Detecting damage in masonry arch railway bridges

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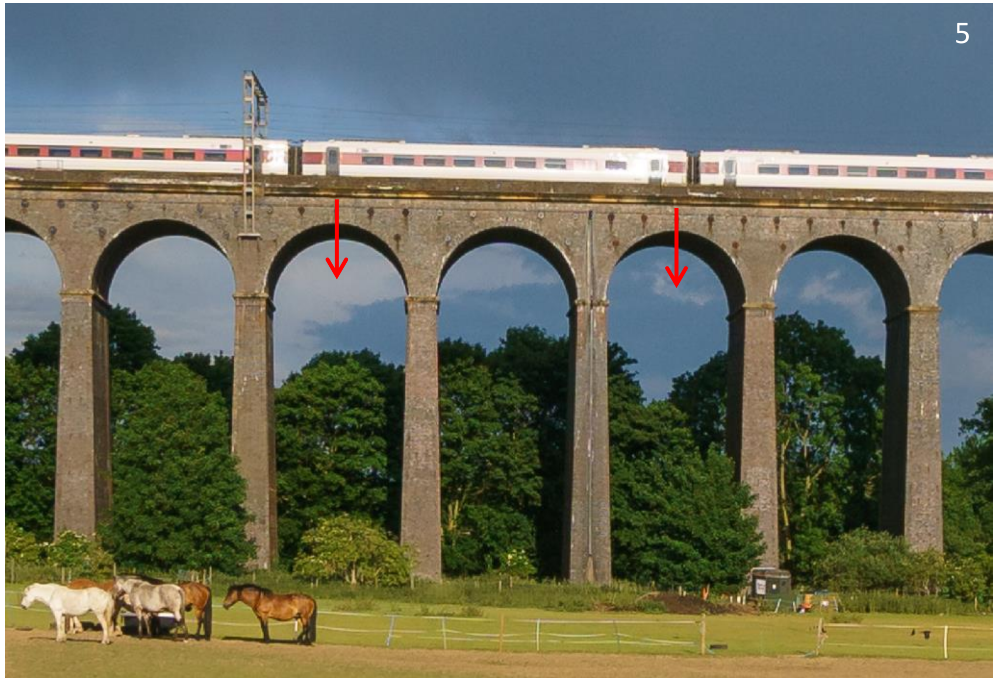
Masonry arch bridges

- 40% of the railway bridges in the UK [1]
- Many constructed during the 19th century [1]
- Subjected to different loads today:
  - Loads up to ten times higher [2]
  - Carriages twice as long [3]
  - Speeds twice-thrice as much [4]
- Cracking, spalling and loose material common



[1] Orban (2004), [2] Masterton (2016), [3] Bradley (2016), [4] Bozyigit and Acikgoz (2022), [5] Wikipedia, Digswell Viaduct

Reasons for damage

Rank	Type of damage[A] [1]
1.	Waterproofing damage[C]
2.	Material ageing
3.	Detachment, movement of wing walls
4.	Detachment, movement of spandrel walls
5.	Abutment, pier, foundation problems

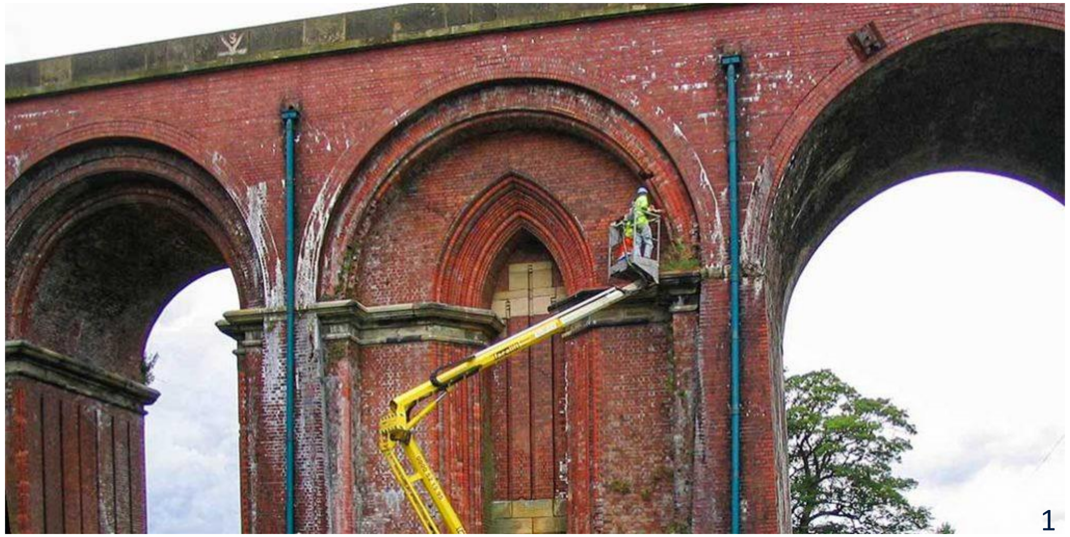
[2]

- Cracking due to foundation movements (loading or scour)
- Spandrel wall cracking due to loading
- Material degradation due to water ingress (efflorescence, staining and spalling)

[1] Orban, 2004, [2] Malena et al., 2021

Damage detection (practice)

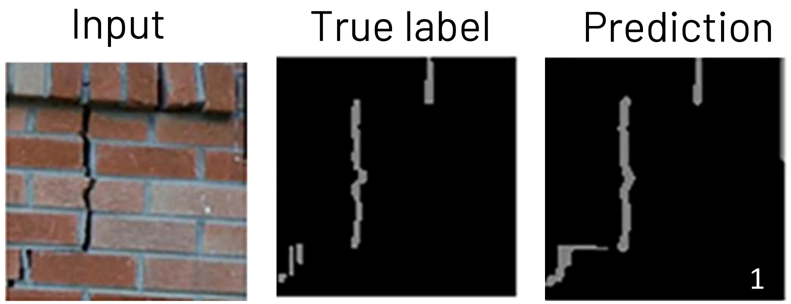
- Periodic visual and tactile on-site inspections.
- Exploration of technological solutions to improve inspections:
  - Laser scanning
  - Photogrammetry
- Monitoring to understand the impact of damage on bridge response.



[1] Sandberg, 2023, [2] Bill Harvey Associates, 2016,
[3] Helmerich et al., 2012

Damage detection (research)

- Application of machine learning tools to detect and classify defects from images.
- Requires large labelled training datasets.
- Sensitive to mortar joints, surface defects and light conditions.
- Focussed on visible damage (e.g. uses brightness change around cracks). Local information – significance unclear.



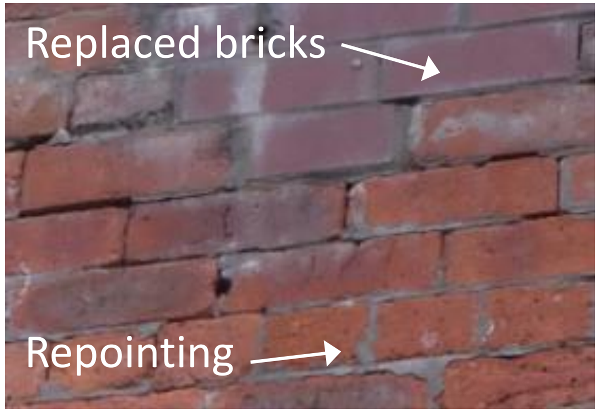
[1] Dais et al., 2020, [2] Brackenbury. 2022

Hidden damage

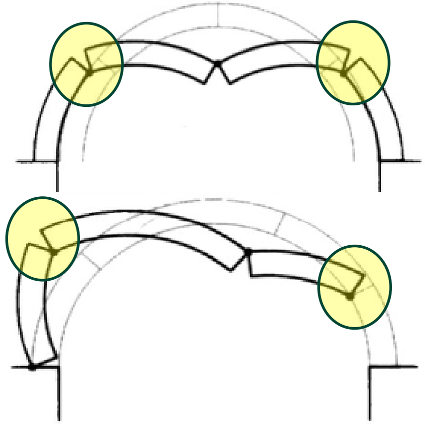
- Damage may be hidden by repair:
  - Replacements
  - Repointing
  - Renders

- Damage may be hidden as it is internal (e.g. extrados cracks).

- The strength of the material may have reduced without apparent changes in its visual appearance.



