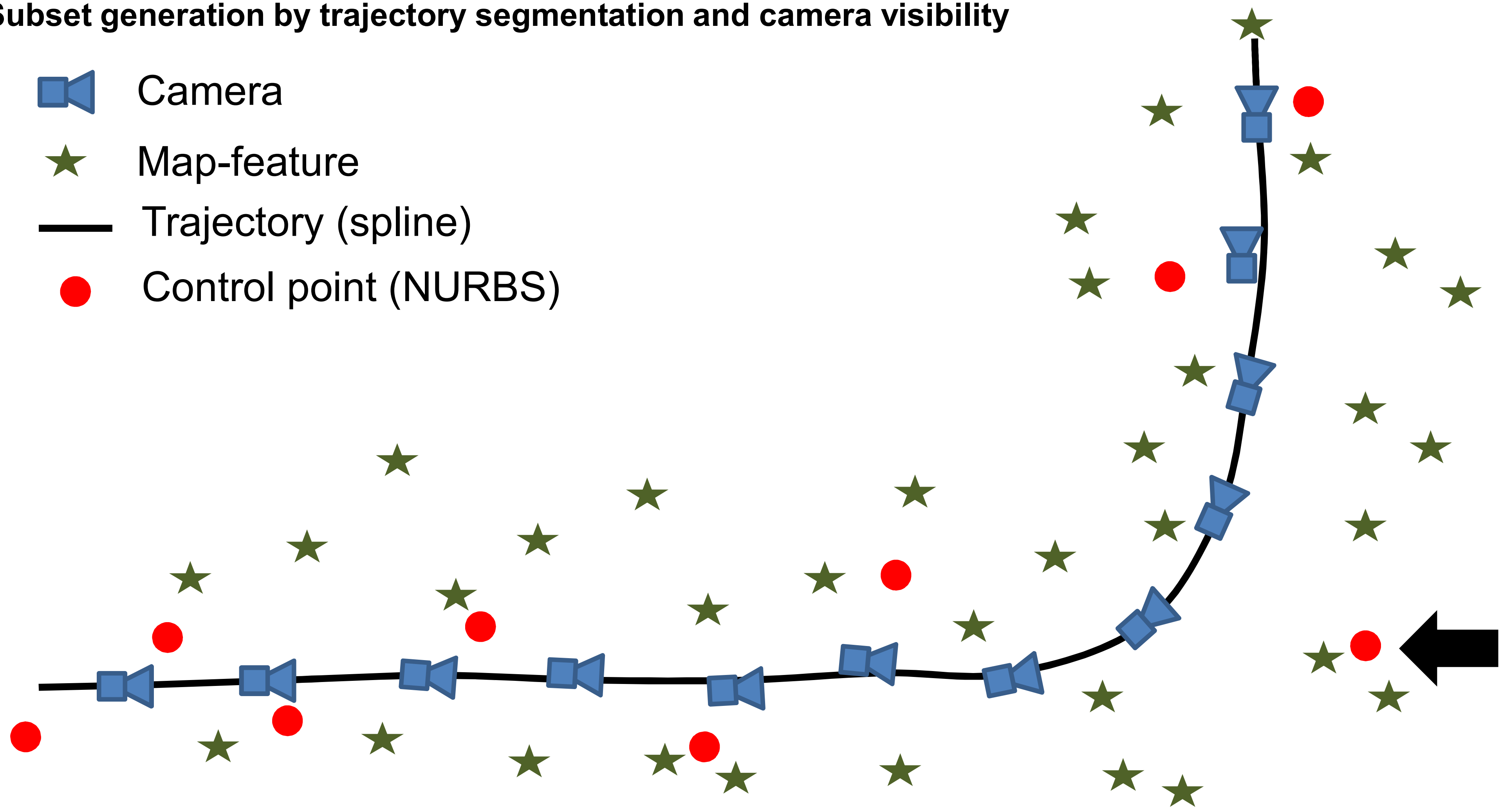


Online POint cloud COmpression (O-POCO)
Subset generation by trajectory segmentation and camera visibility



