

Shape based classification of seismic building structural types

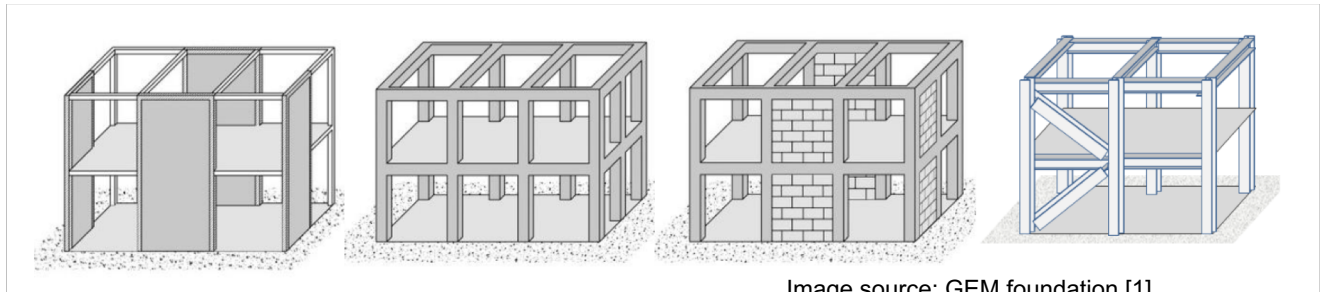
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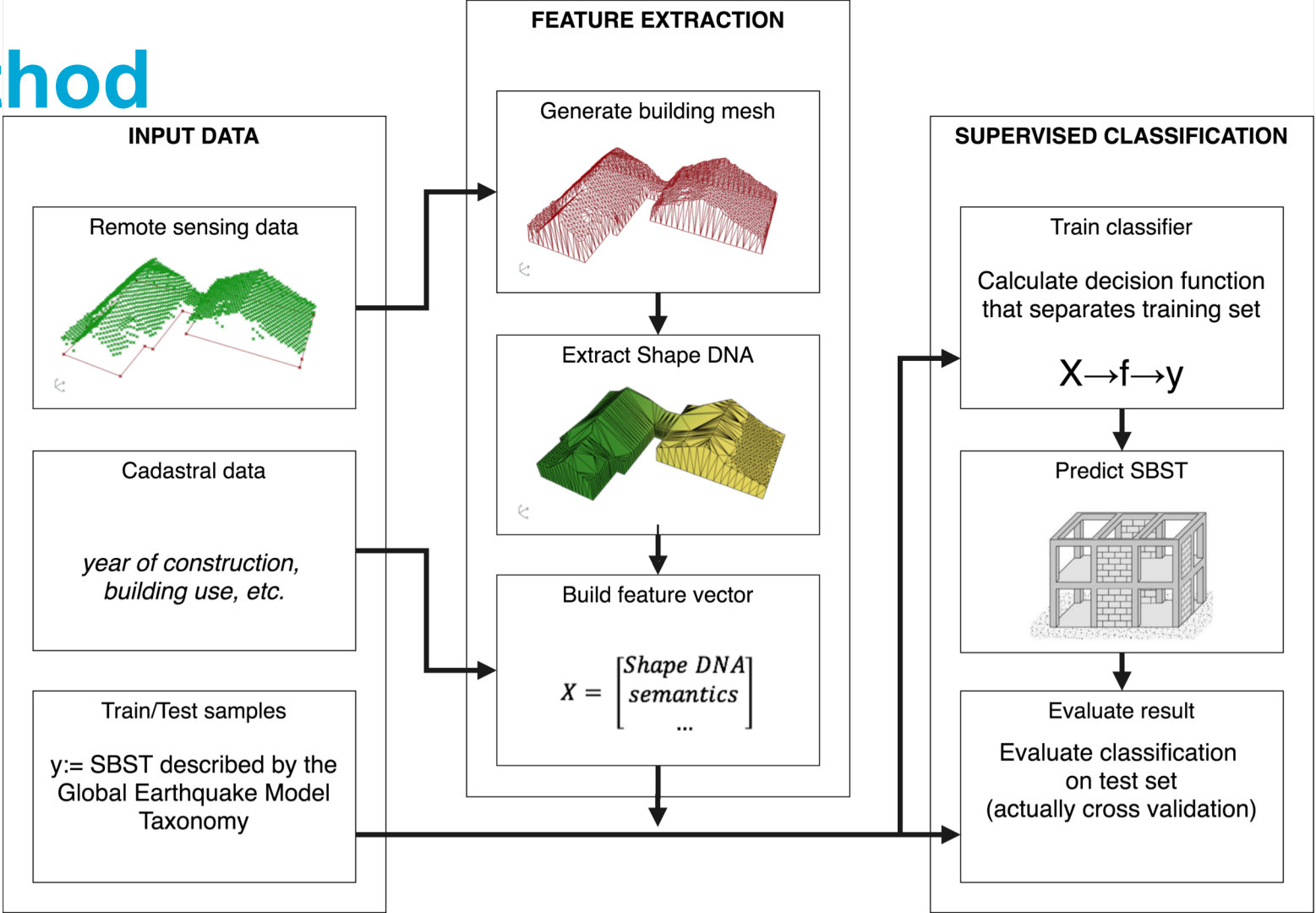
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Seismic building structural type