[1]



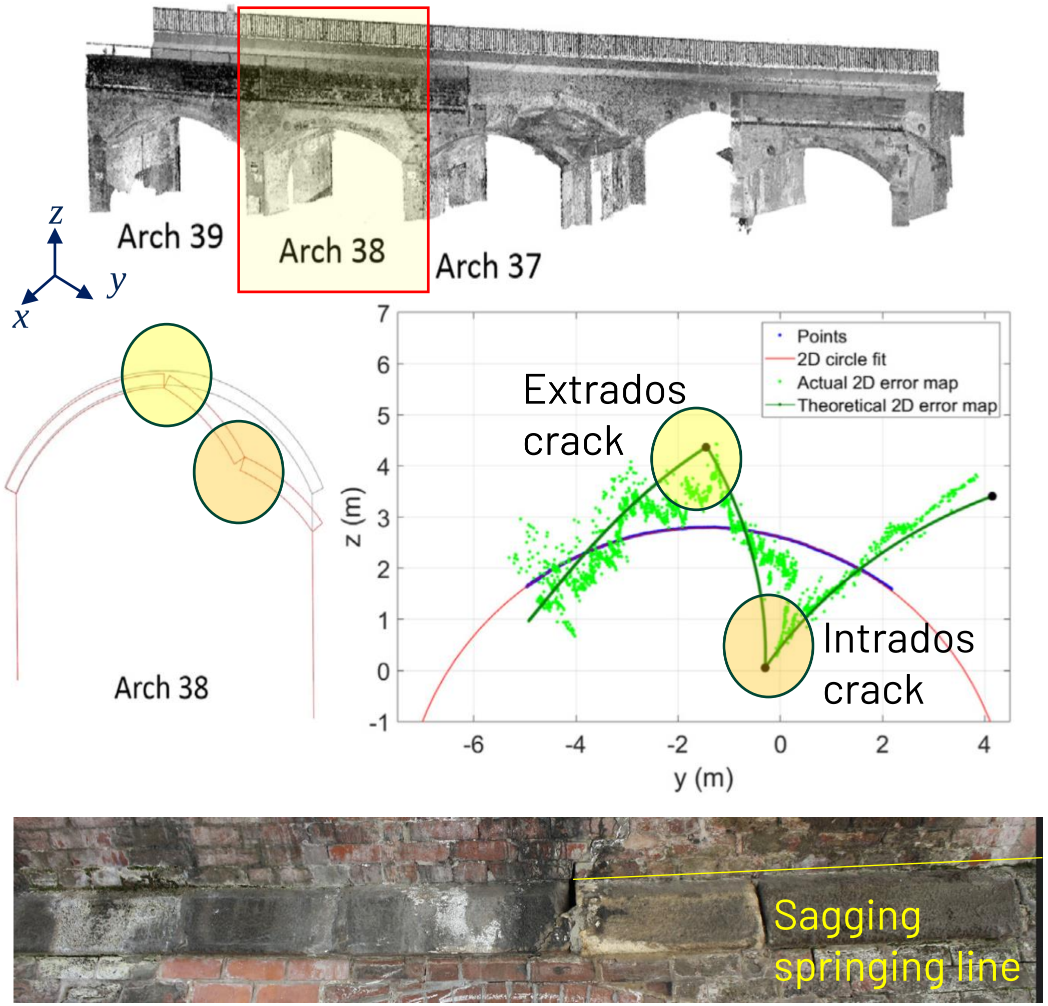
Extrados cracks not visible from soffit

[1]

[1] Ashurst, 2011.

Identify hidden damage - I

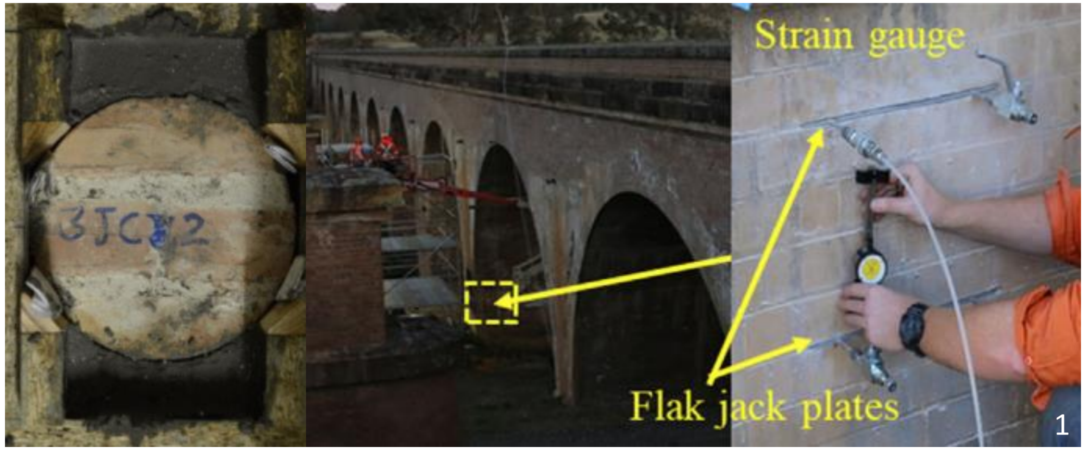
- Geometric distortions include: change in curvatures, unaligned joints.
- Surface repairs do not affect underlying geometric distortions in the bridge.
- Internal damage causes distinctive geometric distortions on the surface.
- Can highlight significant structural defects but current algorithms are case-specific.

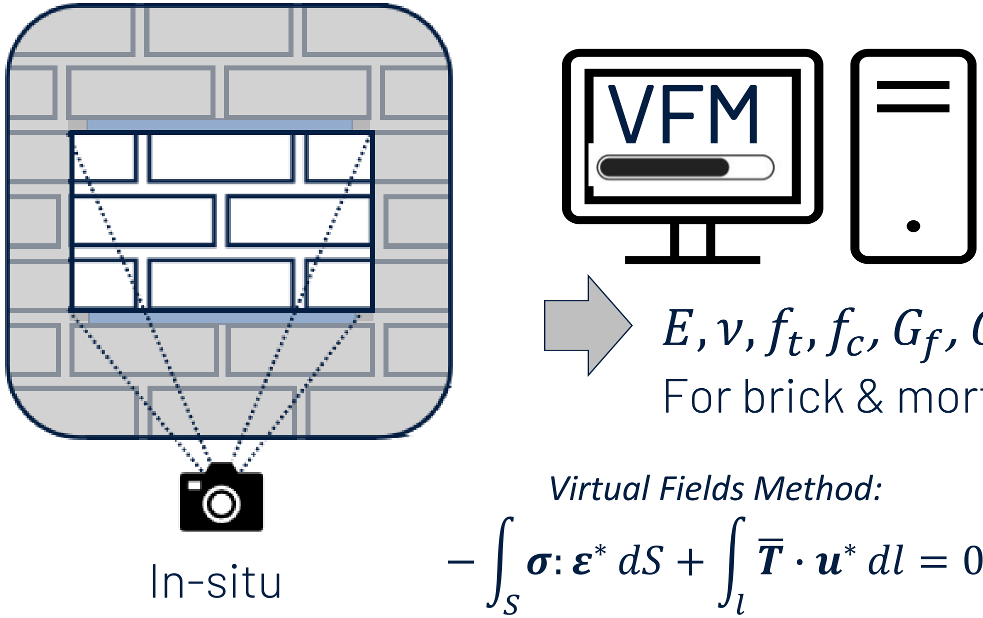


[1] Ye et al., 2018.

Identify hidden damage - II

- Material degradation 'hidden'; needs to be quantified via elasticity, strength and post-peak parameters from load tests.
- Sampling mortar unfeasible. Cored sample tests provide insufficient data.
- In-situ flat jack testing and inverse identification an option. May require running thousands of analyses[2].
- Need a rapid solution that can inform modelling and repair decisions.





$E, \nu, f_t, f_c, G_f, G_c$

For brick & mortar.

Virtual Fields Method:

$$-\int_S \boldsymbol{\sigma} : \boldsymbol{\varepsilon}^* \, dS + \int_l \overline{\boldsymbol{T}} \cdot \boldsymbol{u}^* \, dl = 0$$

 [1] Dorji et al., 2021., [2] Chisari et al., 2015.

Research directions

I. Geometric crack detection

- We want to use geometric distortions to enable robust (light and surface treatment independent) crack (incl. hidden ones) detection.

Subject of today's talk, ongoing work

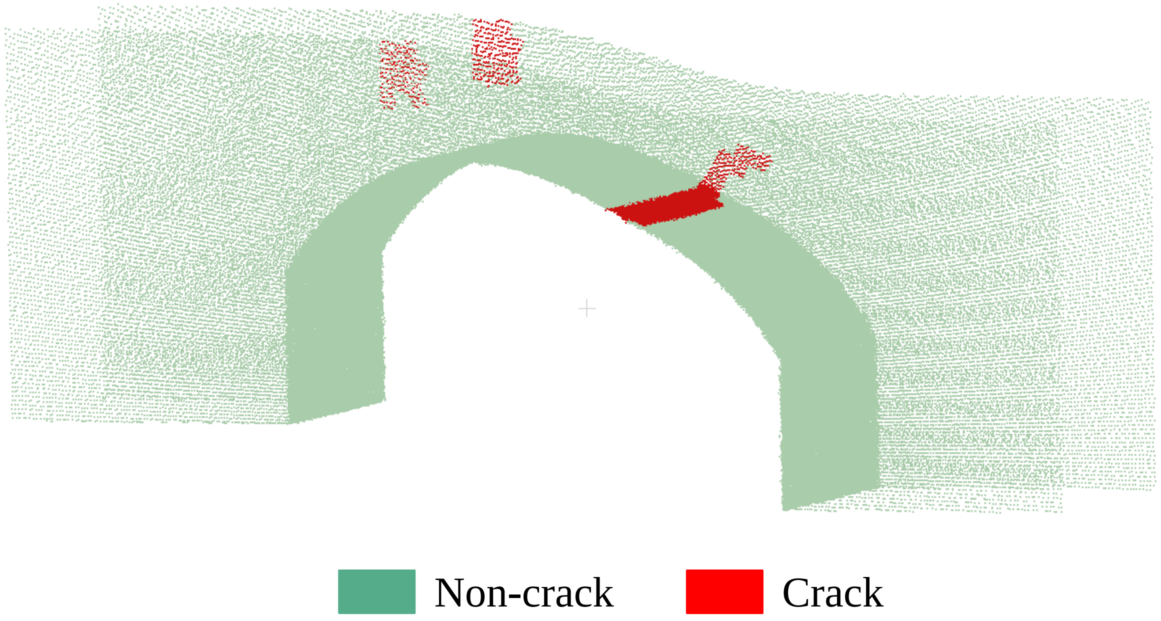
II. In-situ material identification

- Virtual Fields Method (VFM) identifies all constitutive parameters directly from strain measurements.
- Can identify brick and mortar properties simultaneously.
- Can handle in-situ loading uncertainty.

