“Multimodal Scanning of Cultural Heritage Assets for their multi-layered digitization and preventive conservation via spatiotemporal 4D Reconstruction and 3D Printing”

Spatiotemporal Simulation & Reconstruction, Decision support system

Scan4Reco AUTH Workshop

Presenter:

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Presentation's outline

Scan4Reco approach for:

- *3D Reconstruction of an artwork*
- *Spatio-temporal simulation of ageing*
  - *Ageing simulation for appearance*
  - *Ageing simulation for geometry*
- *Conservation Oriented Decision Support System (DSS)*

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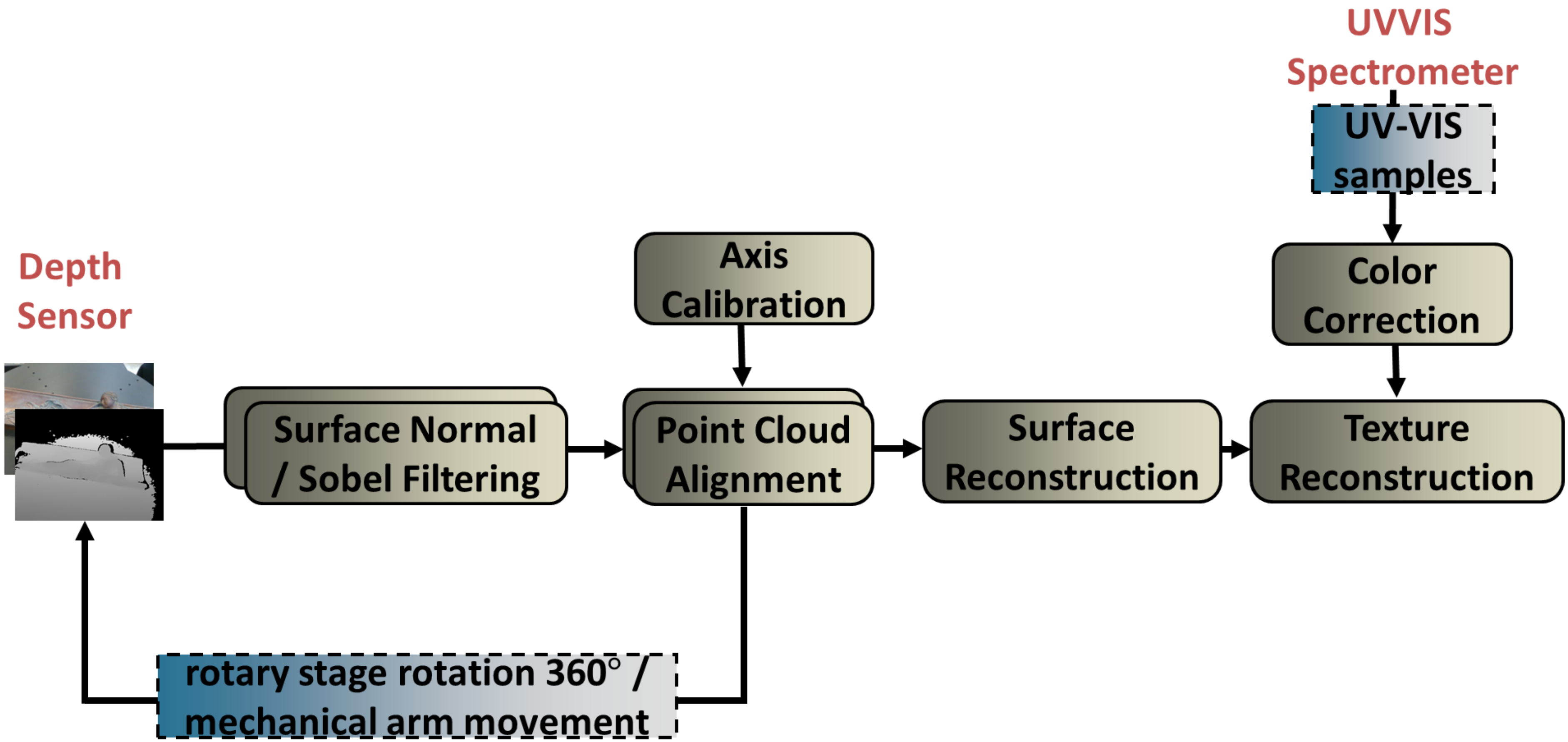
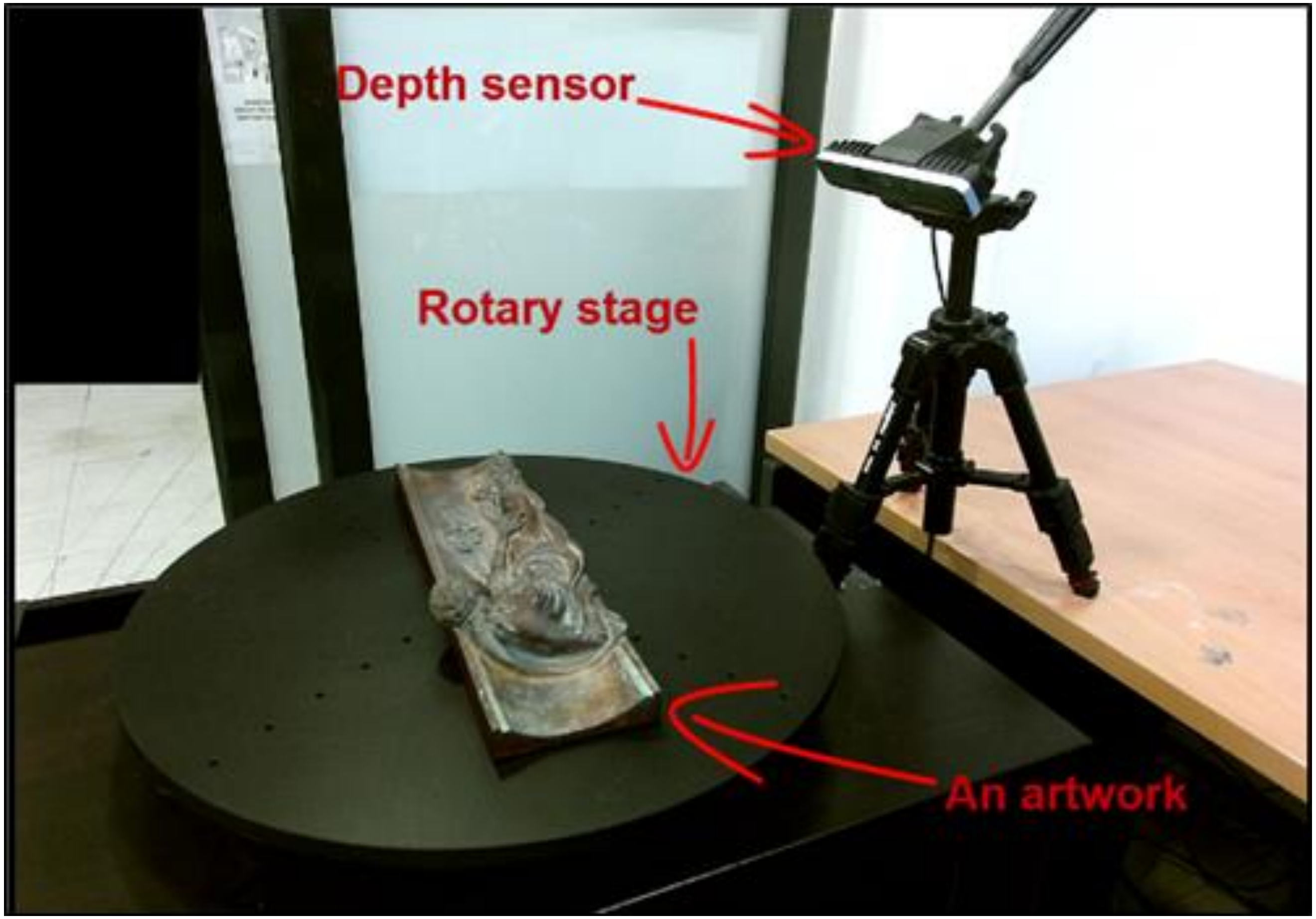
3D Reconstruction