- Describes **main load bearing structure** of a building from which its seismic performance can be inferred
- **Motivation:**
 - Important input for **seismic risk assessment**
- **Problem:**
 - Commonly **not available on large scale**



Method

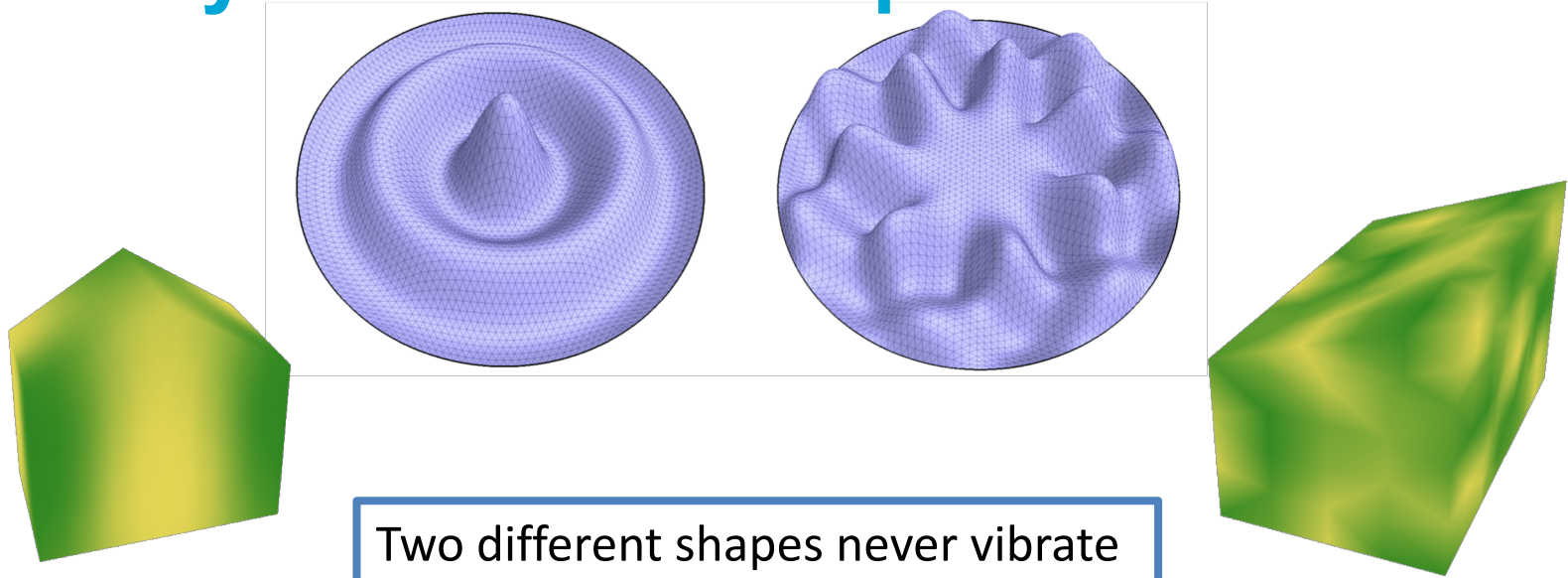


Related Work - TALK FOR SLIDE 3

- *Use of remote sensing data (e.g. LiDAR, aerial images) and ancillary (geo-)information (e.g. cadastral data) to predict SBSTs in a supervised machine learning approach*
 - *SBSTs often predicted with coarse spatial and typological granularity*
 - *e.g. masonry building, high rise building, ...*
 - ***-> use of Global Earthquake Model taxonomy, an internationally standardised scheme for seismic risk assessment. Buildings are described with 13 attributes that uniquely describe SBST.***
 - *Geometric features often regarded as most important features in classification*
 - *e.g. footprint area, building height, etc., more detailed features difficult to extract from unstructured remote sensing data and unknown which ones are important, e.g. façade area?*
 - ***-> use of Shape DNA, a global shape descriptor based on eigenvalues of Laplace-Beltrami operator that can be applied on polygonal mesh***
 - ***What is Shape DNA:***

Shape DNA

“Can you hear the shape of a drum?”