EPSRC funded ongoing MINT project, another talk.

Geometric crack detection

- Laser scanning commonly used to generate 3D point cloud models.
- Can we use the data to train a machine learning model to detect cracks?
- Data is unlabelled and true labels are not known. Data volume insufficient.

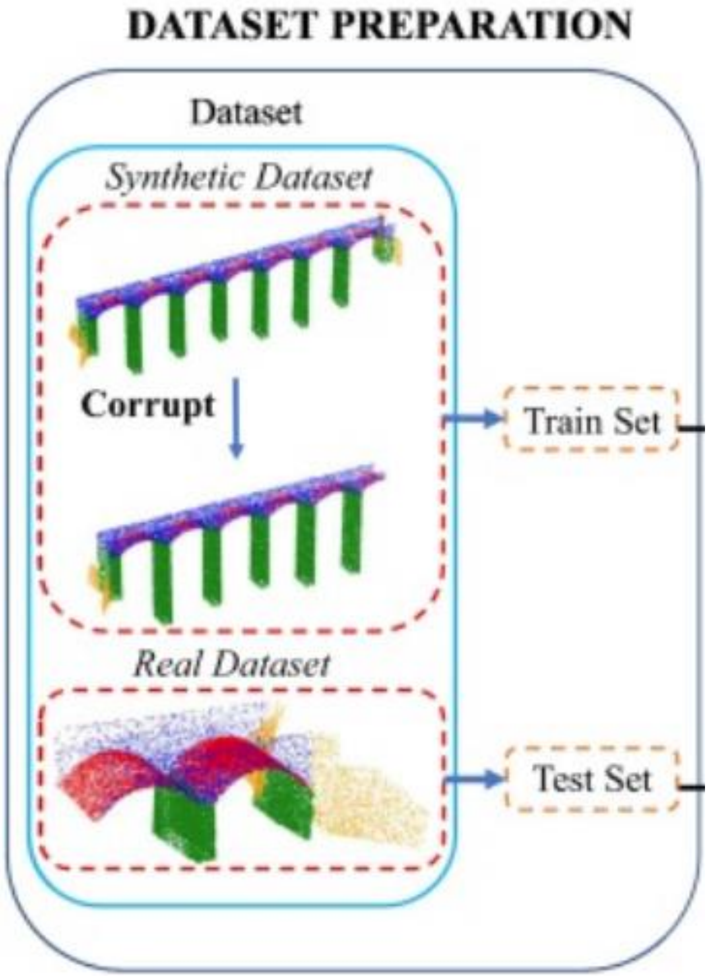


Synthetic data generation

- In a previous study, we trained a deep learning model to conduct semantic segmentation of bridge point clouds using synthetic data that we generated.

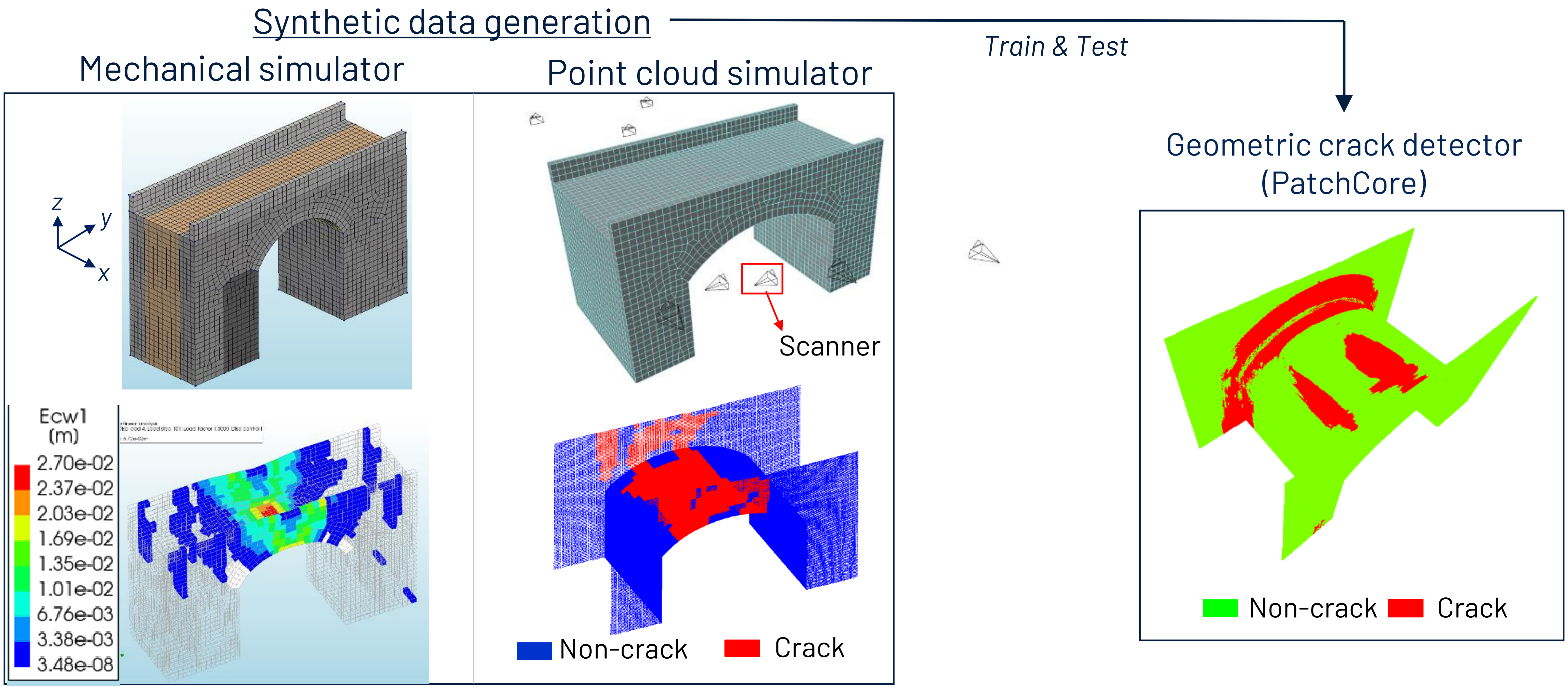
- We then tested the model using real data and achieved state of the art accuracy.

- Can we simulate geometric distortions and laser scan data collection realistically?



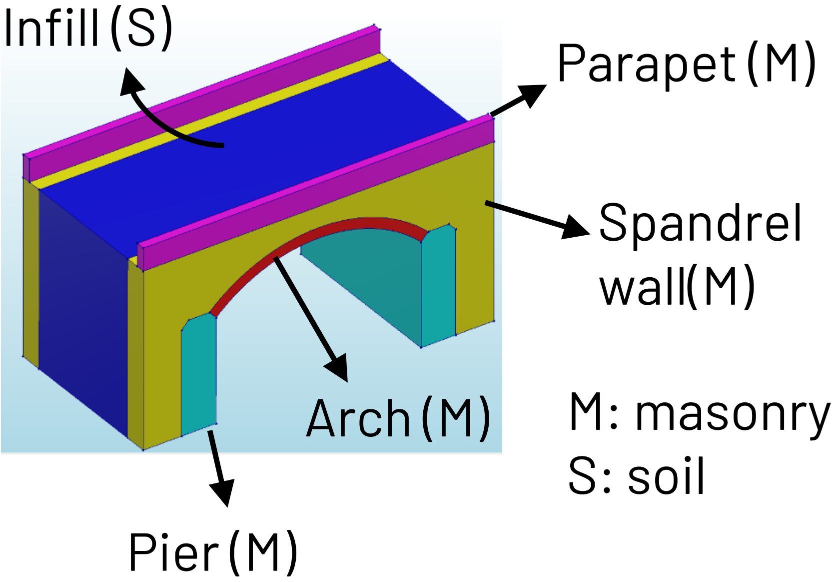
 [1] Jing et al., 2022

Research pipeline

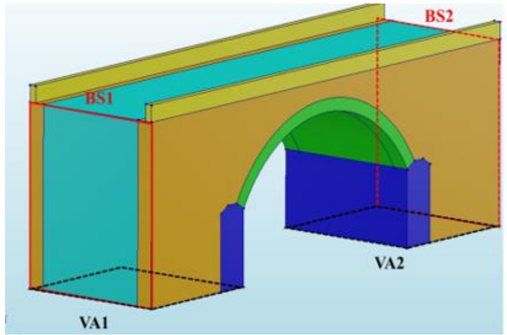


Mechanical simulator I

- Only single-span bridges (85% of stock)
- Homogenised masonry (easy meshing and computational efficiency)
- Masonry: Total strain based rotating crack model
- Soil: Drucker-Prager plasticity with K_0 initialization
- Interfaces between components