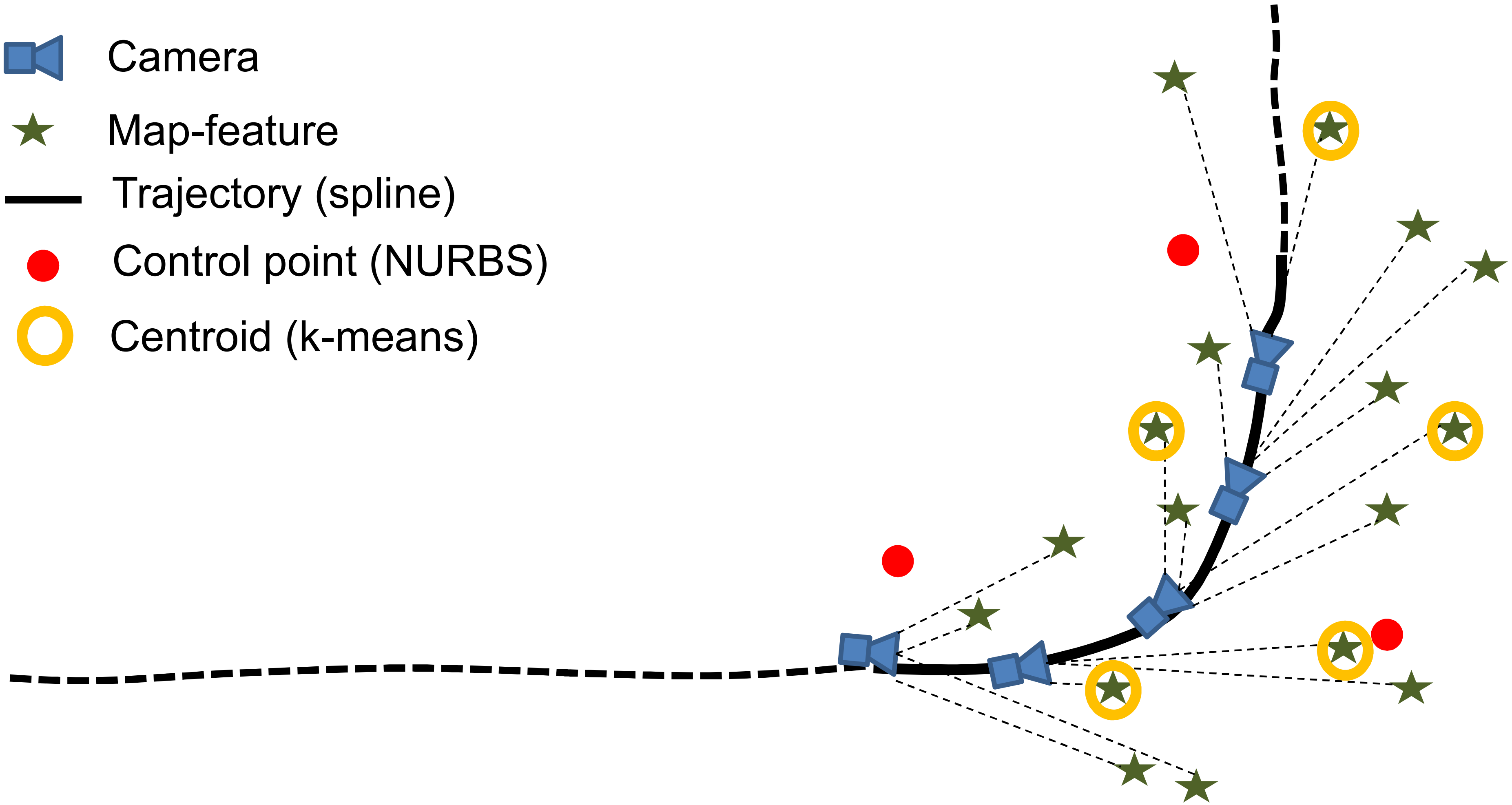
Online POint cloud COmpression (O-POCO)

Subset generation by trajectory segmentation and camera visibility



Online POint cloud COmpression (O-POCO)

Subset generation by trajectory segmentation and camera visibility



Online POint cloud COmpression (O-POCO)

Table. Relocalisation mean error [in meters].