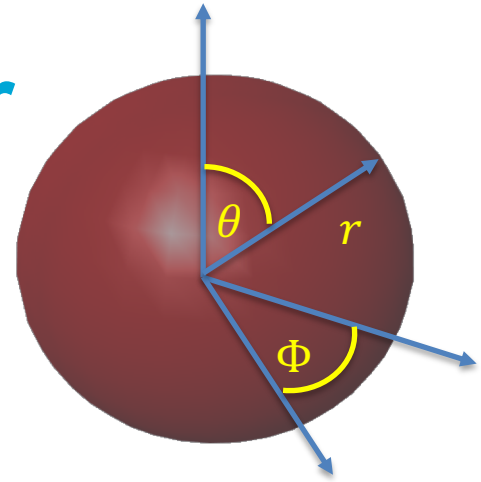
Two different shapes never vibrate
at the same frequencies

Laplace - Beltrami operator

continuous case on a sphere S

$$\Delta f := \operatorname{div} (\operatorname{grad} f)$$

$$f: S \rightarrow \mathbb{R}$$



$$\Delta_S = \frac{1}{r^2} \frac{\partial}{\partial r} \left(r^2 \frac{\partial}{\partial r} \right) + \frac{1}{r^2 \sin \theta} \frac{\partial}{\partial \theta} \left(\sin \theta \frac{\partial}{\partial \theta} \right) + \frac{1}{r^2 \sin^2 \theta} \frac{\partial^2}{\partial \phi^2}.$$

Helmholtz equation:

$$\Delta f = -\lambda f$$

λ is our shape descriptor

Shape DNA

- Laplace-Beltrami spectra as 'Shape-DNA' of surfaces and solids [2]:

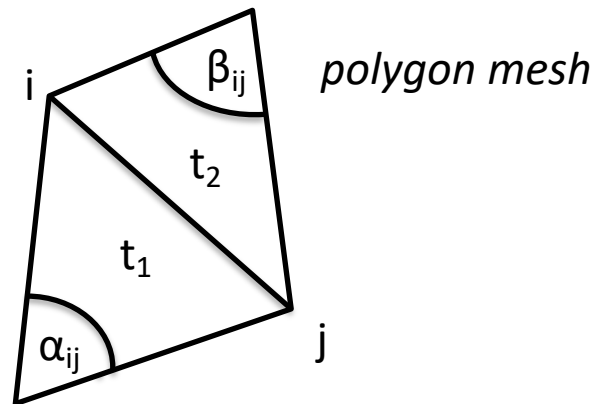
$$\Delta f = -\lambda f$$

$$A_{\text{cot}} \mathbf{f} = -\lambda B \mathbf{f}, \quad \mathbf{f} := (f(\mathbf{p}_i))_{i=1}^n,$$

