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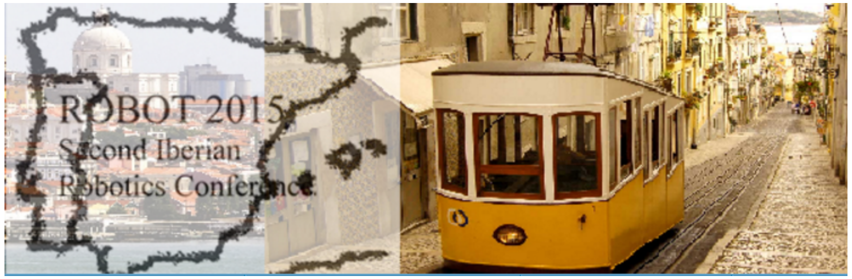

Building Fuzzy Elevation Maps from a Ground-based 3D Laser Scan for Outdoor Mobile Robots

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OUTLINE

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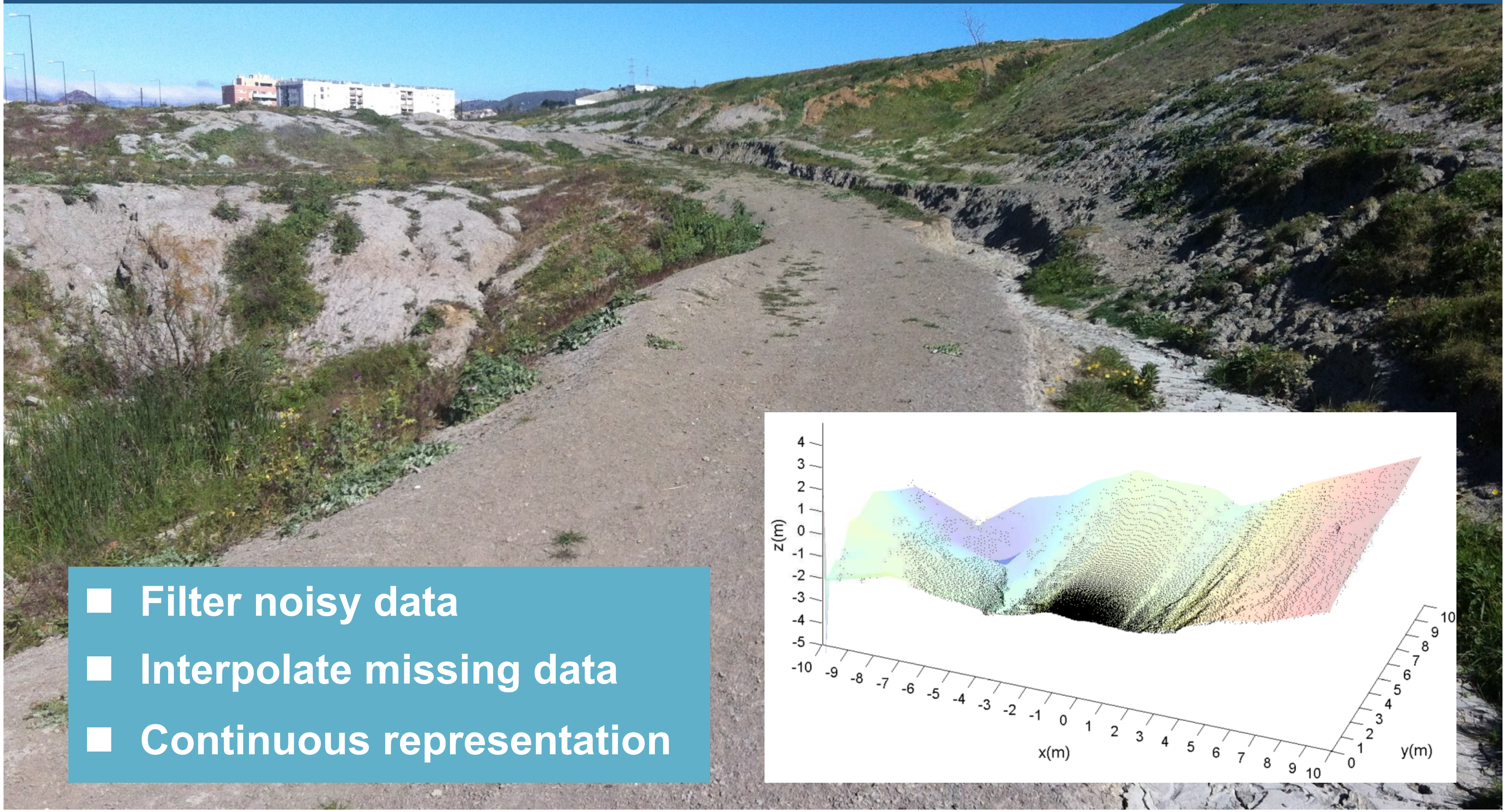
1. FUZZY ELEVATION MAPS

3D terrain modeling from onboard range sensors is crucial for many field robotics applications