	Relocalisation mean error [m]		
Windows size	Offline	Key-frame	O-POCO
6 cameras	0.258 (41)	2.370 (78)	2.632 (41)
10 cameras	0.424 (41)	1.573 (92)	1.405 (99)
15 cameras	0.362 (41)	1.167 (101)	0.589 (119)
20 cameras	0.328 (41)	0.839 (110)	0.203 (138)
25 cameras	0.354 (41)	0.762 (115)	0.157 (147)

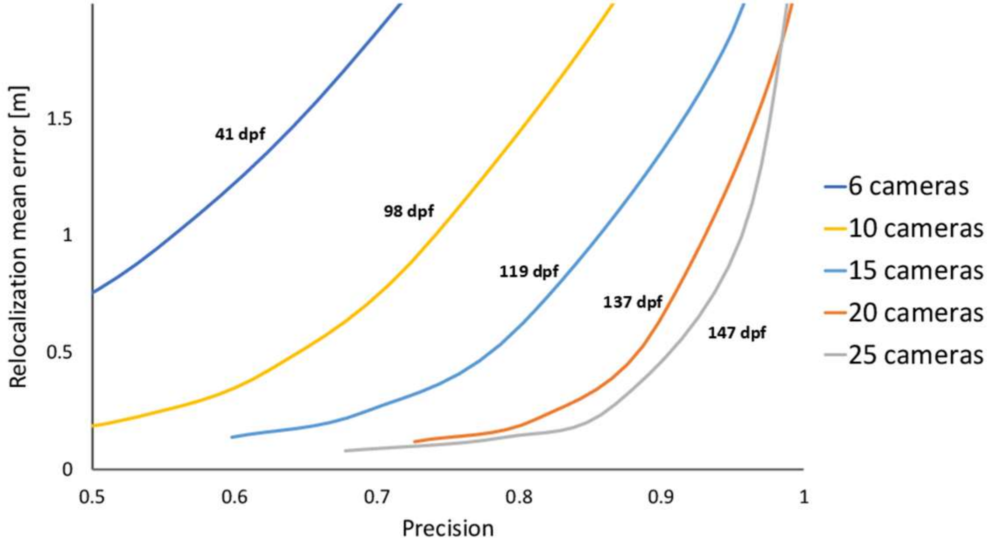
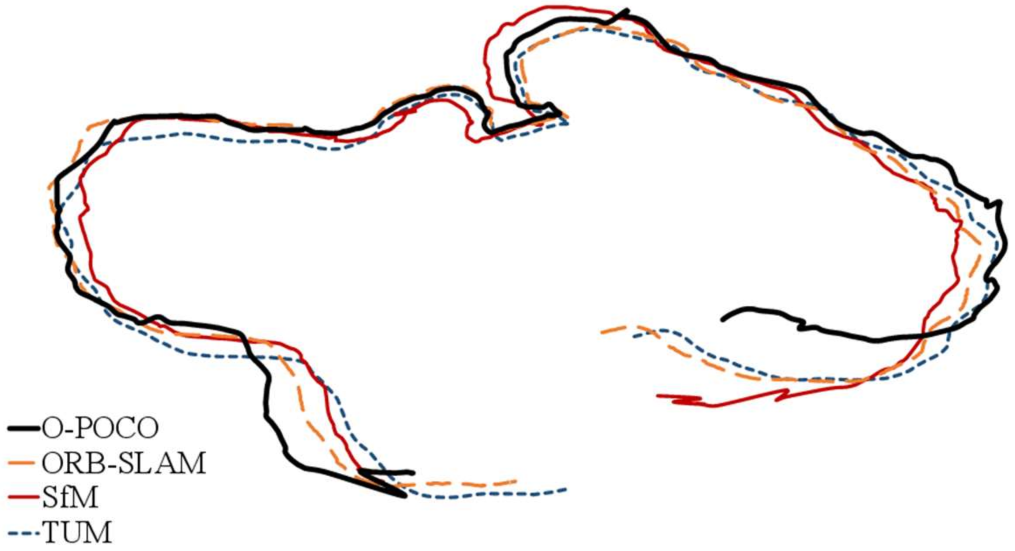