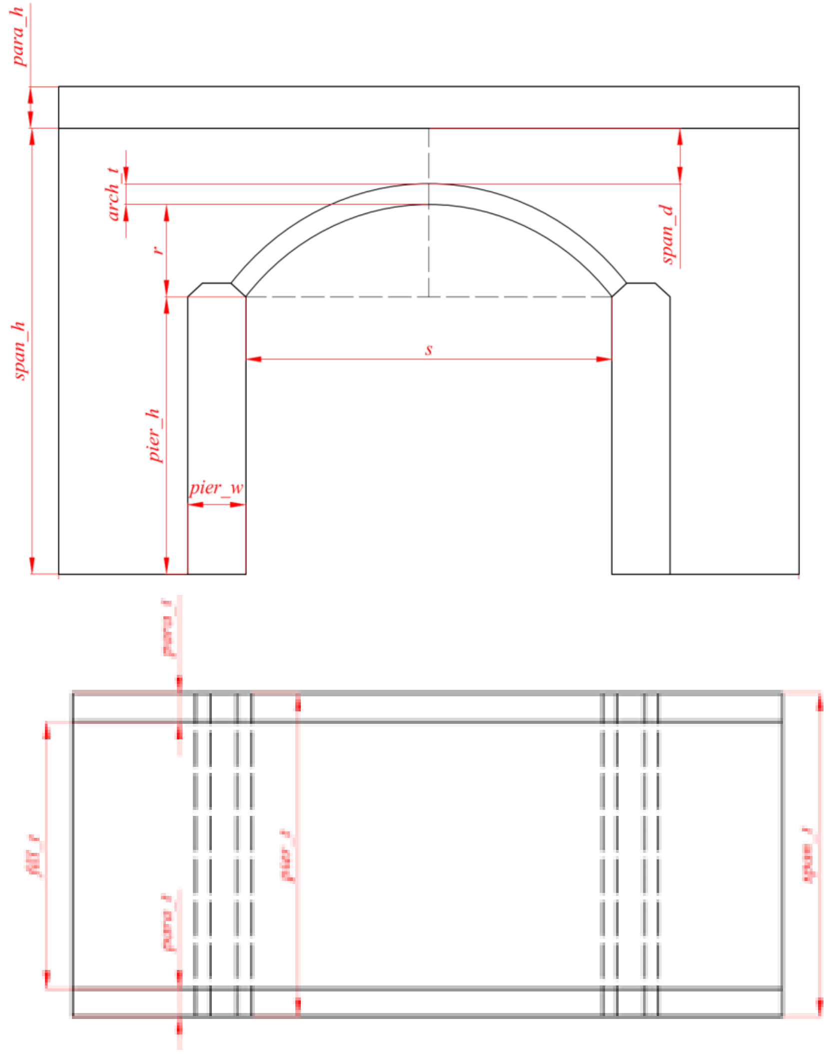
M: masonry
S: soil



BS1/2: normally fixed
VA1/2: fixed

Mechanical simulator II

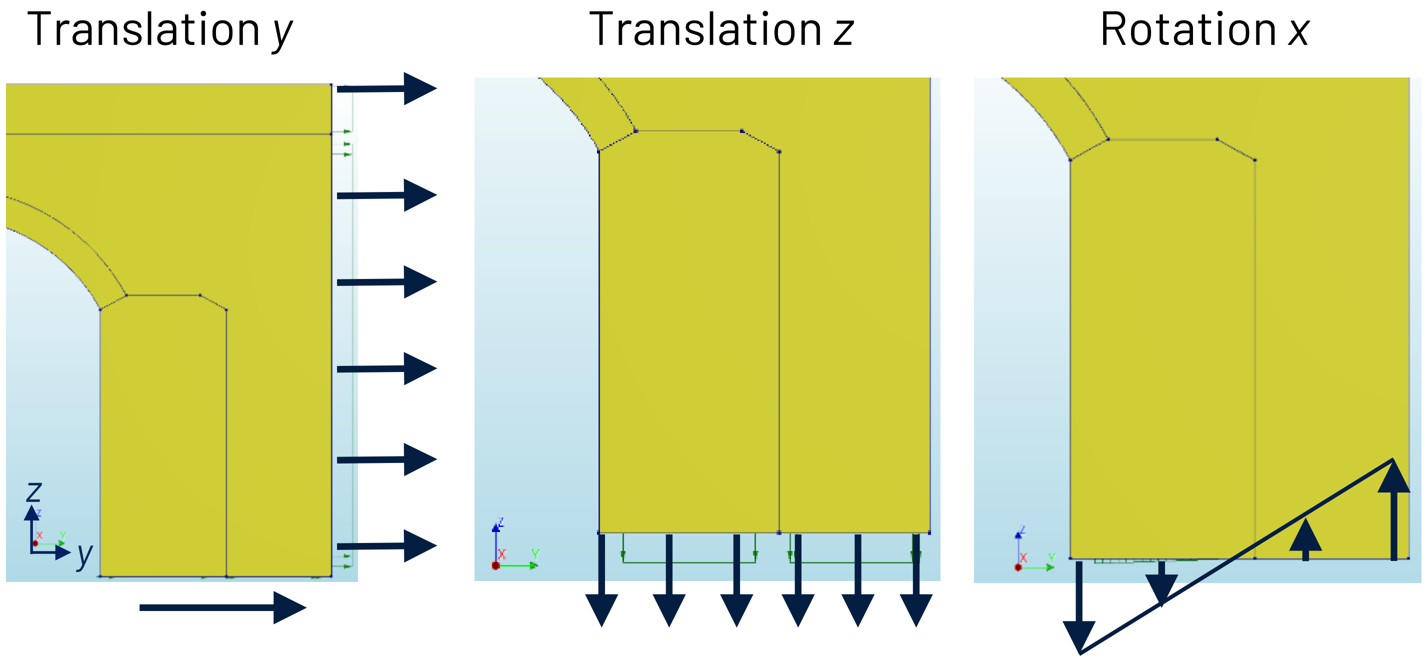
- Bridge geometry parametrically defined.
- Geometry obtained randomly from ranges by Brencich et al. (2007) and Oliveira et al. (2010).
- Material properties randomly from Giardina et al. (2015).
- Model generation automatic.



Mechanical simulator III

- Model foundation movements
  - 5^{th} most common damage source (Orban, 2004)

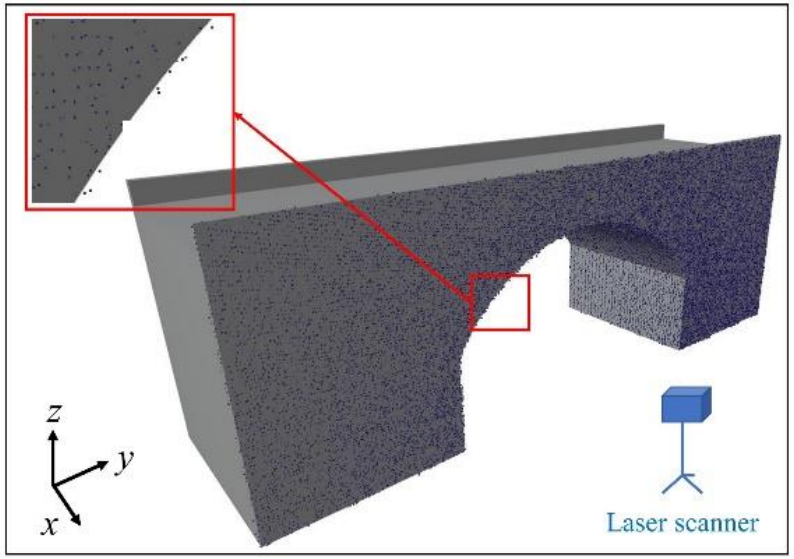
- Translation in *z or y* and rotation in *x*-axis randomly combined.



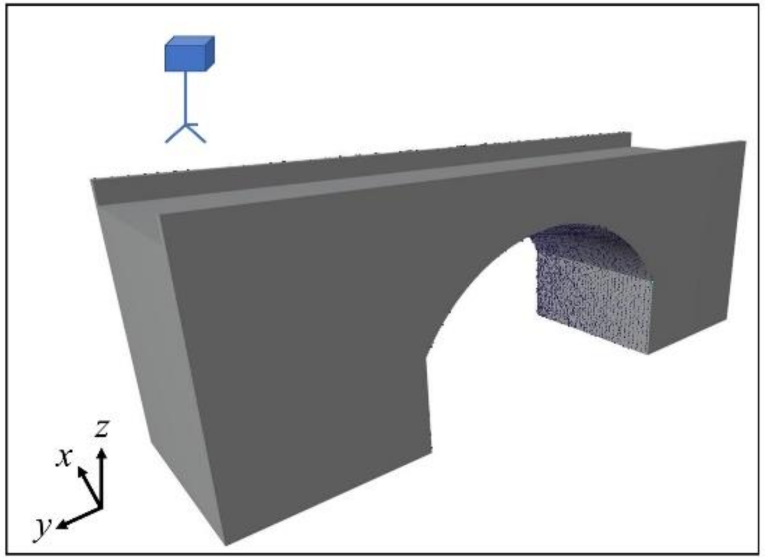
Point cloud simulator I

- Simulate laser scan data collection process using *ray tracing*.
- Laser scan position parametrically defined and randomly assigned.