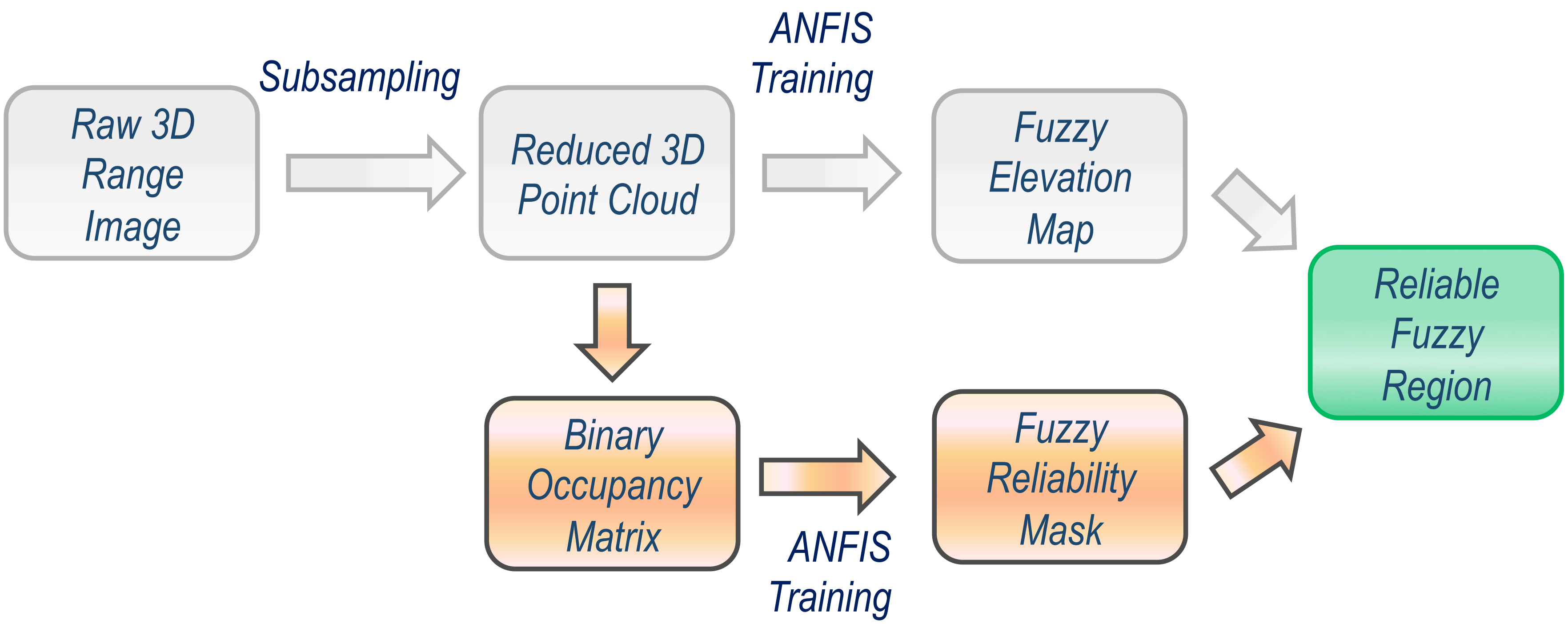
- **Natural environments**
  - *Search & Rescue*
- **Onboard 3D scanner**
  - *Huge amount of data*
  - *Resolution decreases with range*
  - *Need for compact representation*

Fuzzy surfaces offer an interesting alternative to tesselated models for terrain elevation



- **Filter noisy data**
- **Interpolate missing data**
- **Continuous representation**

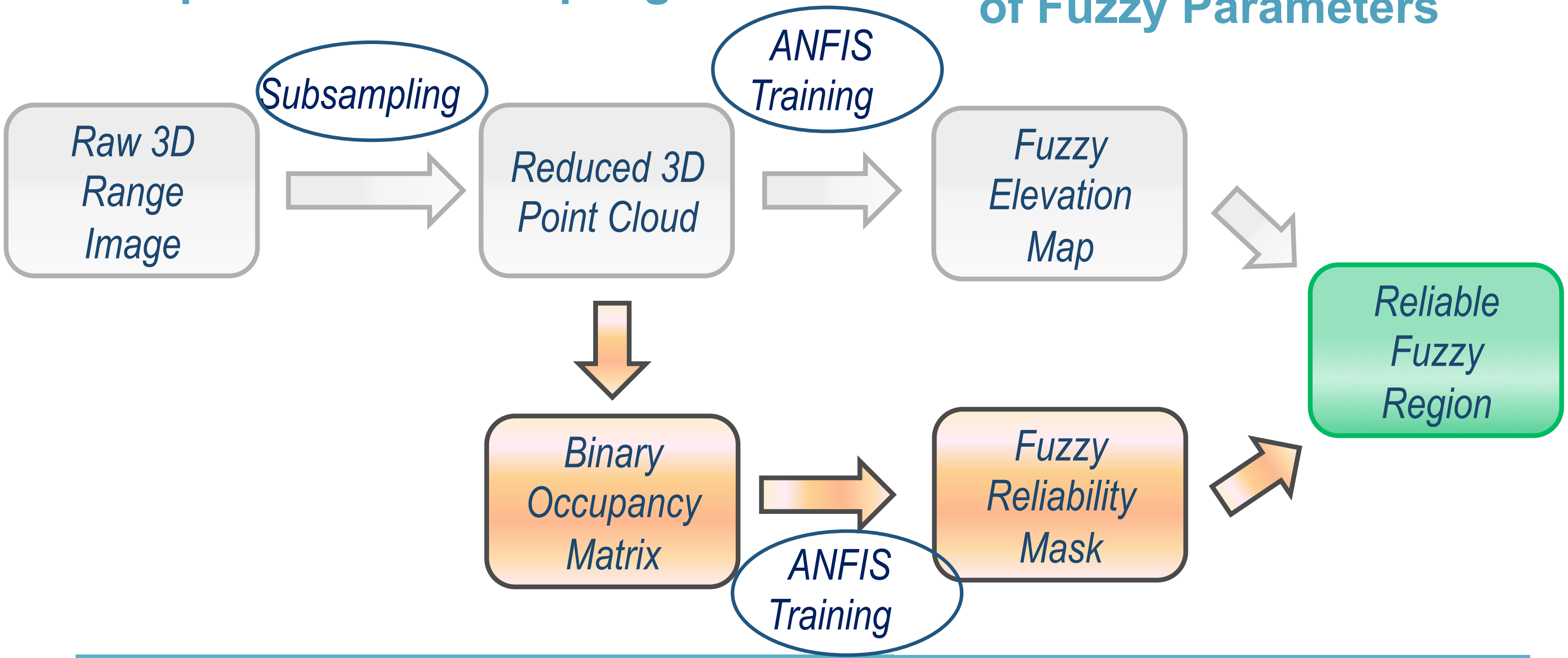
The Fuzzy Elevation Map method (FEM) can produce a reliable fuzzy elevation region