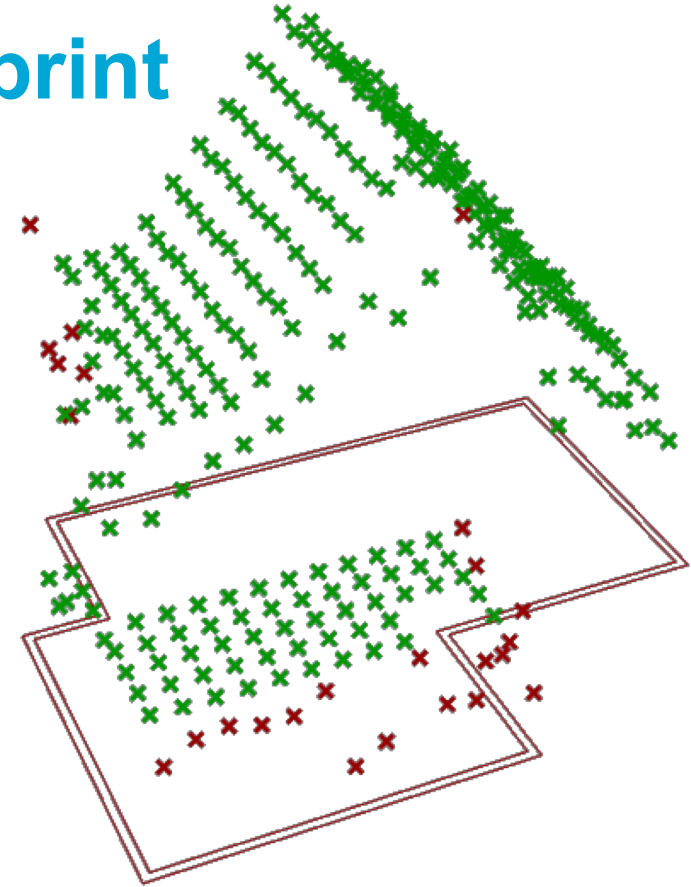
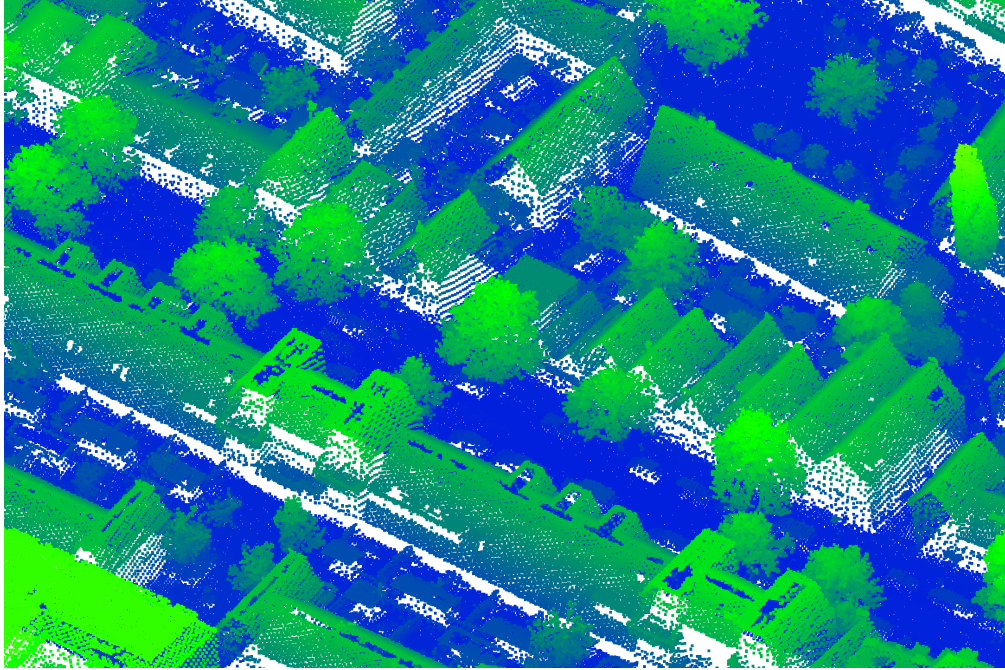
where

$$A_{\text{cot}}(i,j) := \begin{cases} \frac{\cot \alpha_{ij} + \cot \beta_{ij}}{2} & (i,j) \text{ edge,} \\ -\sum_{k \in N(i)} A_{\text{cot}}(i,k) & i = j, \end{cases}$$