Architecture



3D Reconstruction

Setup

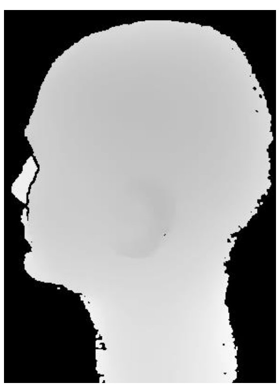


- Coordinate systems registration of rotary table and depth sensor

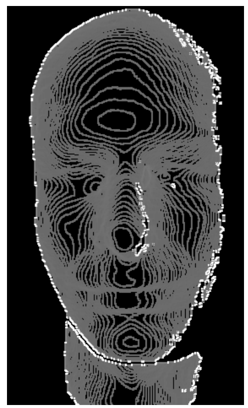
3D Reconstruction

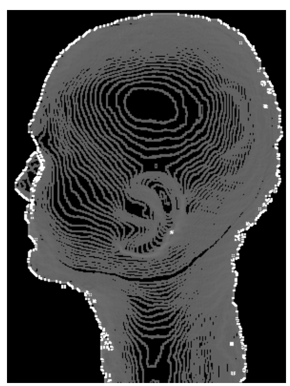
Preprocessing

Original
depth map

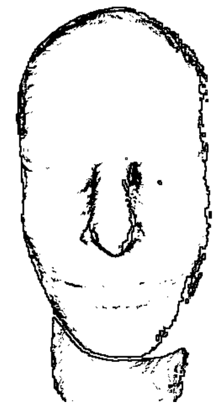


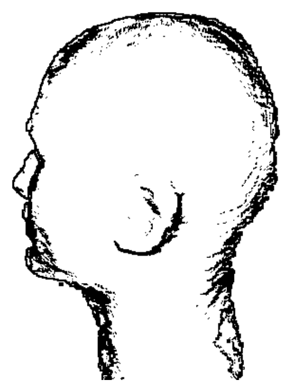
Estimated gradient.
Brighter areas
indicate bigger gradient





Thresholding.
Black areas of
depth map will be
discarded





Resulted
depth map

3D Reconstruction

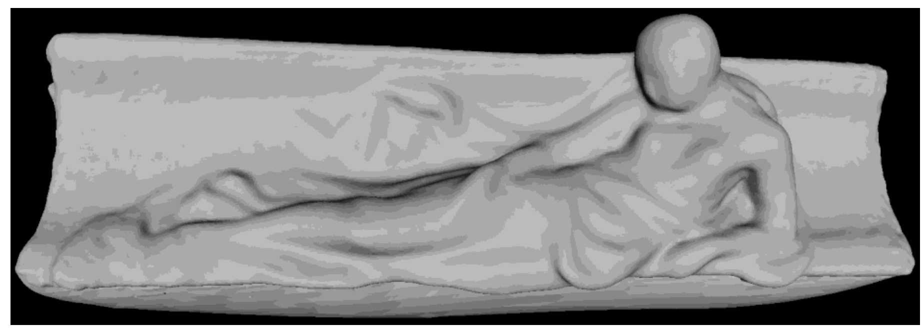
Texture Reconstruction (1/3)

- 1st step: Camera View Selection
  - select the camera view c_j, where f_i is more clearly visible

$$\boxed{\arg\max_{c_j} \sum_{f_i} n_{f_i} \bullet r_{c_j}}$$

- $\boldsymbol{n}_{f_i}$ - the surface normal of face f_i
- $\boldsymbol{r}_{c_j}$ - the principal axis of camera view c_j

4 camera views



meshed model

textured model

3D Reconstruction

Texture Reconstruction (2/3)

- 2nd step: Color Adjustment
  - texture patches have color discontinuities

  - adjust texture patches’ colors to achieve a smooth color transition at seams

$$\arg\min_{a} \overbrace{\sum_{u \text{ lies on a seam}} \left(c_{u_{left}} + a_{u_{left}} - \left(c_{u_{right}} + a_{u_{right}}\right)\right)^2}^{\text{adjusted color is as similar as possible}} + \overbrace{\sum_{u_i, u_j \text{ are in the same patch}} \left(a_{u_i} - a_{u_j}\right)^2}^{\text{minimize differences between same texture patch}}$$

$$+ \underbrace{\sum_{u \text{ with UV-VIS information}} \left(c_u + a_u - p_u\right)^2}_{\textbf{adjusted color is as similar as possible to the corresponding UV-VIS info}}$$

- $c_{u_{left}}, c_{u_{right}}$ - the vertex color to the left and right patches
- $a_{u_{left}}, a_{u_{right}}$ - the correction to the left and right patches
- p_u- the corresponding UVVIS sample

3D Reconstruction
Texture Reconstruction (3/3)

Without UVVIS information	With UVVIS information
	

- more lively colors revealing finer details of the faces, the letters, etc.