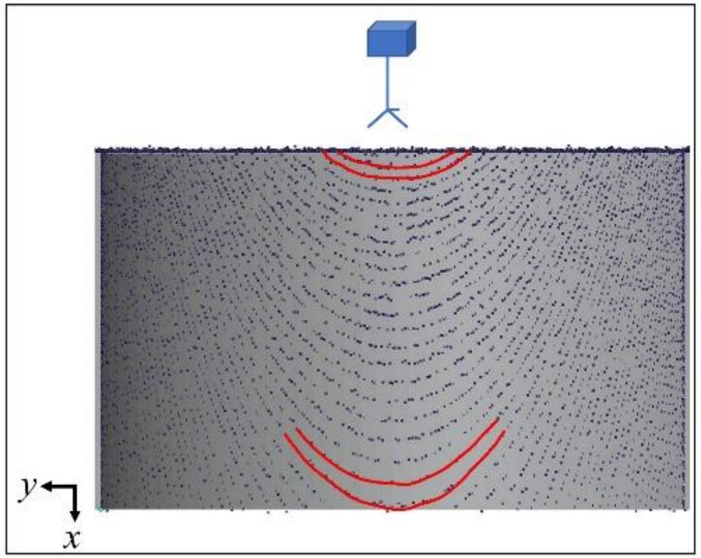
Measurement Noise



Occlusion

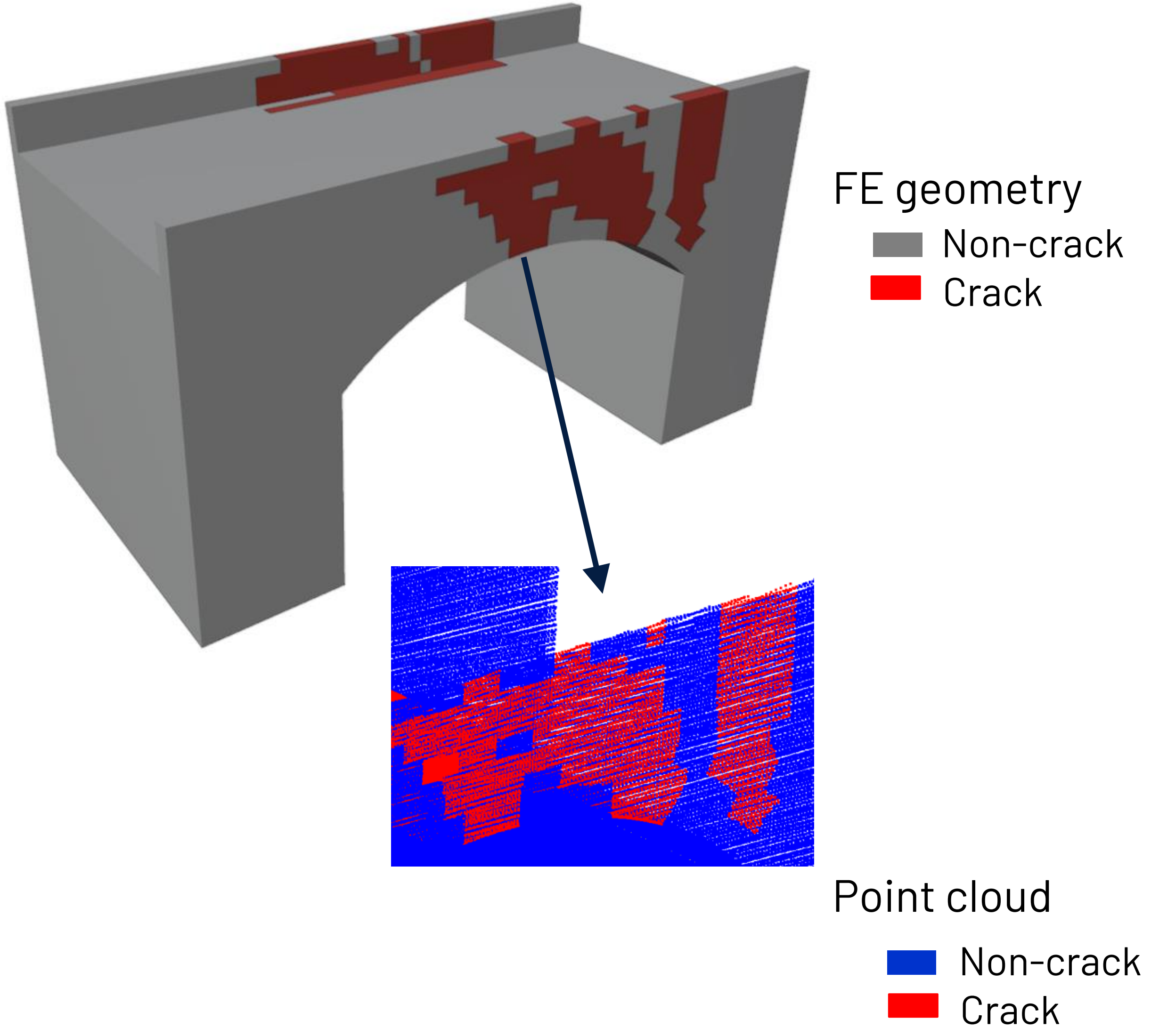


Varying point density



Point cloud simulator II

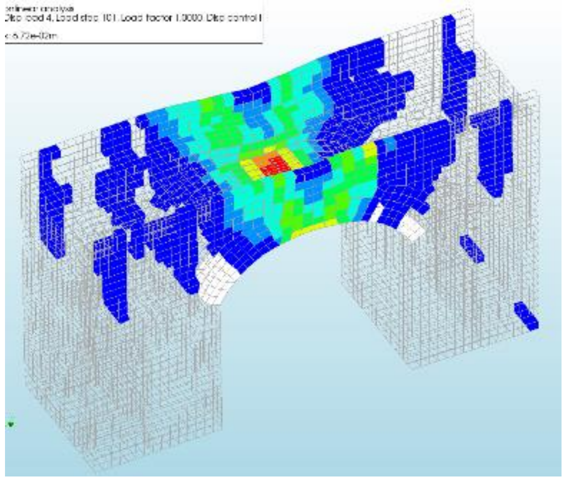
- Geometries in the 3D environment are constructed using finite element deformed positions.
- Elements with a crack width at element centre greater than 5mm are labeled as 'crack'.
- Point clouds inherit labels.

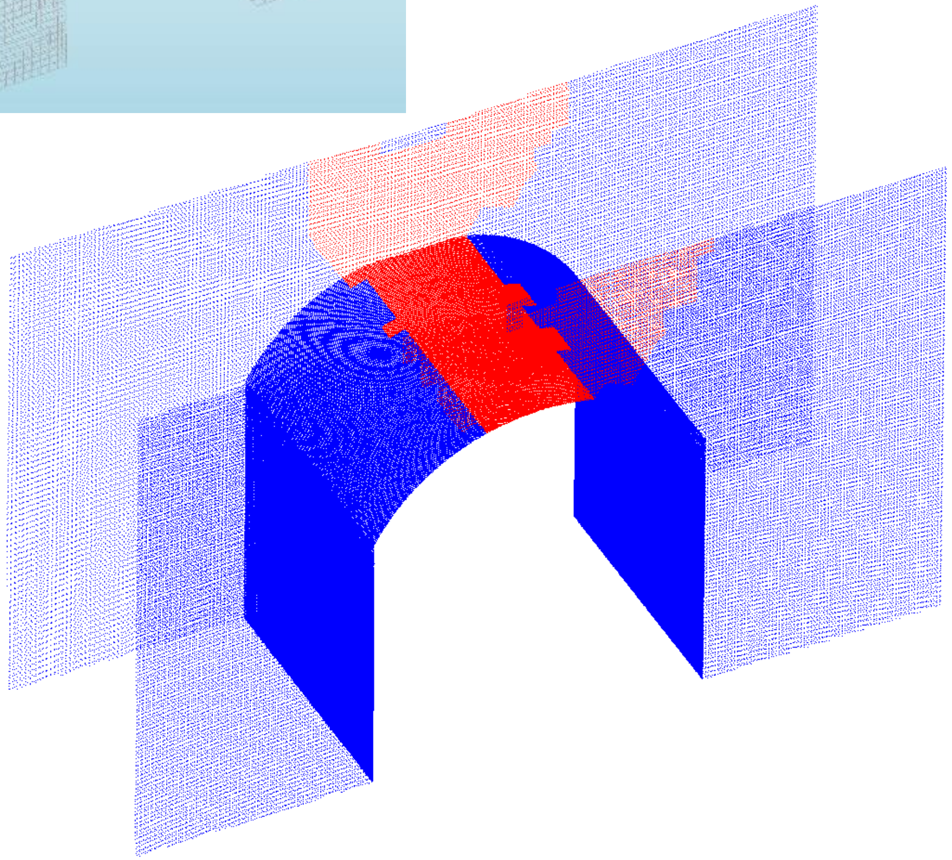


Synthetic data

- Over 200 bridge models generated and analysed automatically.