Proposed **contributions** aim to improve FEM computational speed and performance

1. Spherical Subsampling

2. Systematic definition of Fuzzy Parameters



- **Performance Analysis**
  - Outstanding obstacles
  - Comparison with Q-Slim

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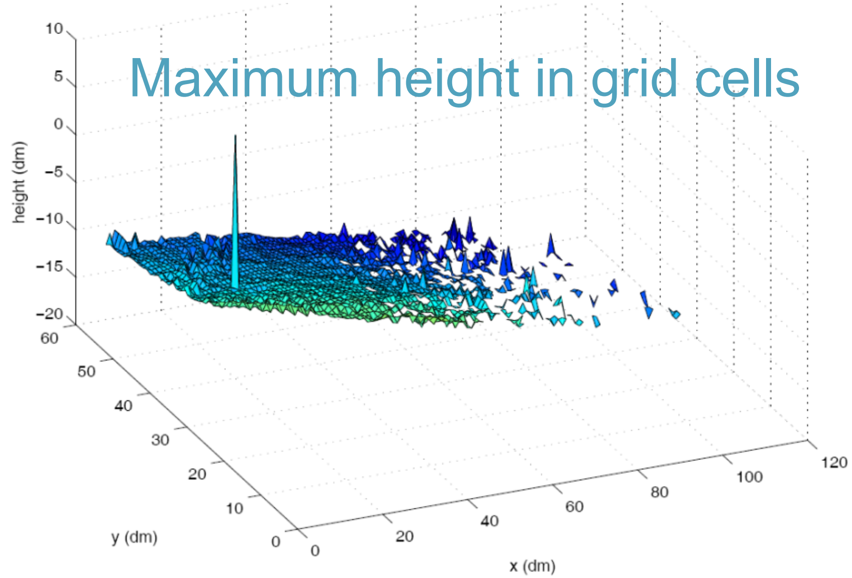
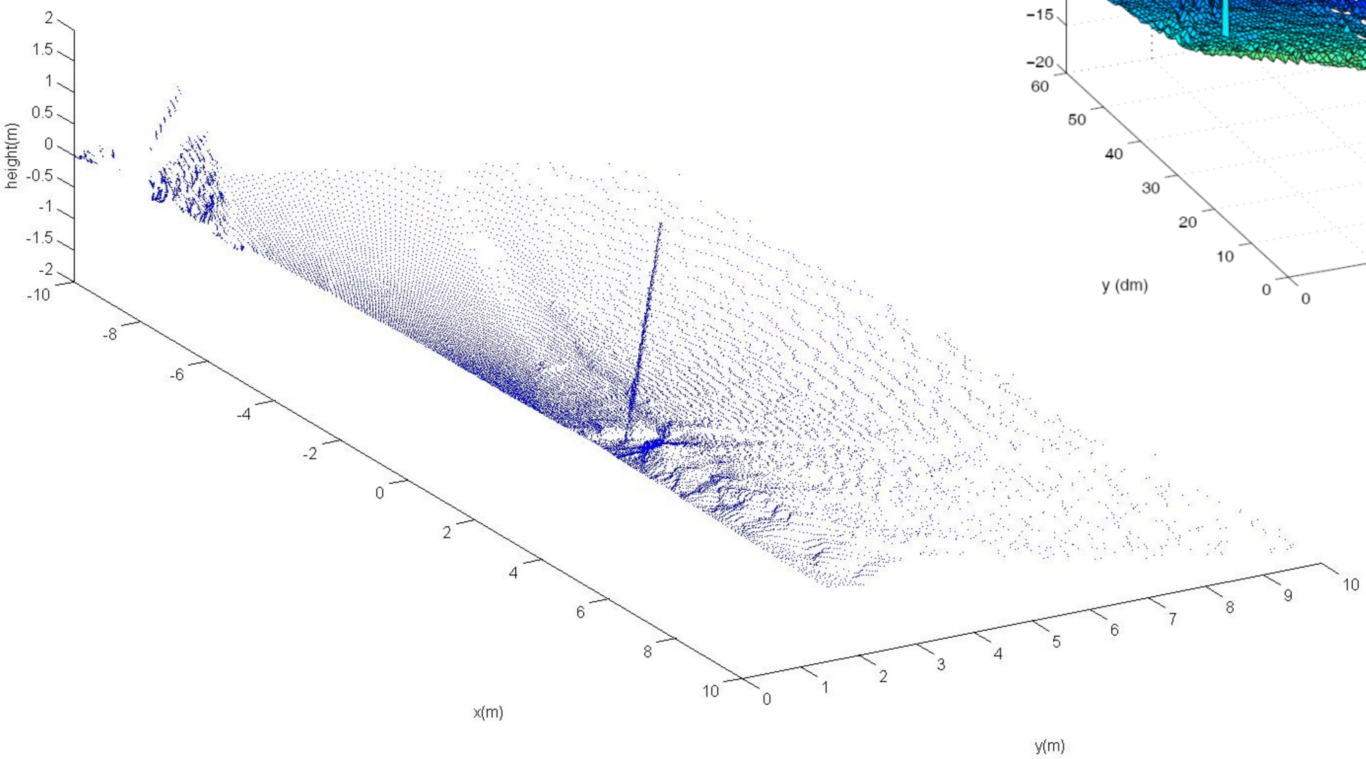
2. PERFORMANCE IMPROVEMENTS