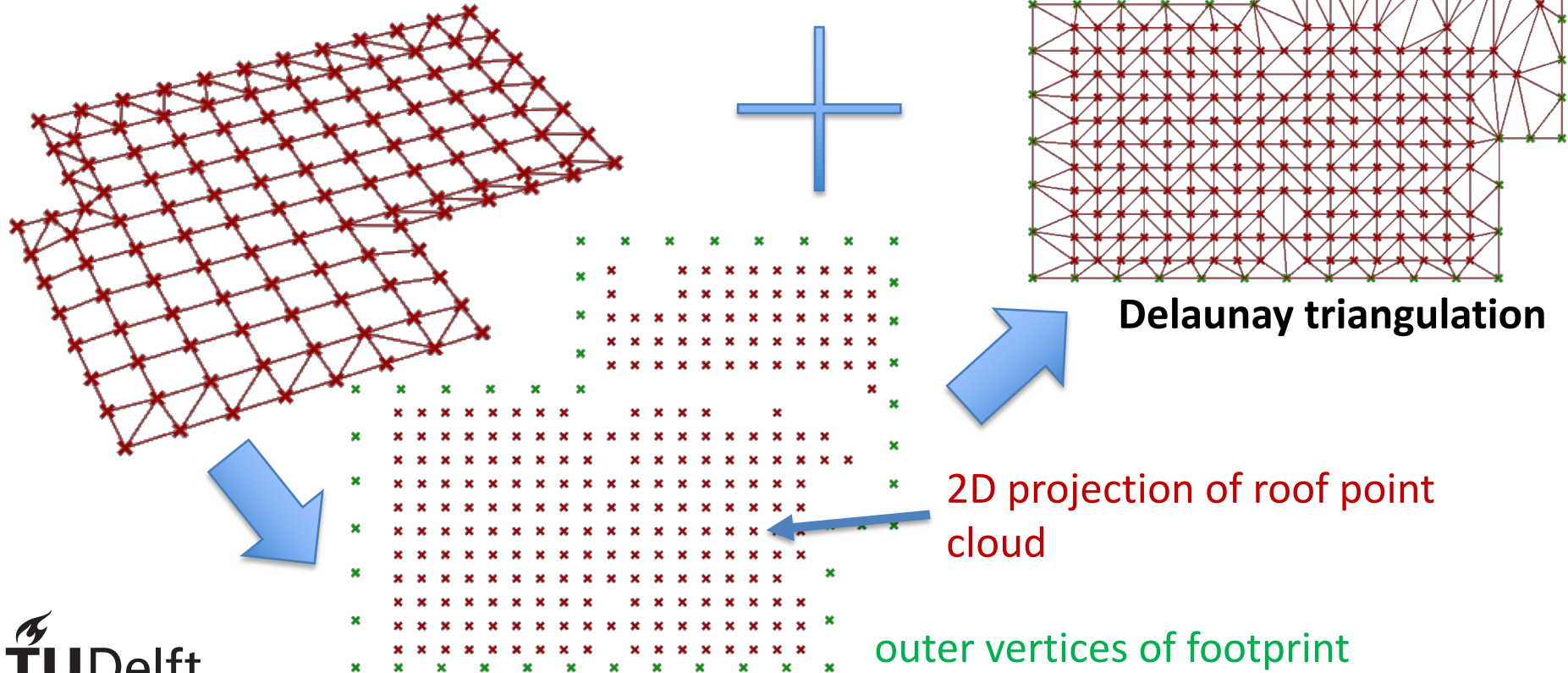
$$B(i,j) := \begin{cases} \frac{|t_1| + |t_2|}{12} & (i,j) \text{ edge,} \\ \frac{\sum_{k \in N(i)} |t_k|}{6} & i = j, \end{cases}$$