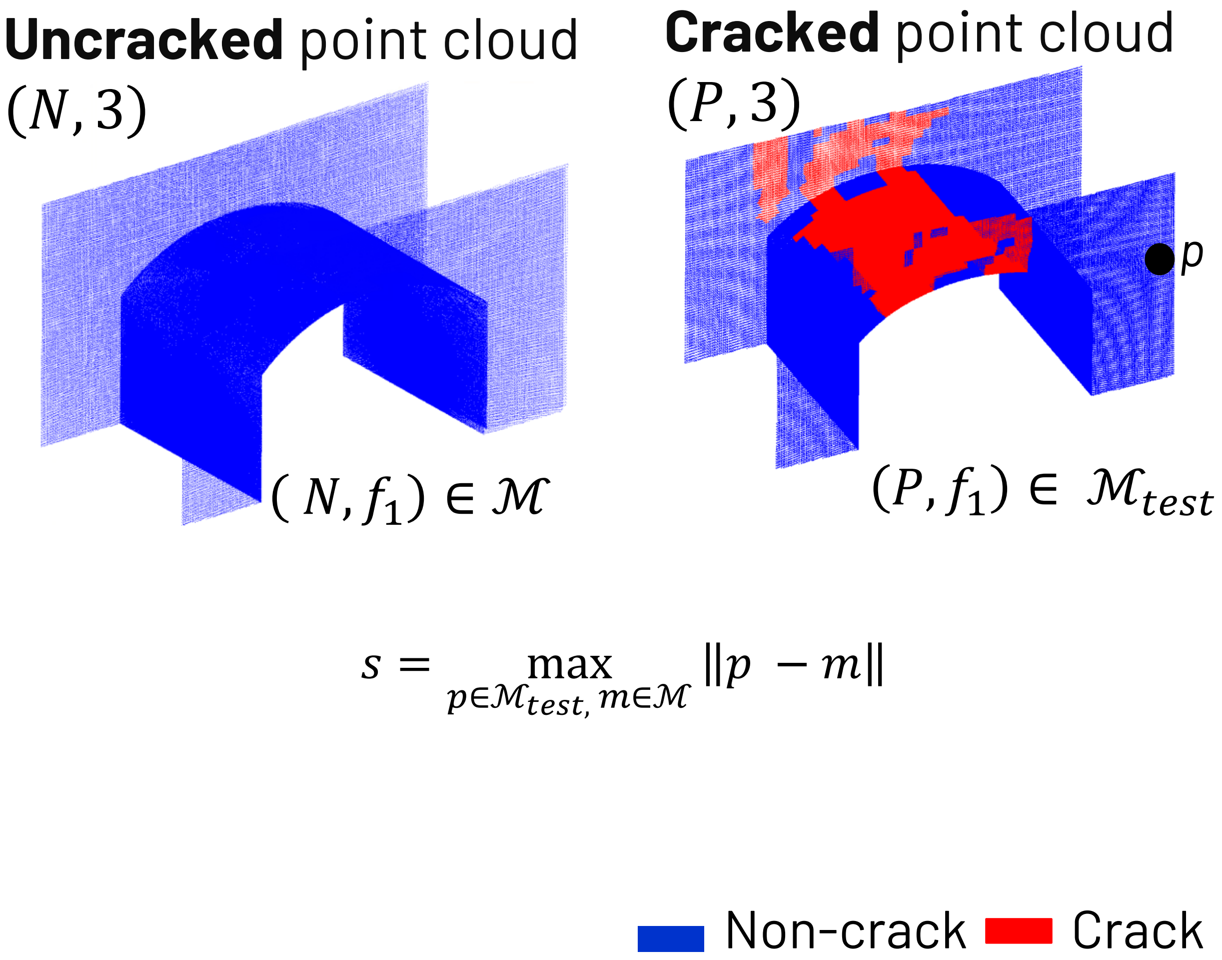
- Labelled point clouds of these obtained at various stages of loading (including undeformed and final stage)





Geometric crack detection |

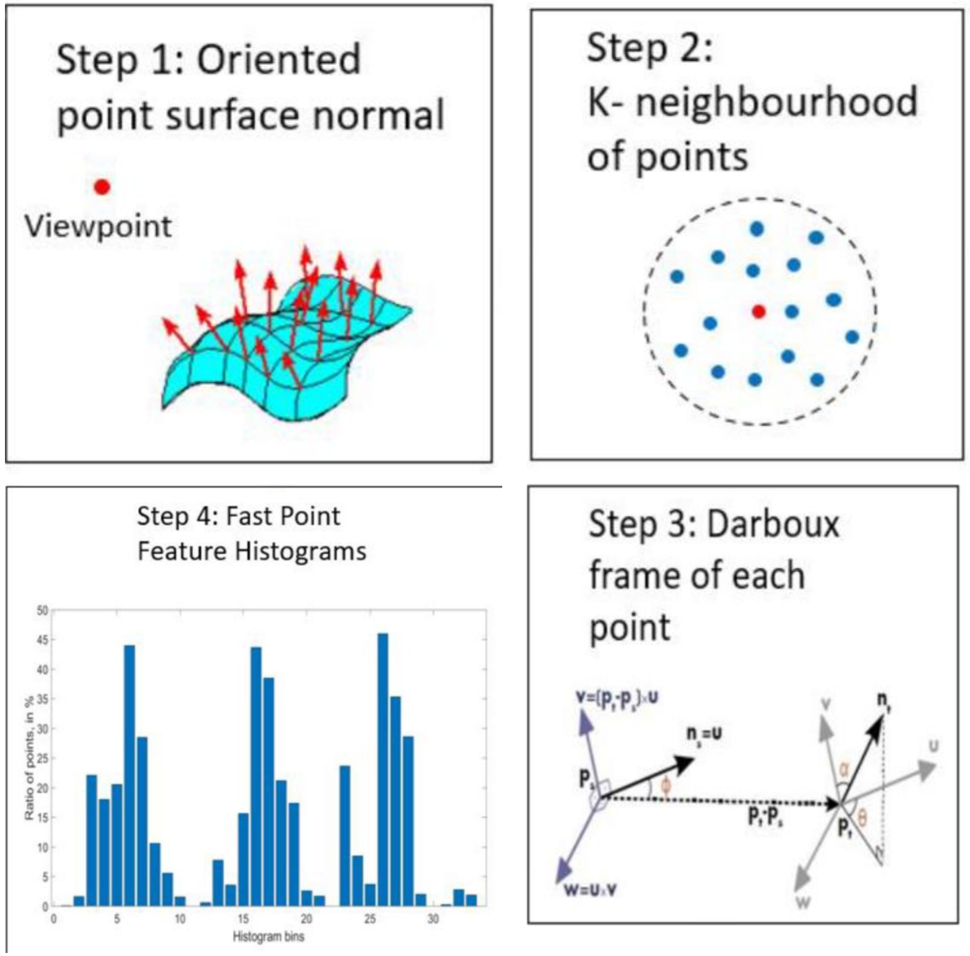
- Anomaly detection technique called PatchCore. Unsupervised learning.
- Creates a memory bank *M* of ‘normal geometric features’ from uncracked point clouds.
- Point *p* in cracked cloud matched to nearest memory bank cluster *m* and an anomaly score *s* calculated.



$$s = \max_{p \in \mathcal{M}_{test},\, m \in \mathcal{M}} \|p - m\|$$

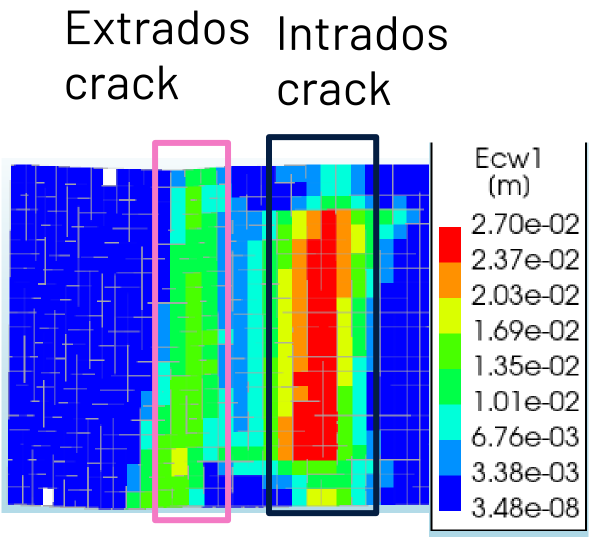
Geometric crack detection II

- Geometric features represented by Fast Point Feature Histograms (FPFH).
- Features encode statistical data on normal and geodesic curvature and geodesic torsion.
- Invariant to translation and rotation.