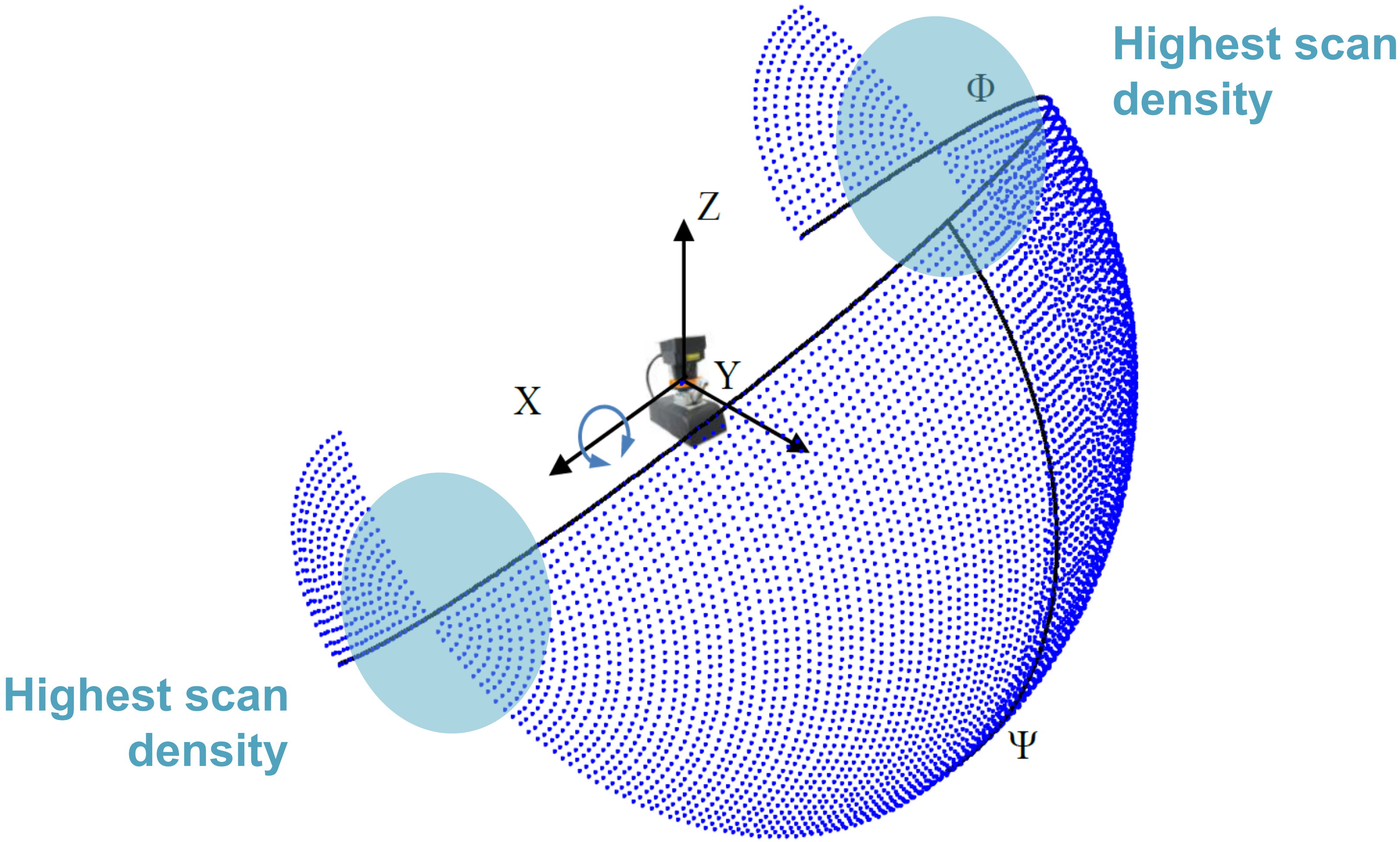
Subsampling can reduce fuzzy identification speed and homogenize data distribution