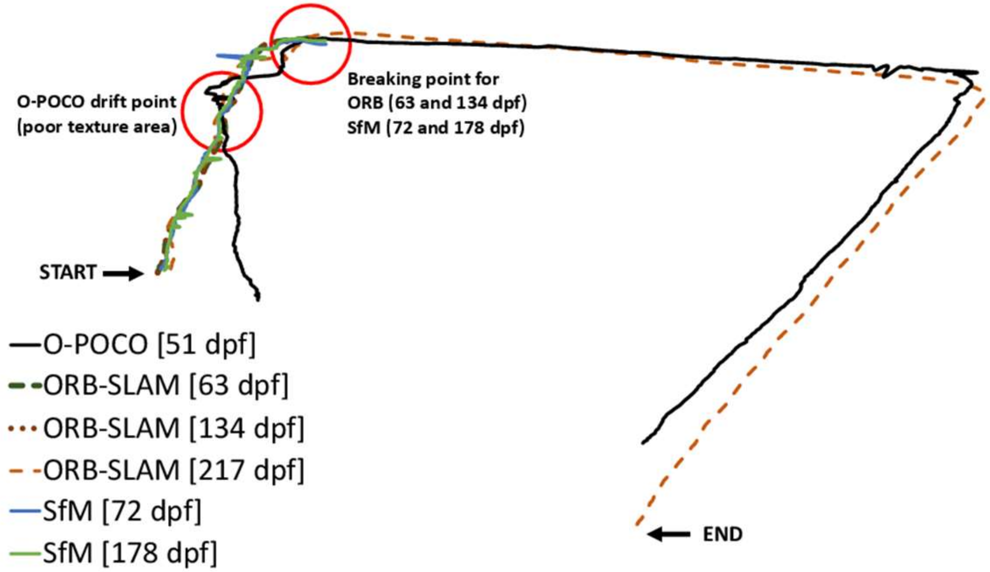
Figure. O-POCO's relocalisation and compression performance versus precision.

A sequential implementation of this algorithm using a windows size of 12 cameras takes on average **67 ms per frame** in a desktop with an i7 CPU (2.80 GHz) and 8 GB RAM.

Online POint cloud COmpression (O-POCO)

ORB-SLAM was used to compare the mapping performance. Results are as follow,





(a) (b) (c) (d)

(a) (b) (c) (d)

Point Cloud Entropy

To know the information loss after compression, the three best compression methods are taken and calculated the relative entropy between the complete point cloud and its compressed version; a comparison with three non optimal methods is show to illustrate the differences.

The relative entropy $D(p||q)$ of the probability mass function p with respect to the probability mass function q is defined by

$$D(p||q) = \sum_{x} p(x) \log \frac{p(x)}{q(x)}$$

where,

$$0 \log \tfrac{0}{0} = 0, \qquad 0 \log \tfrac{0}{q} = 0, \qquad \mathrm{p} \log \tfrac{p}{0} = \infty$$

Point Cloud Occupancy

Besides, the compressed and full point clouds' occupancy grid is calculated and their intersection is calculated.

Given

$$og_c \in og_f$$

where og_c and og_f are the occupancy grid from the compressed map and the full map, respectively; then, the intersection is defined as

$$In = \sum_{i=0}^{n-1} og_c \oplus og_f$$

with the operator $\oplus$ indicating the exclusive disjunction.

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Online POint cloud COmpression (O-POCO)*

We introduce a series of metrics to measure other information levels apart from point cloud size (we performed a mapping process without compression (135 dpf on average) and using O-POCO (51 dpf)).

Point Cloud Entropy	0.019
Map-feature geometry preservation	0.003 meters
Point Cloud Occupancy	97 % (at 1cm radius)

*L. Contreras and W. Mayol-Cuevas, “O-POCO: Online POint cloud COmpression mapping for visual odometry and SLAM.,” in ICRA IEEE, 2017 (accepted).

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Final Remarks and Future Work

Final remarks

We show how introducing relocalisation performance as a measure for more compact maps is possible while preserving geometry, occupancy and entropy.

We propose, model, and evaluate a series of methods – both online and offline – that use the exploration trajectory information together with map feature's qualities such as visibility and descriptor similarity to produce compression methods that are better than a range of baseline alternatives.

**Thinking:*These approaches were presented in two conference papers in IROS and ICRA*.

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