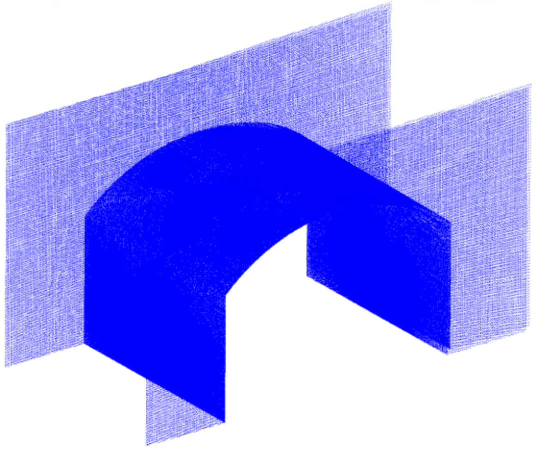


Example case I

- Vertical settlement of pier.
- Point clouds generated at different stages of loading (here, undeformed and final settlement of 7.9cm)

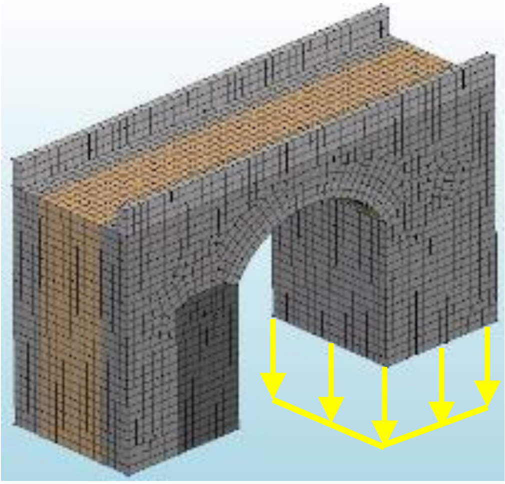


Arch (top view) crack widths

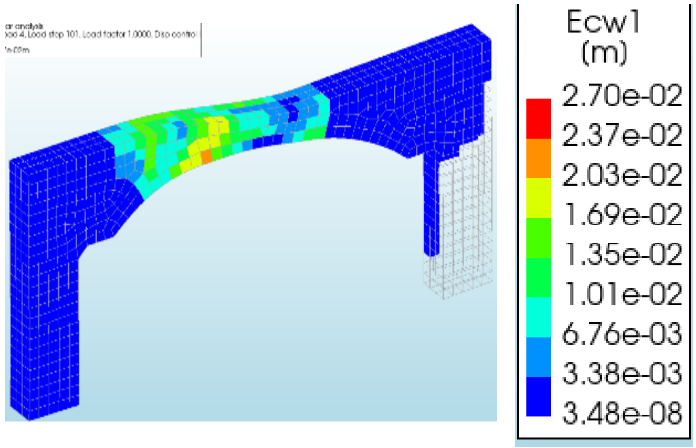


Undeformed point cloud

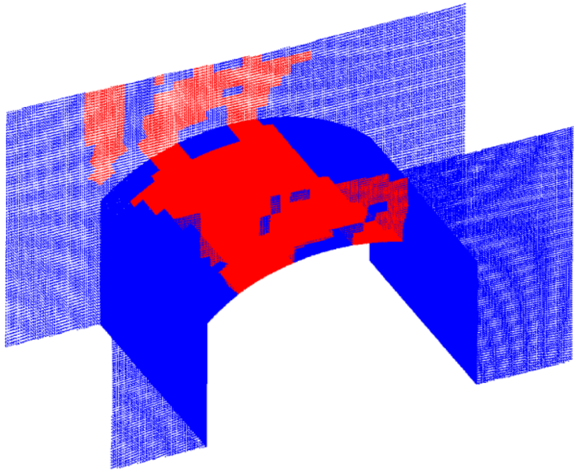
FE model



$\Delta z = 7.9$cm

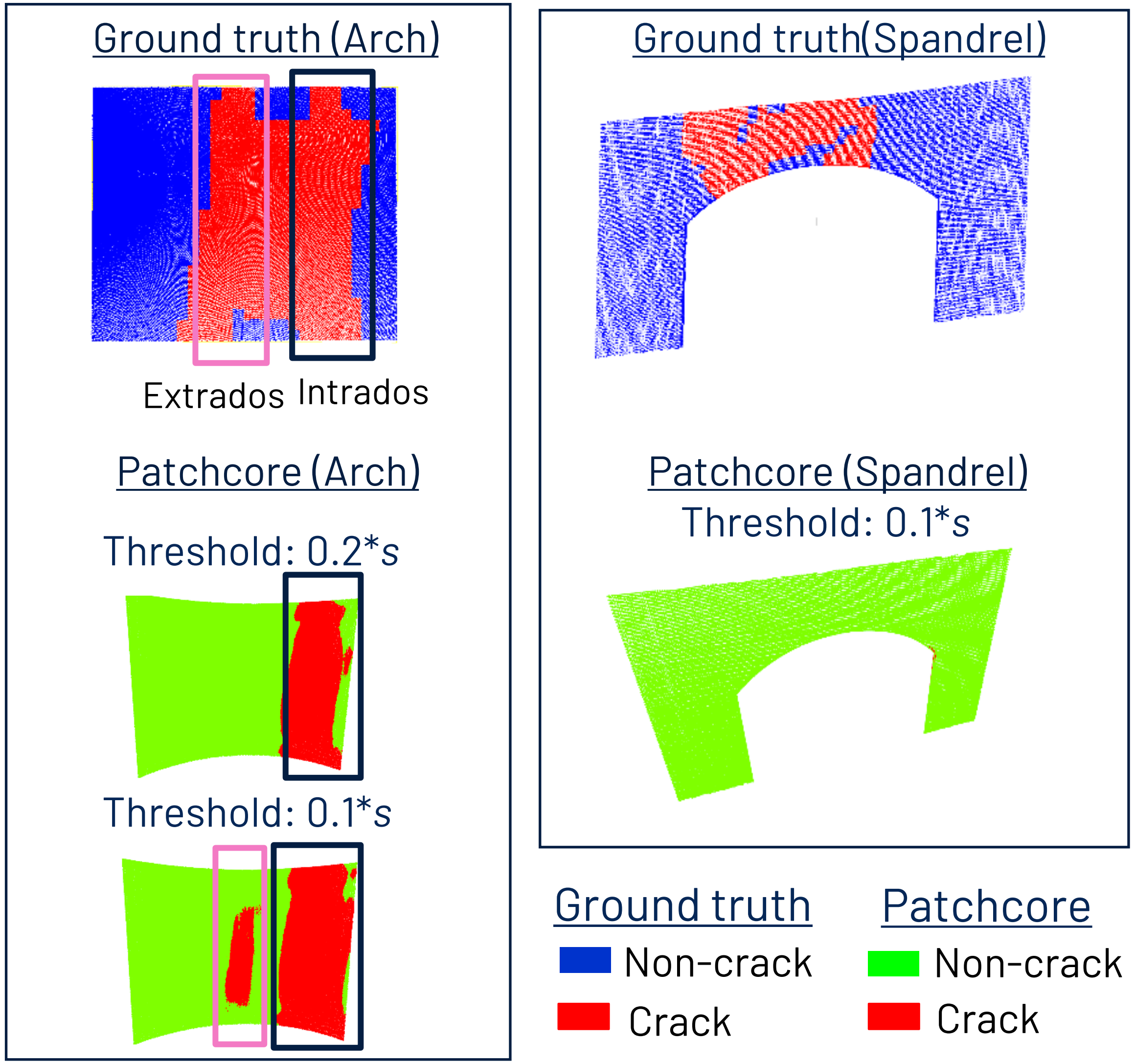


Spandrel (side view) crack widths



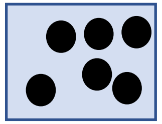
Deformed point cloud

Example case II

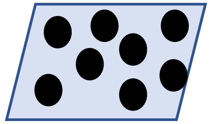


- Arch crack (out of plane): Detected but sensitive to threshold *s*. Possible to detect hidden extrados cracks.
- Spandrel crack (in plane): not detected for any value of *s*.

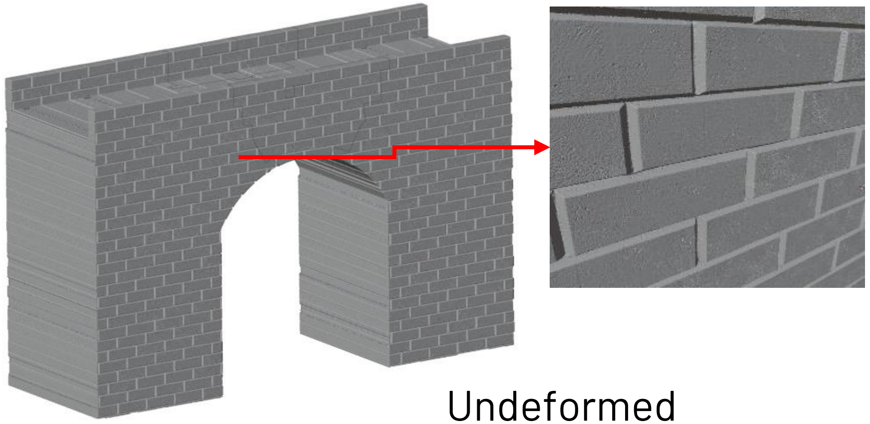
Troubleshooting



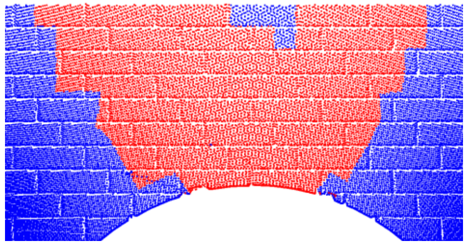
Undeformed planar object (zero normal and geodesic curvature)



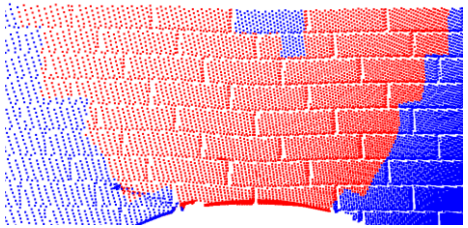
Sheared planar object (zero normal and geodesic curvature)



Undeformed



Deformed



- Cracks due to in-plane deformation do not create curvature variations.
- However, they change the horizontality of bed joints.
- Feature vector which enables positional encoding needed for crack detection. Possible to add colour.