- **Raw point cloud example:**





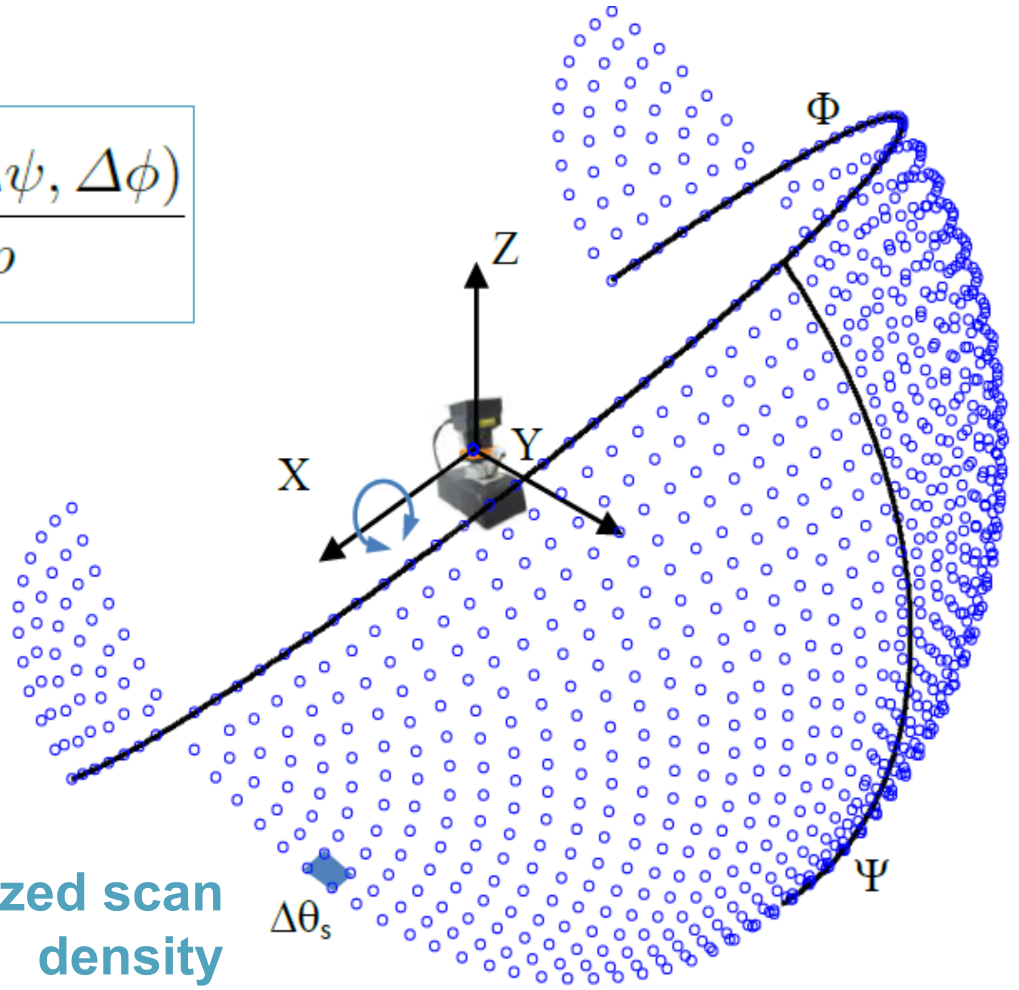
Spherical subsampling is a fast range-independent method for sensors with a pitching 2D scanner



Spherical subsampling is a fast range-independent method for sensors with a rotating 2D scanner

$$\Delta\theta_s = \frac{\max(\Delta\psi, \Delta\phi)}{p}$$

$$0 < p \leq 1$$



Homogeinized scan density

ANFIS Training starts from an **uneven Standard Fuzzy Partition** and zero-order Sugeno inference

- **Standard Fuzzy Partition (SPF)**

$$\sum_{\forall i,j} \omega_{ij}(x,y) = 1$$

  - *Firing strength:*

$$\omega_{ij}(x,y) = \mu_{F_i}(x)\,\mu_{F_j}(y)$$

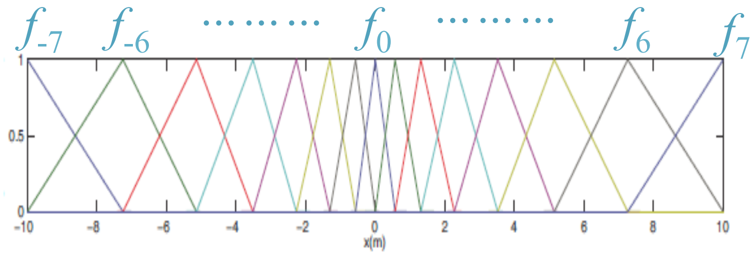
- **Zero-order Sugeno inference**
  - *Constant consequents:*

$$G_{ij}(x,y) = a_{ij}$$

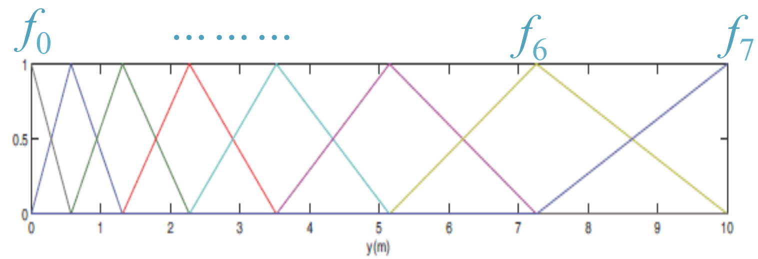
- **Terrain elevation:**

$$z = H(x,y) = \sum_{\forall i,j} (\omega_{ij}(x,y)\,a_{ij})$$

X (sideways) membership functions:



Y (forward) membership functions:



f_i : peak values

$$f_i = \mathrm{sign}(i)\left(\frac{r^{|i|}-1}{r^k-1}\right)u_{max}$$

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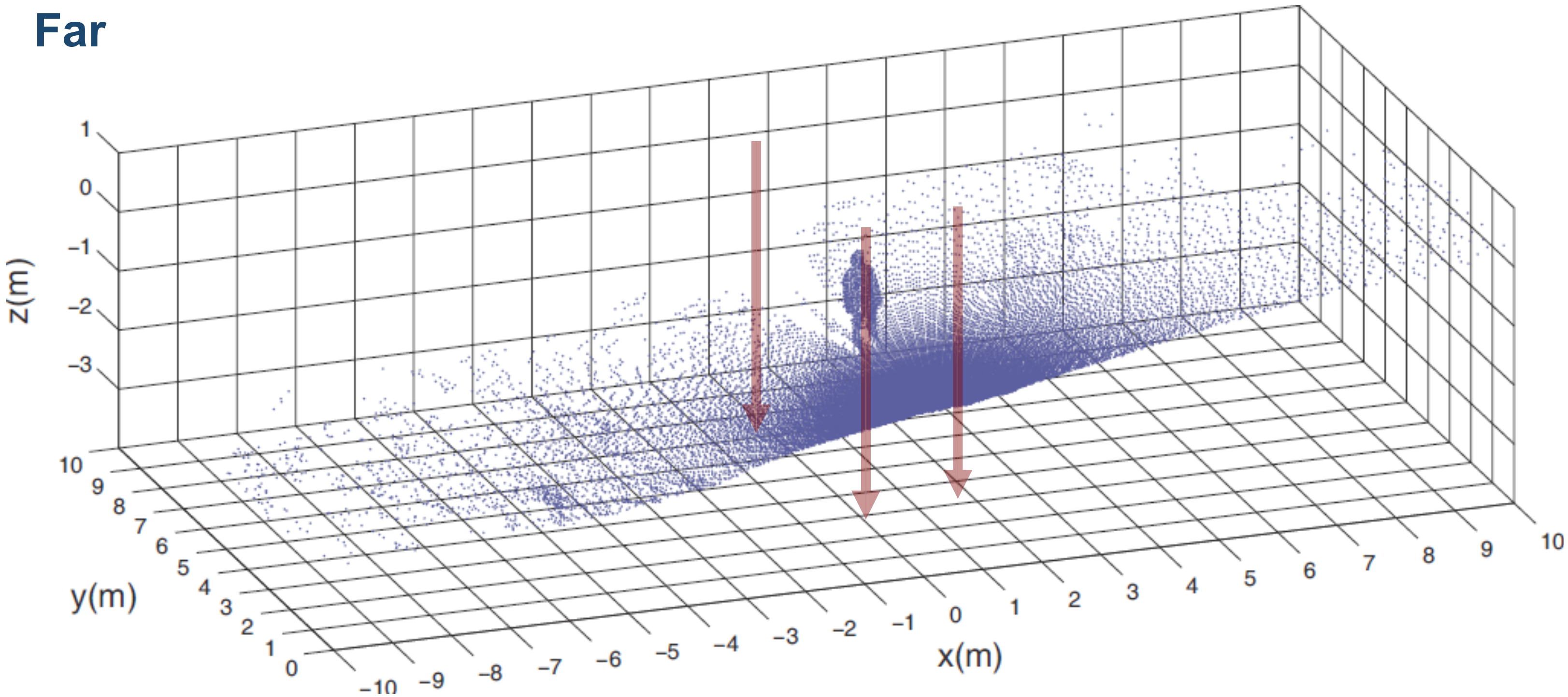
3.
EXPERIMENTAL RESULTS

Experiments have been performed with a pitching Hokuyo sensor designed for mobile robotics

- **UnoLaser 3D Scanner** (UTM-30LX):
  - *30m range*
  - *1 m above ground*
  - *$\Delta\Psi$= 0.278º*
  - *Scan time: 12.43s*
  - *Up to 505036 points*

The position of a standing obstacle has been modified in four different scans

- **No obstacle**
- **Close front**
- **Close side**
- **Far**



Fuzzy Performance Evaluation with a QuadCore Intel Core i7 at 2.2 GHz

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Adjustment is more accurate with no (close) standing obstacles

Obs-tacle	p	Training points	No. of rules	RMSE (m^2)	Time (s)
None	-	186767	15 × 8	0.0237	[illegible]
			7 × 4	0.0413	[illegible]
	1	115423	15 × 8	0.0237	[illegible]
			7 × 4	0.0420	[illegible]
	0.75	65019	15 × 8	0.0238	[illegible]
			7 × 4	0.0421	[illegible]
	0.5	28916	15 × 8	0.0238	22.07
			7 × 4	0.0421	9.07
	0.1	1180	15 × 8	0.2568	11.90
			7 × 4	0.0451	5.90
Close -side	-	187600	15 × 8	0.0951	177.00
			7 × 4	0.1283	115.00
	1	115525	15 × 8	0.0955	80.87
			7 × 4	0.1295	48.87
	0.75	65122	15 × 8	0.0955	40.33
			7 × 4	0.1295	20.33
	0.5	28939	15 × 8	0.0956	21.07
			7 × 4	0.1295	9.07
	0.1	1174	15 × 8	0.1580	10.89
			7 × 4	0.1305	4.89

Obs-tacle	p	Training points	No. of rules	RMSE (m^2)	Time (s)
Far	[illegible]	[illegible]	[illegible]	0.0369	174.00
			[illegible]	0.0558	117.00
	[illegible]	[illegible]	[illegible]	0.0369	80.84
			7 × 4	0.0563	47.84
	0.75	64666	15 × 8	0.0369	41.32
			7 × 4	0.0564	20.32
	0.5	28770	15 × 8	0.0370	21.12
			7 × 4	0.0564	9.12
	0.1	1168	15 × 8	0.4484	10.96
			7 × 4	0.0642	5.96
Close -front	-	189688	15 × 8	0.0871	174.00
			7 × 4	0.1259	119.00
	1	117941	15 × 8	0.0879	87.65
			7 × 4	0.1262	50.65
	0.75	66465	15 × 8	0.0872	44.26
			7 × 4	0.1262	21.26
	0.5	29554	15 × 8	0.0872	23.05
			7 × 4	0.1262	10.05
	0.1	1206	15 × 8	0.1568	11.19
			7 × 4	0.1495	5.19