Metric Error	Without UVVIS	With UVVIS
Mean	19.06	**2.40**
Std	12.37	**3.75**
Median	16.00	**1.00**
95th	43.00	**9.00**

3D Reconstruction

Textured 3D models

Ageing simulation in appearance
Problem formulation

- **Simulating for corruption prevention:**
  - Identify susceptible spots on artworks for **corruption prevention**
  - Simulation of material appearance over time
  - Forwards and backwards simulation:
    - how much **reversible** a destruction is

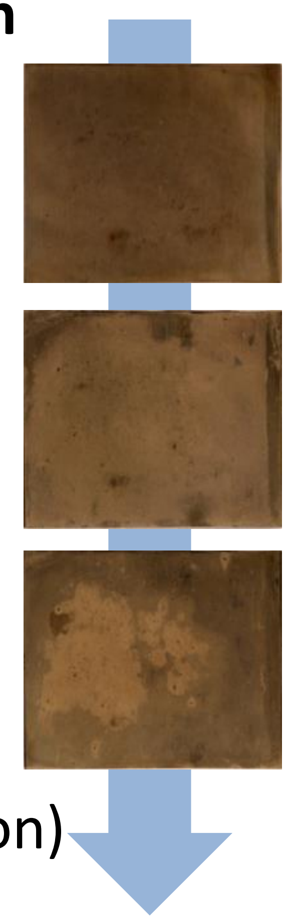
❖ Solving the problem:

Data collection

1. Recording appearance of material samples
2. Artificial ageing in ovens (3 time instances)
3. TRI colour (RGB) images of the aging process

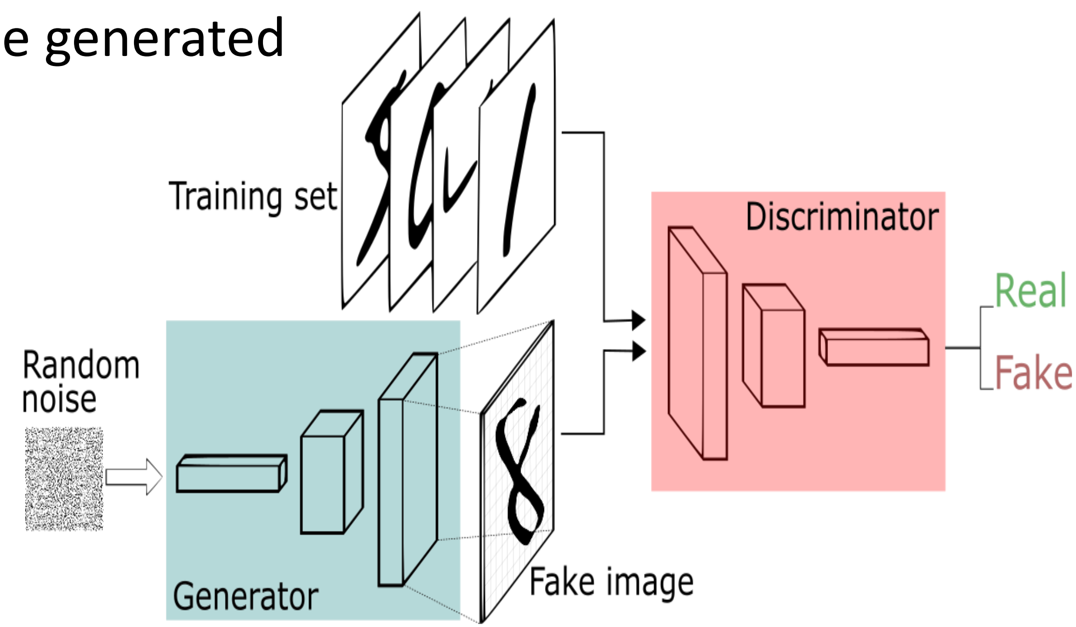
Model training

4. **Material Aging Model** (purpose of this presentation)