Conclusions

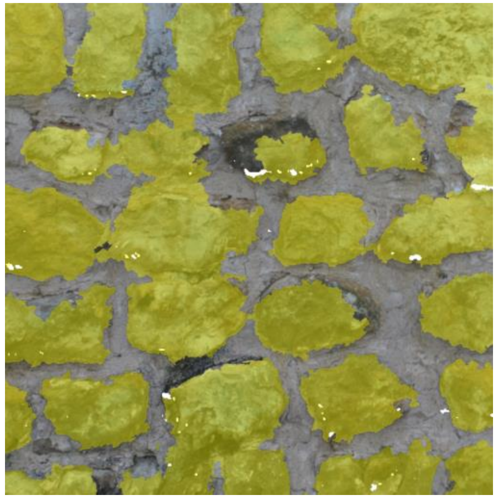
- Explored the new idea of geometric crack detection.
- Mechanical and point cloud simulators developed to create distorted geometry data which reflects real cracking behaviour.
- Crack detection via anomaly detection technique Patchcore: successful for out of plane cracks (including hidden cracks) and a failure for in plane cracks.
- Representation of masonry texture and the adoption of a new feature vector being investigated to improve crack detection.

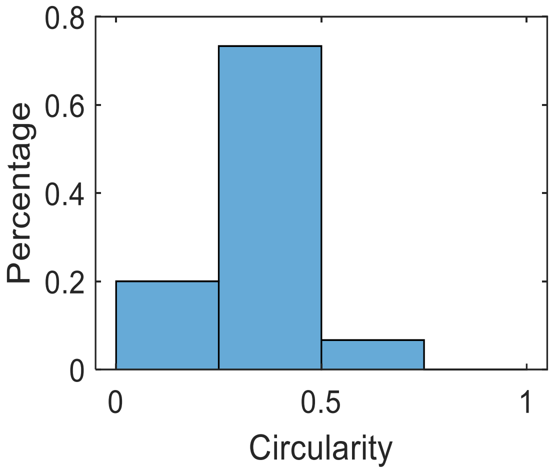
Conclusions (general)

- Defect detection techniques can be developed using data generated through advanced mechanical and 3D modelling techniques.
- This creates the possibility to detect not only visible defects but also hidden ones. It enables a new focus on structural (rather than local) defects.
- The simulators provide a solution to data scarcity in civil engineering and enable the uptake of artificial intelligence algorithms.

Material quality evaluation

- Masonry quality evaluation (segmentation, morphology and defect evaluation)
- To develop quantitative measures of material quality using geometry and colour
- Can be customised for railway applications



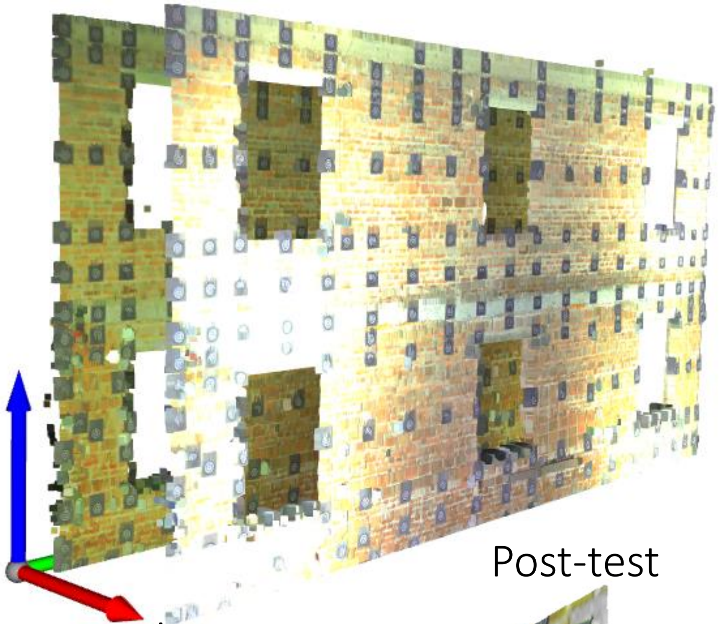


Monitoring - static

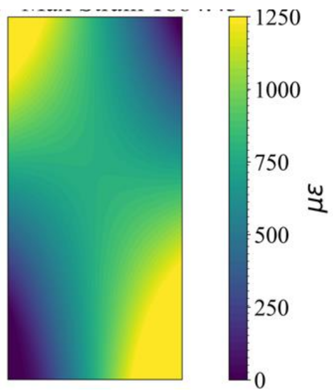
- Bridge owners interested in new cracks forming and old cracks propagating

- Instead of detecting cracks, can we do long-term non-contact monitoring?

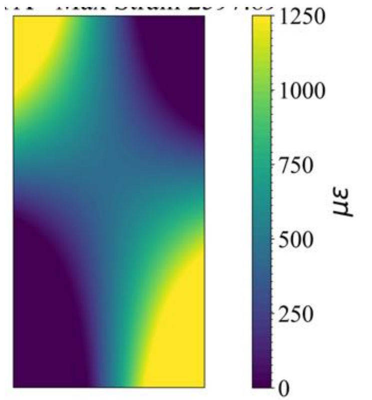
- Comparing point clouds to obtain *full-field* displacements and strains.



DIC strains

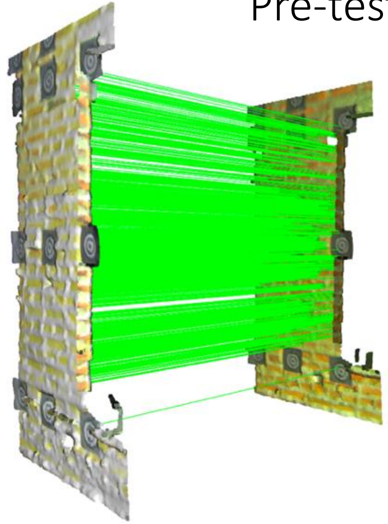


Laser scanning strains



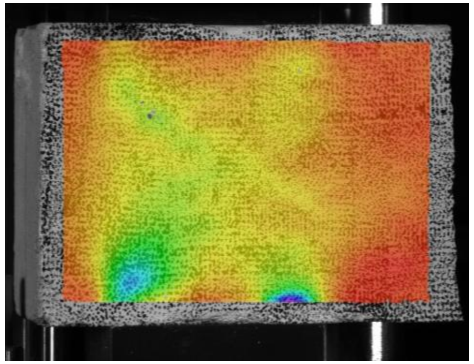
Post-test

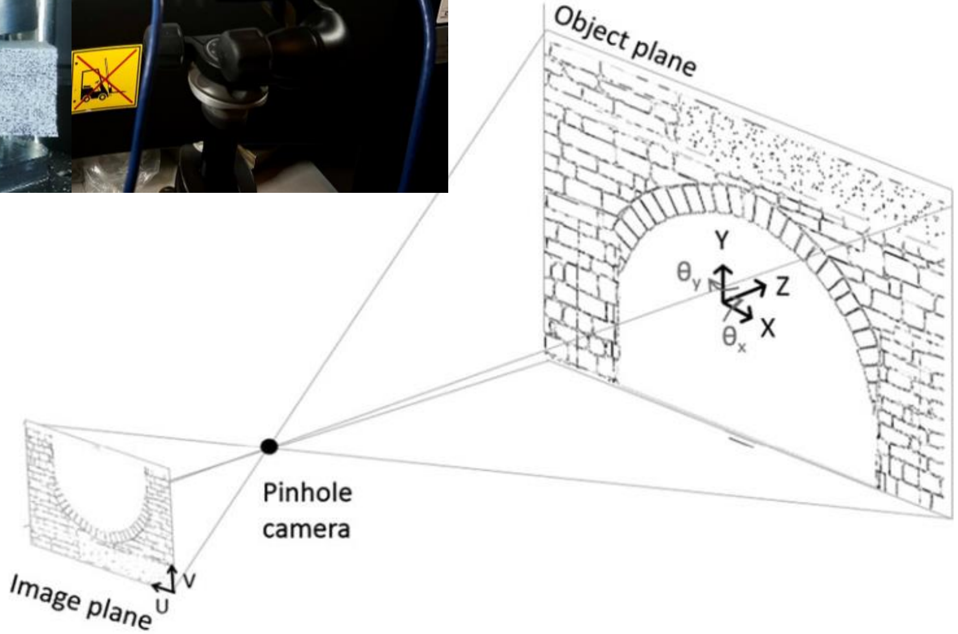
Pre-test



Monitoring - dynamic

- Useful for understanding for response – only when you have enough data.
- DIC a promising tool –3D DIC needed as movement but limited measurement volumes.
- A vision-based system able to resolve 3D motion needed; depth camera systems being explored.





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