Fuzzy Performance Evaluation with a QuadCore Intel Core i7 at 2.2 GHz

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Obstacle	p	Training points	No. of rules	RMSE (m^2)	Time (s)	Obstacle	p	Training points	No. of rules	RMSE (m^2)	Time (s)
None	-	186767	15 × 8	0.0237	176.00	None	-	[illegible]	15 × 8	0.0369	174.00
			7 × 4	[illegible]	[illegible]				7 × 4	0.0558	117.00
	1	115423	[illegible]	[illegible]	[illegible]		1	[illegible]	15 × 8	0.0369	80.84
			7 × 4	[illegible]	[illegible]				[illegible]	0.0563	47.84
	0.75	65019	[illegible]	[illegible]	[illegible]		0.75	[illegible]	[illegible]	0.0369	41.32
			7 × 4	[illegible]	[illegible]				[illegible]	0.0564	20.32
	0.5	28916	[illegible]	[illegible]	[illegible]		0.5	[illegible]	15 × 8	0.0370	21.12
			7 × 4	0.0421	9.07				7 × 4	0.0564	9.12
	0.1	1180	15 × 8	0.2568	11.90		0.1	1168	15 × 8	0.4484	10.96
			7 × 4	0.0451	5.90				7 × 4	0.0642	5.96
Close-side	-	187600	15 × 8	0.0951	177.00	Close-side	-	189688	15 × 8	0.0871	174.00
			7 × 4	0.1283	115.00				7 × 4	0.1259	119.00
	1	115525	15 × 8	0.0955	[illegible]		1	[illegible]	15 × 8	0.0879	87.65
			7 × 4	0.1295	[illegible]				7 × 4	0.1262	50.65
	0.75	65122	15 × 8	0.0955	[illegible]		0.75	[illegible]	15 × 8	0.0872	44.26
			7 × 4	0.1295	[illegible]				7 × 4	0.1262	21.26
	0.5	28939	15 × 8	0.0956	[illegible]		0.5	[illegible]	15 × 8	0.0872	23.05
			7 × 4	0.1295	[illegible]				7 × 4	0.1262	10.05
	0.1	1174	15 × 8	0.1580	10.89		0.1	1206	15 × 8	0.1568	11.19
			7 × 4	0.1305	4.89				7 × 4	0.1495	5.19

Spherical subsampling significantly reduces computation time without much effect on RMSE

Overadjustment to small data sample

Fuzzy Performance Evaluation with a QuadCore Intel Core i7 at 2.2 GHz

Obstacle	p	Training points	No. of rules	RMSE (m^2)	Time (s)
None	-	186767	15 × 8	0.0237	[illegible]
			7 × 4	0.0413	[illegible]
	1	115423	15 × 8	0.0237	[illegible]
			7 × 4	0.0420	[illegible]
	0.75	65019	15 × 8	0.0238	43.33
			7 × 4	0.0421	21.33
	0.5	28916	15 × 8	0.0238	22.07
			7 × 4	0.0421	9.07
	0.1	1180	15 × 8	0.2568	11.90
			7 × 4	0.0451	5.90
Close-side	-	187600	15 × 8	0.0951	177.00
			7 × 4	0.1283	115.00
	1	115525	15 × 8	0.0955	80.87
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	0.75	65122	15 × 8	0.0955	40.33
			7 × 4	0.1295	20.33
	0.5	28939	15 × 8	0.0956	21.07
			7 × 4	0.1295	9.07
	0.1	1174	15 × 8	0.1580	10.89
			7 × 4	0.1305	4.89