Previous Work
Vanilla GAN Architecture

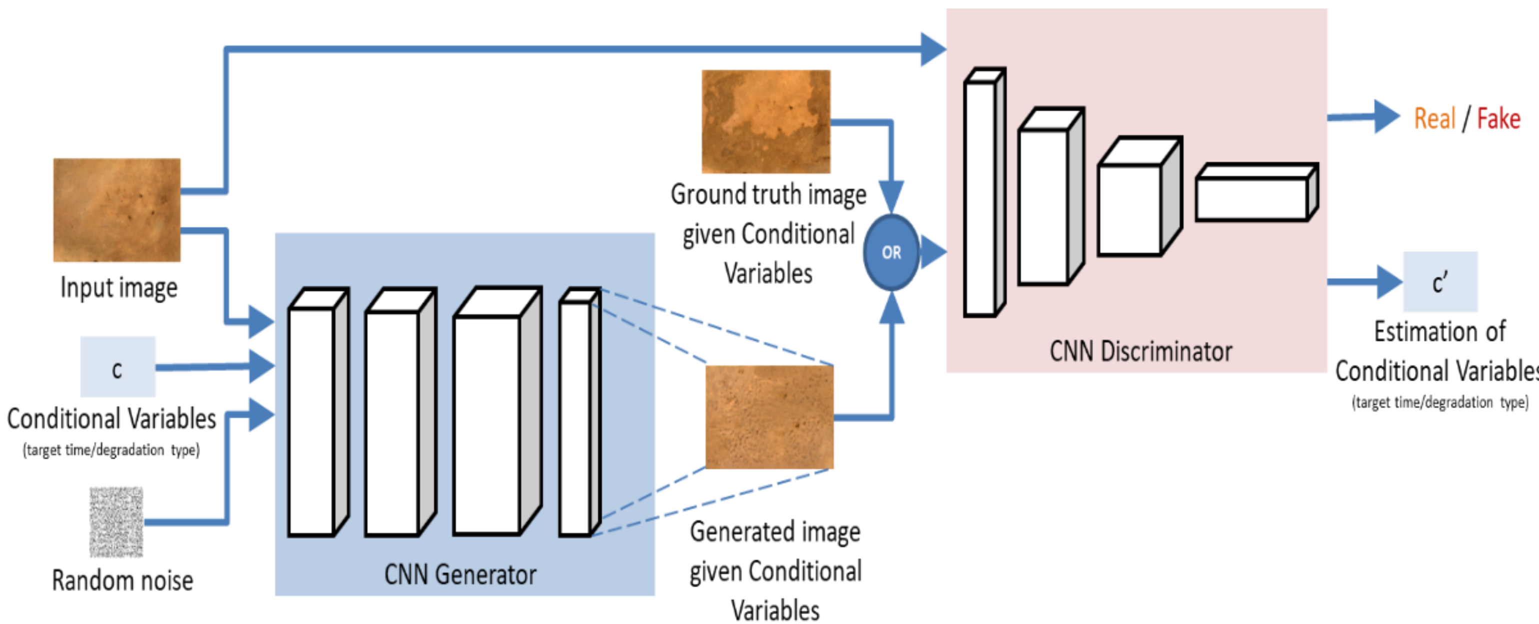
- Generative Adversarial Networks (GAN) has 2 sub-networks:
  - **Generator Network**: Its goal is to fool the Discriminator into recognizing the generated image as real
  - **Discriminator Network**: Its goal is to learn to discriminate between real and generated images (Fake images)
- As the accuracy of both networks improves, the quality of the generated images increases.



Proposed method 1/4

GAN framework

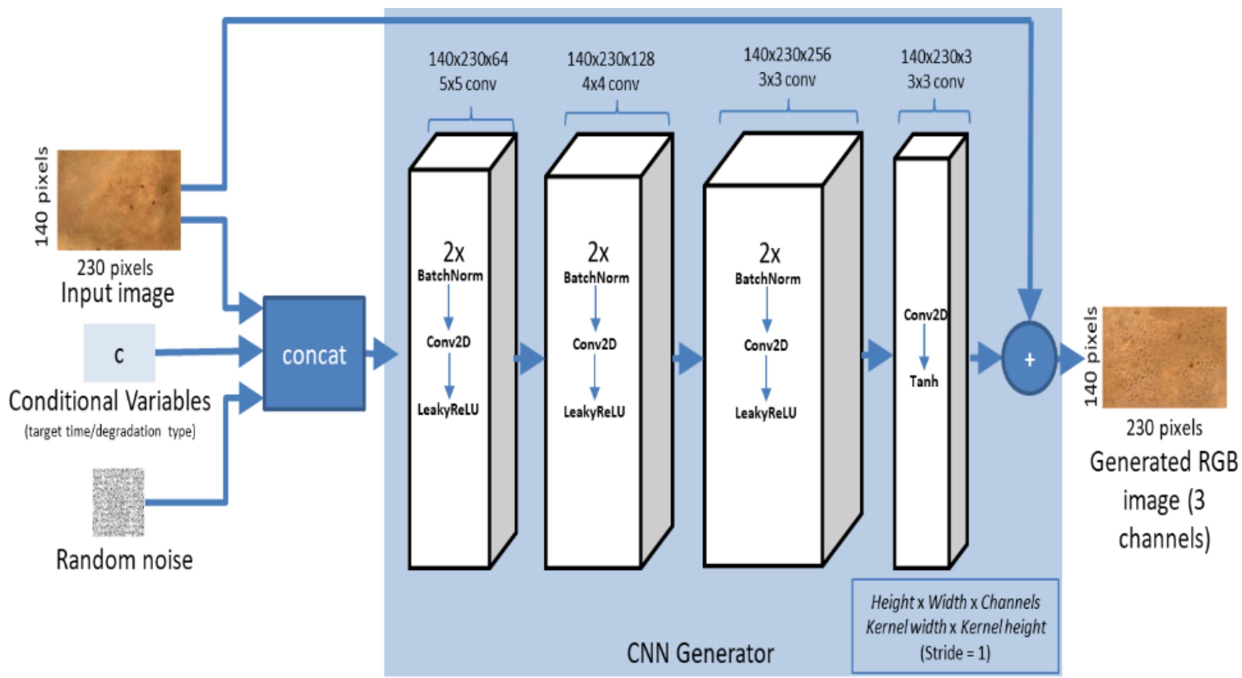
- **Conditional image-to-image translation** task, i.e. given: input image, conditional variables → generate the degraded image
- Both the generator and the discriminator are **Convolutional Neural Networks (CNN)** → Appropriate for image generation or recognition tasks, Low number of parameters