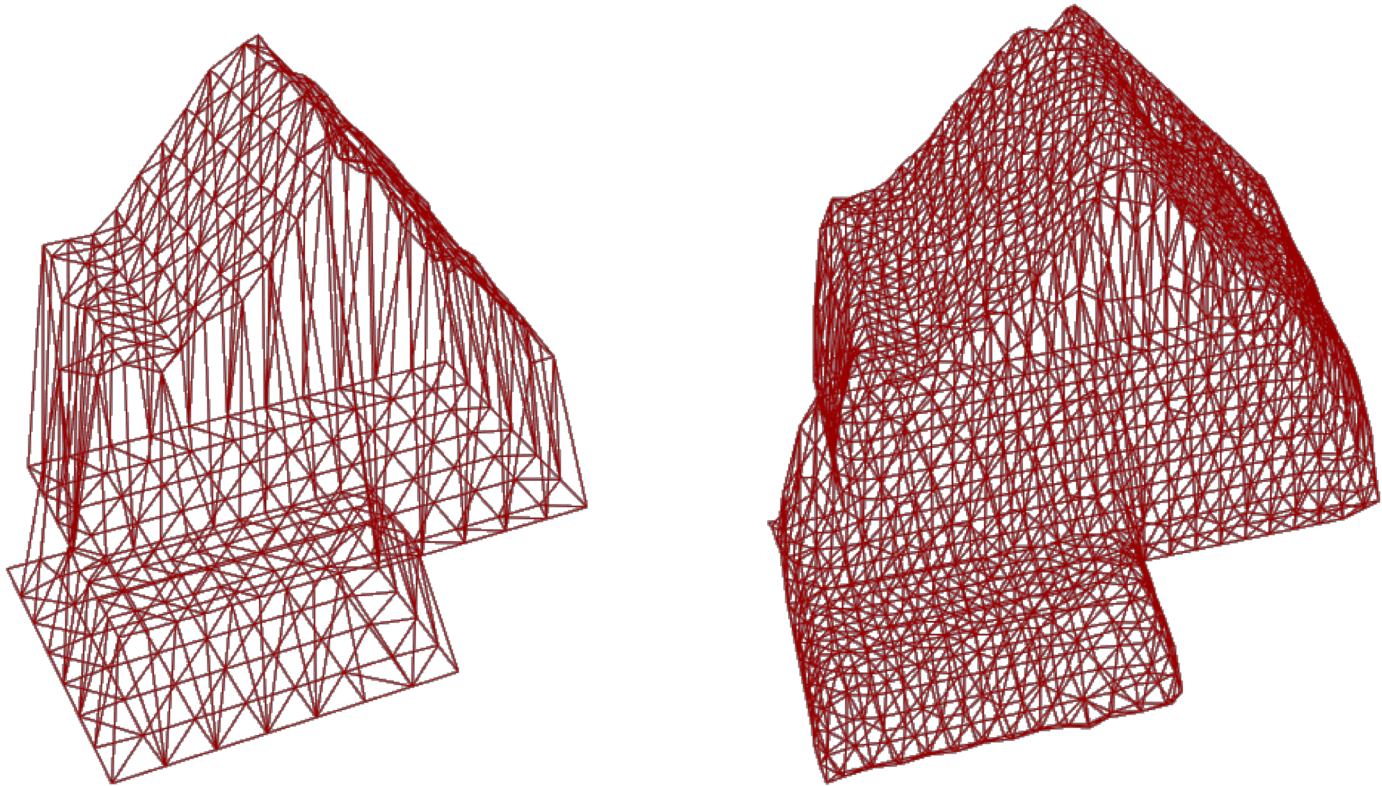
Create building mesh: LiDAR point cloud + footprint



Delaunay triangulation



Mesh refinement



Start in controlled environment: Synthetic building models

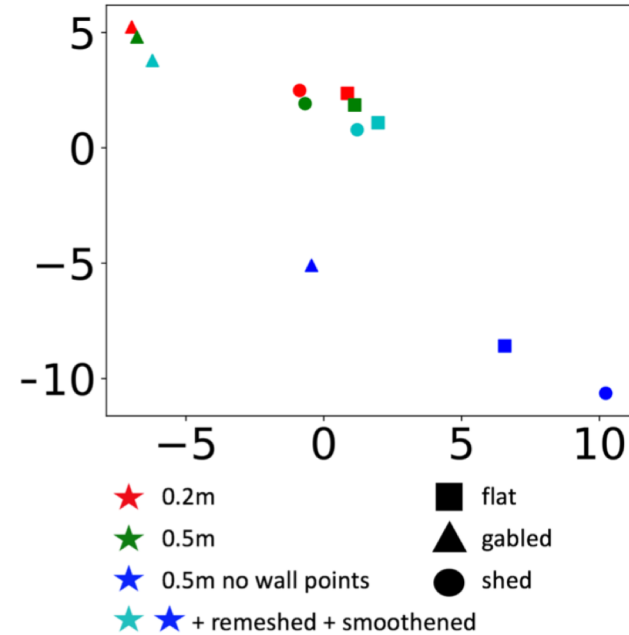
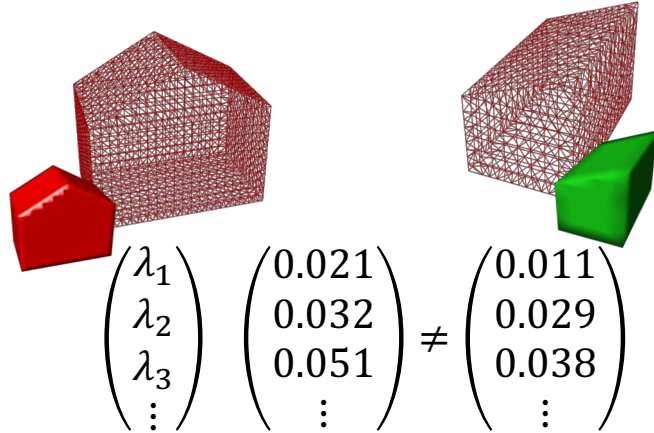


Figure 5. MDS plot of Shape DNA of synthetic building models. The legend shows the grid spacing of the meshing and different roof types of the models. It is clearly visible that remeshing and smoothing of the models without wall points increases the accuracy of the extracted Shape DNA.