Obstacle	p	Training points	No. of rules	RMSE (m^2)	Time (s)
Far	[illegible]	…673	15 × 8	0.0369	174.00
			7 × 4	0.0558	117.00
	[illegible]	…768	15 × 8	0.0369	80.84
			7 × 4	0.0563	47.84
	0.75	64666	15 × 8	0.0369	41.32
			7 × 4	0.0564	20.32
	0.5	28770	15 × 8	0.0370	21.12
			7 × 4	0.0564	9.12
	0.1	1168	15 × 8	0.4484	10.96
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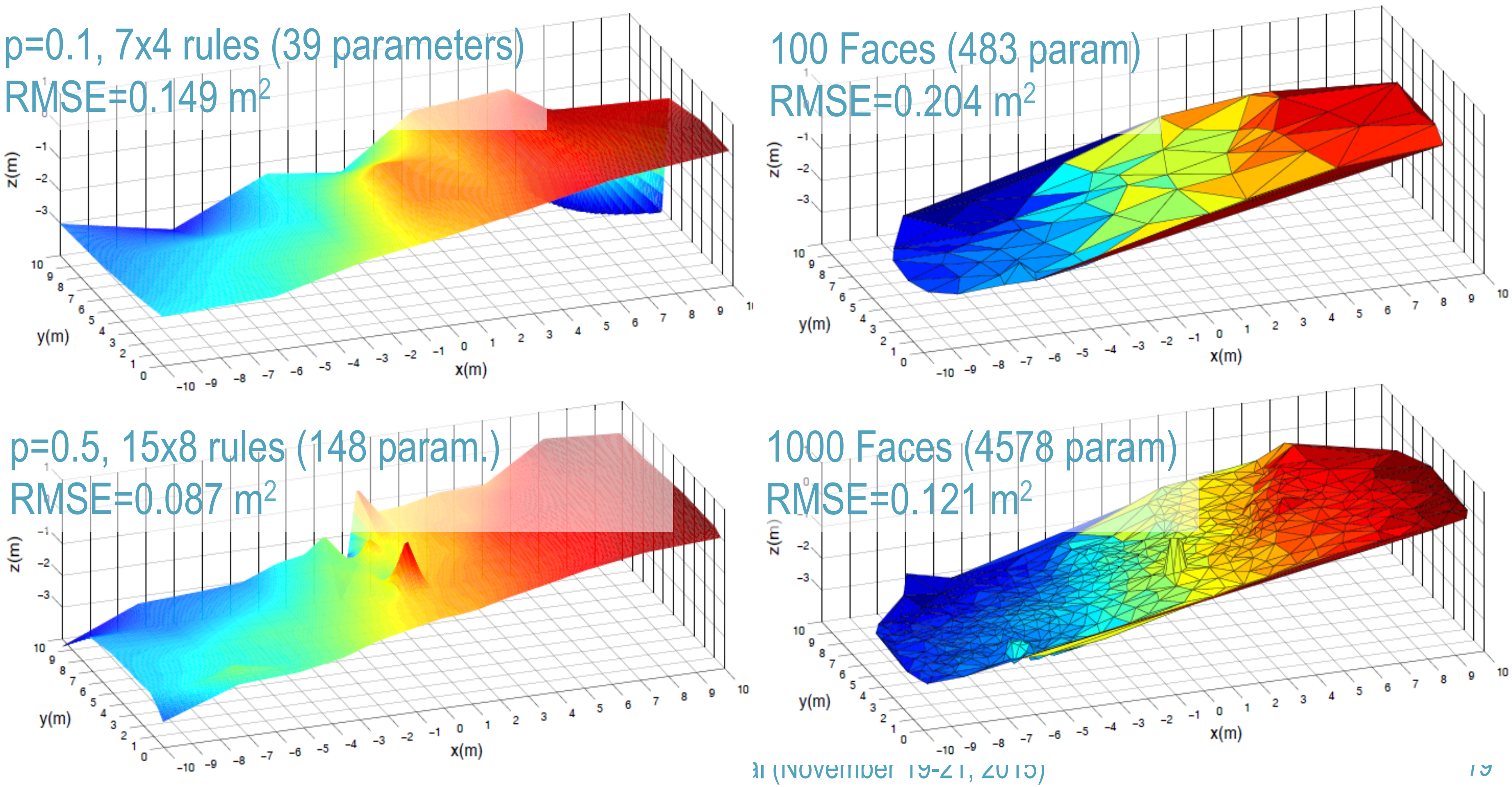
Close-front	-	189688	15 × 8	0.0871	174.00
			7 × 4	0.1259	119.00
	1	117941	15 × 8	0.0879	87.65
			7 × 4	0.1262	50.65
	0.75	66465	15 × 8	0.0872	44.26
			7 × 4	0.1262	21.26
	0.5	29554	15 × 8	0.0872	23.05
			7 × 4	0.1262	10.05
	0.1	1206	15 × 8	0.1568	11.19
			7 × 4	0.1495	5.19

Compromise between time and accuracy

Computation time, model size, and accuracy outscore tesselated QSlim elevation maps, especially with outstanding obstacles

- **Close-front obstacle**



Performance is significantly improved with respect to original FEM

Scene	Modeling method	Characteristics	RMSE (m^2)	Time (s)	Number of parameters
No obstacle	ANFIS	$15 \times 8, p = 0.5$	0.0238	22.07	143
		$7 \times 4, p = 0.1$	0.0451	5.90	39
		15×8 ([23])	0.0468	31.01	406
	QSlim	1000 faces	0.0250	29.17	4590
		100 faces	0.0357	29.17	483
Far obstacle	ANFIS	$15 \times 8, p = 0.5$	0.0370	21.12	143
		$7 \times 4, p = 0.1$	0.0642	5.96	39
		15×8 [23]	0.0660	31.20	406
	QSlim	1000 faces	0.0383	32.21	4572
		100 faces	0.0783	32.03	471
Close-side obstacle	ANFIS	$15 \times 8, p = 0.5$	0.0956	21.07	143
		$7 \times 4, p = 0.1$	0.1305	4.89	39
		15×8 [23]	0.1256	32.14	406
	QSlim	1000 faces	0.1349	29.14	4578
		100 faces	0.1959	29.14	477
Close-front obstacle	ANFIS	$15 \times 8, p = 0.5$	0.0872	23.05	143
		$7 \times 4, p = 0.1$	0.1495	5.19	39
		15×8 [23]	0.1303	33.07	406
	QSlim	1000 faces	0.1212	33.18	4569
		100 faces	0.2038	33.16	477

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4.
CONCLUSIONS

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Conclusions

- **Ground based terrain modeling approach**
- **Fuzzy Elevation Maps**
  - *Compact*
  - *Continuous*
  - *Manage noisy and missing data.*
- **Proposed improvements**
  - *Spherical subsampling for training data selection*
  - *Uneven membership functions with Standard Fuzzy Partition and Zero-order Sugeno inference*
- **Successful results with respect to original FEM and QSlim**
- **Future work**
  - *Global maps*
  - *Alternatives to ANFIS*