Proposed method 2/4

Architecture of Generator

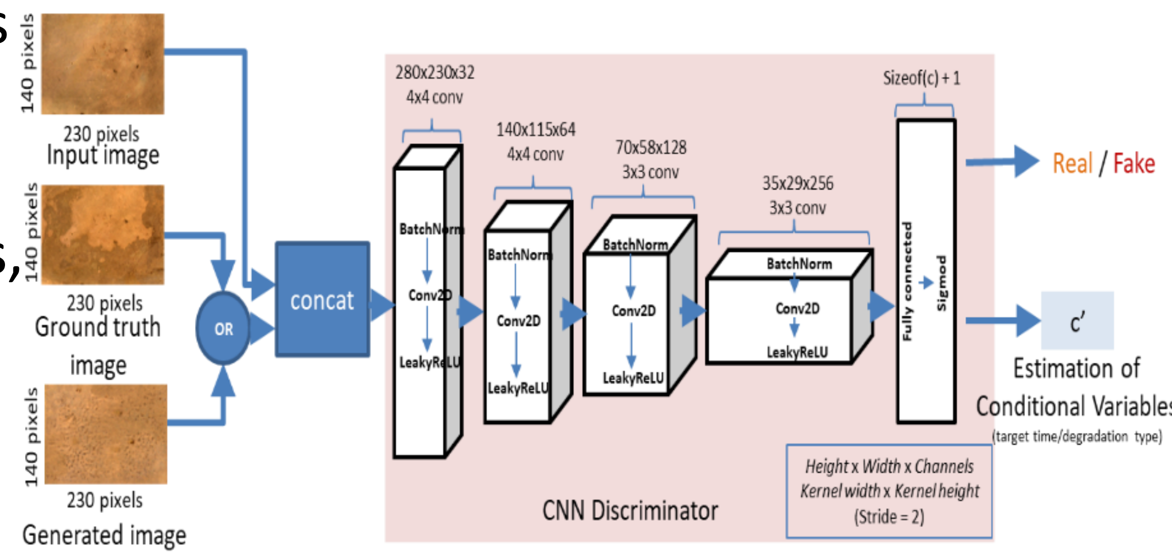
- **Input**: image that must be degraded, conditional variables and noise, **Output**: degraded image
- **Generated image**: sum of final layer and input image
  →model only (un)degradations, higher quality results
- **Deep Learning**: 20 layers including convolutions, batch normalizations, and activations (leaky relu, tanh)



Proposed method 3/4

Architecture of Discriminator

- **Input**: initial image and degraded image (either ground truth or generated), **Output**: conditional variables, probability that the degraded image is real
- **Estimation of conditional variables**: Directly encoded by the loss function → Faster train, Better results
- **Deep Learning**: 14 layers including batch normalizations, activations, convolutions, and fully connected



Proposed method 4/4

Optimization

- **Generator Loss:**

Pixel loss — Adversarial loss

$$L_G = \boxed{\mathbb{E}_{I,c,z}[\ \|G(I,c,z) - I_c\|^2\ ]} + \boxed{\mathbb{E}_{I,c,z}[\ \|concat(c,1) - D(\ G(I,c,z), I)\|^2\ ]}$$