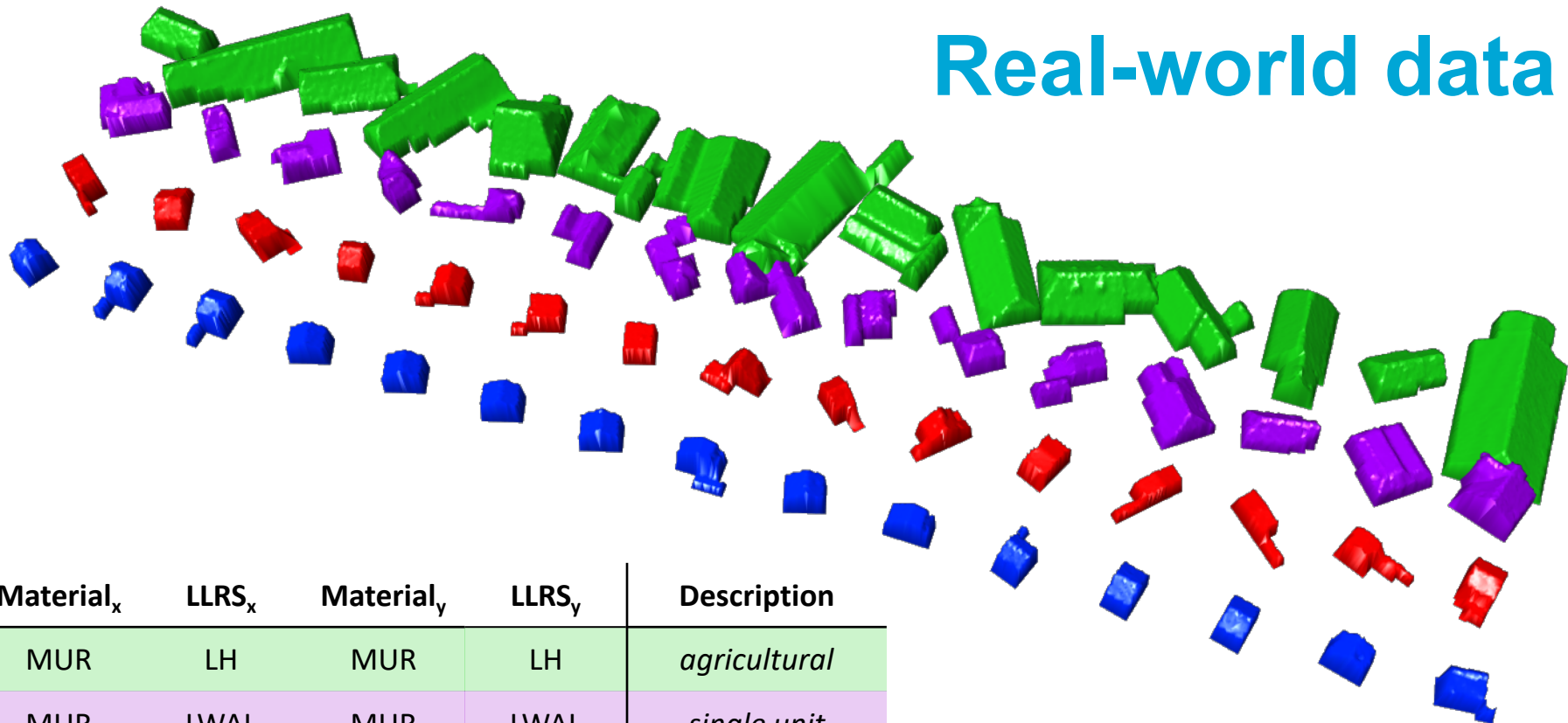
Classification:

Synthetic building models

Samples per class	Extension in m^3	Accuracy in %
100	0	93.2
100	1	90.1
100	4	79.7
100	9	75.0
100	{ 0, 1, 4, 9 }	66.3
200	{ 0, 1, 4, 9 }	74.3
300	{ 0, 1, 4, 9 }	77.6
400	{ 0, 1, 4, 9 }	79.6

Table 1. Results of roof type classification

Real-world data



Material _x	LLRS _x	Material _y	LLRS _y	Description
MUR	LH	MUR	LH	<i>agricultural</i>
MUR	LWAL	MUR	LWAL	<i>single unit</i>
MUR	LWAL	MUR	LN	<i>terraced</i>
CR	LWAL	CR	LN	<i>terraced</i>