Generator *Target image* *Conditional variable* *Input image*

Noise $z \sim U(-1,1)$ *Discriminator*

- **Discriminator Loss:**

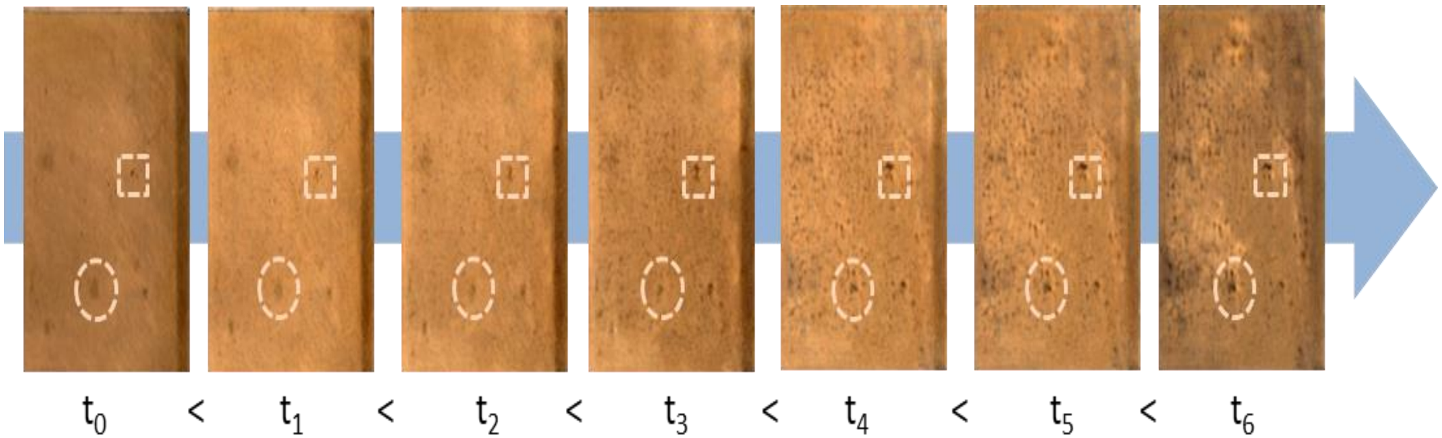
Adversarial loss – true image — Adversarial loss – generated image

$$L_D = \boxed{\mathbb{E}_{I,c,z}[\ \|concat(c,1) - D(\ I_c, I\ )\|^2\ ]} + \boxed{\mathbb{E}_{I,c,z}[\ \|concat(c,0) - D(\ G(I,c,z), I\ )\|^2\ ]}$$

- **Optimization algorithm:** For each mini-batch, compute the losses L_G and L_D and perform one gradient update (for both networks) using Stochastic Gradient Descent (SGD).

Experimental results 1/2

- Application of the degradation model on bronze material
- The trained model takes as a conditional variable only the degradation time
- Image content is preserved (e.g. black spots, border colour on the right of the panel), and degraded over time, by getting rougher/larger
- Degradation procedure also adds additional content, e.g. additional black spots



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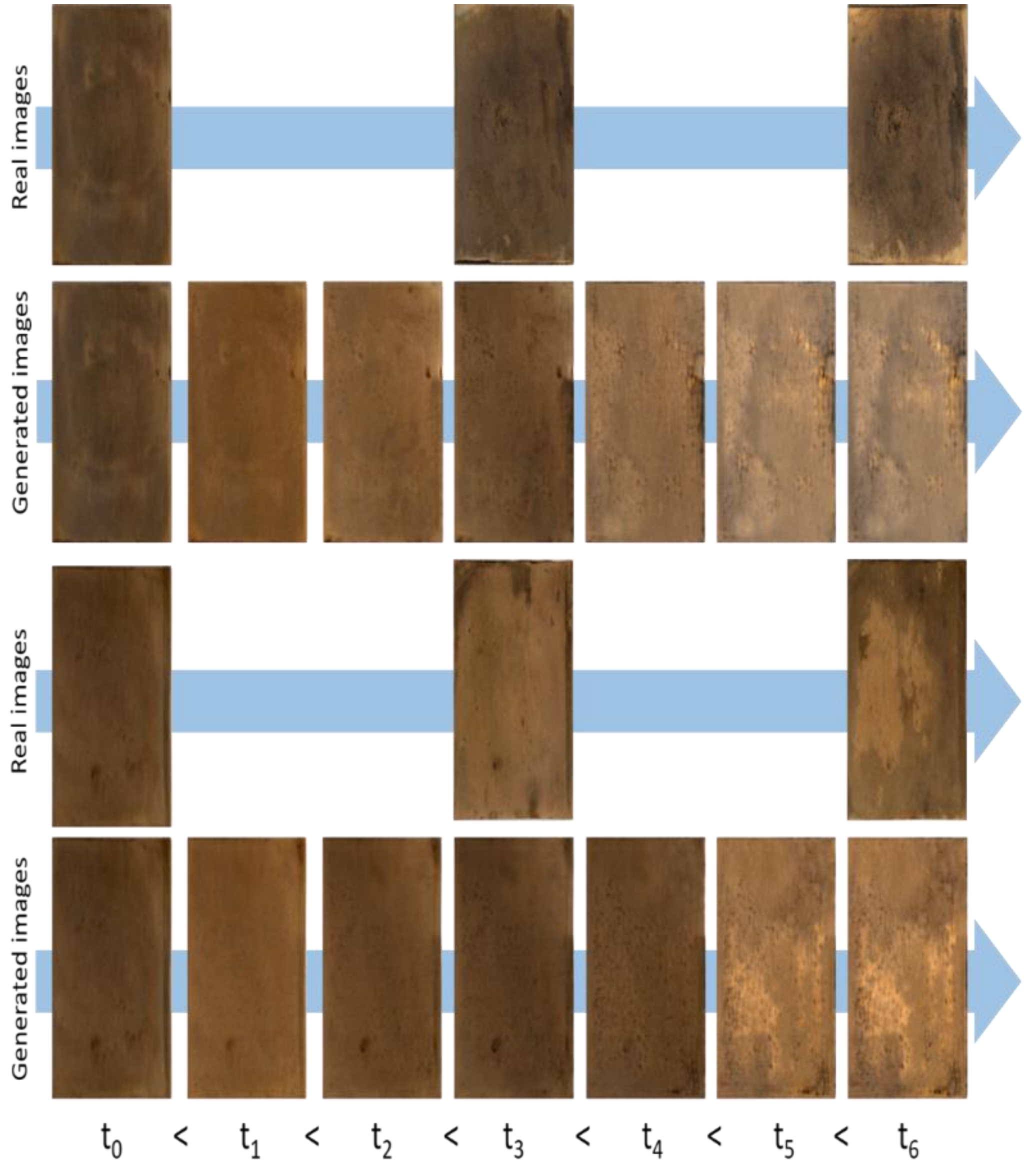
Experimental results 2/2