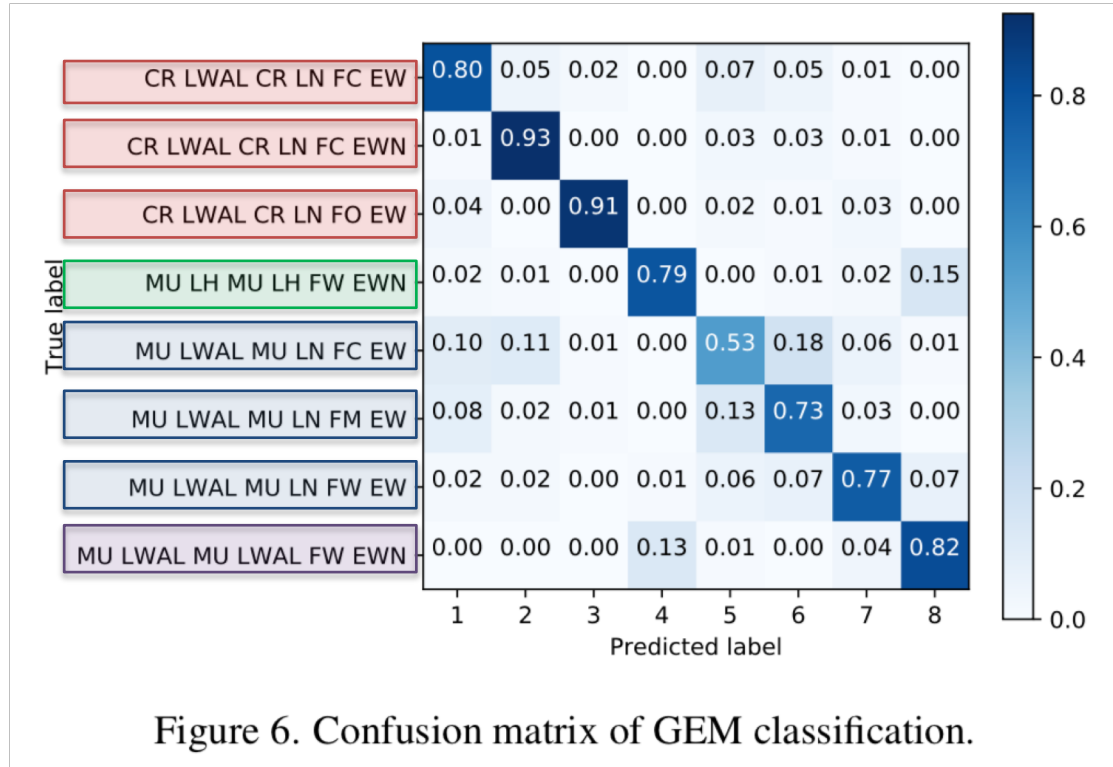
Classification:

Real-world data

2D		3D					Semantic	Accuracy in %
fparea	peri-meter	gutter height	rcount	rangle	sarea	Shape DNA	yoc	
•	•							60.1
•	•						•	75.5
•	•				•		•	78.3
•	•	•	•	•	•		•	79.6
•	•					•	•	75.3

Table 2. Results of SBST classification

Classification: Real-world data



Conclusion – SBST classification

- GEM attributes in our dataset can be predicted with high accuracies, even by only using the **footprint area, perimeter and year of construction**.
- These three features are all explicitly included in the cadastral dataset.

Conclusion – Shape DNA

- Provided that local shape features, such as the footprint area or the number of roof segments can be extracted, they often lead to better results
 - Future Work: Generate semantically structured 3D building model to facilitate local shape feature extraction
- Shape DNA may require a larger number of training samples, which is often problematic and particularly so in SBST classification.
- In situations where a large amount of training data is available and the aim is to classify buildings into uniform geometric groups, Shape DNA can still be useful.
- Furthermore, Shape DNA could be useful in shape retrieval problems, by using the spectrum of real-world buildings to find similar building models, e.g. in a 3D model database.

Bibliography

1. GEM Foundation [2017], 'Global earthquake model.
URL: <https://www.globalquakemodel.org/>
2. Reuter, M., Wolter, F.-E. and Peinecke, N. [2006], 'Laplace-beltrami spectra as 'shape-dna' of surfaces and solids', *Comput. Aided Des.* **38**(4), 342– 366.
URL: <http://dx.doi.org/10.1016/j.cad.2005.10.011>