- Three images representing bronze materials
- Material degradation looks realistic
- Degradation depends on content of the input image



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Ageing simulation in geometry
Problem formulation

- **Modelling surface degradation:**
  - Simulation of changes in surface geometry over time

❖ Solving the problem:

Data collection

- Artificial aging of reference bronze samples in an ageing chamber

Bronze coupon at t_0 | Bronze coupon at t_1 | Bronze coupon at t_2

- High resolution 3D scans in each step (m-prof)

Model training

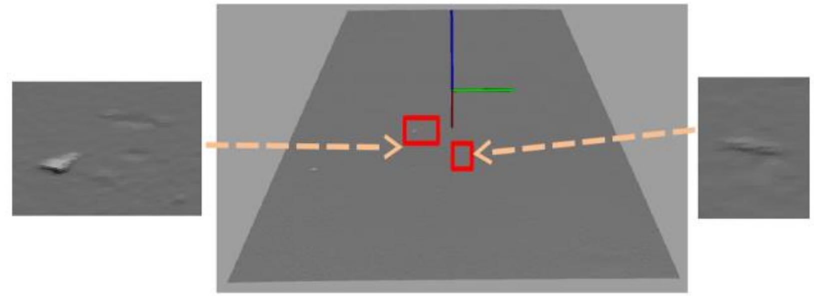
- **Material Ageing Model**

Proposed method 1/4

Surface parameterization

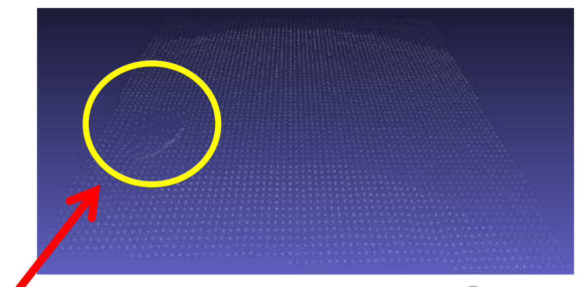
- Point clouds from different ageing steps are registered using ICP

Aligned point clouds for t_0 , t_1 and t_2

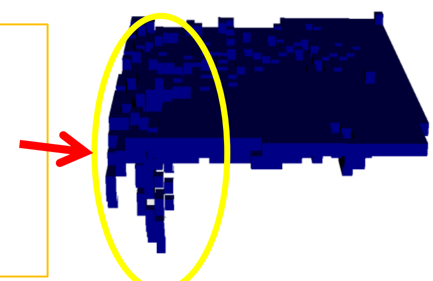


Minor surface anomalies help ICP converge

- Point clouds are parameterized in overlapping 3D occupancy grids, with a rolling cube (32x32x32)
  - Grids in different ageing steps are registered
  - Intermediate grids are interpolated
  - Finer quantization along z-axis to capture anomalies



Note how the dent is captured in the 3D grid

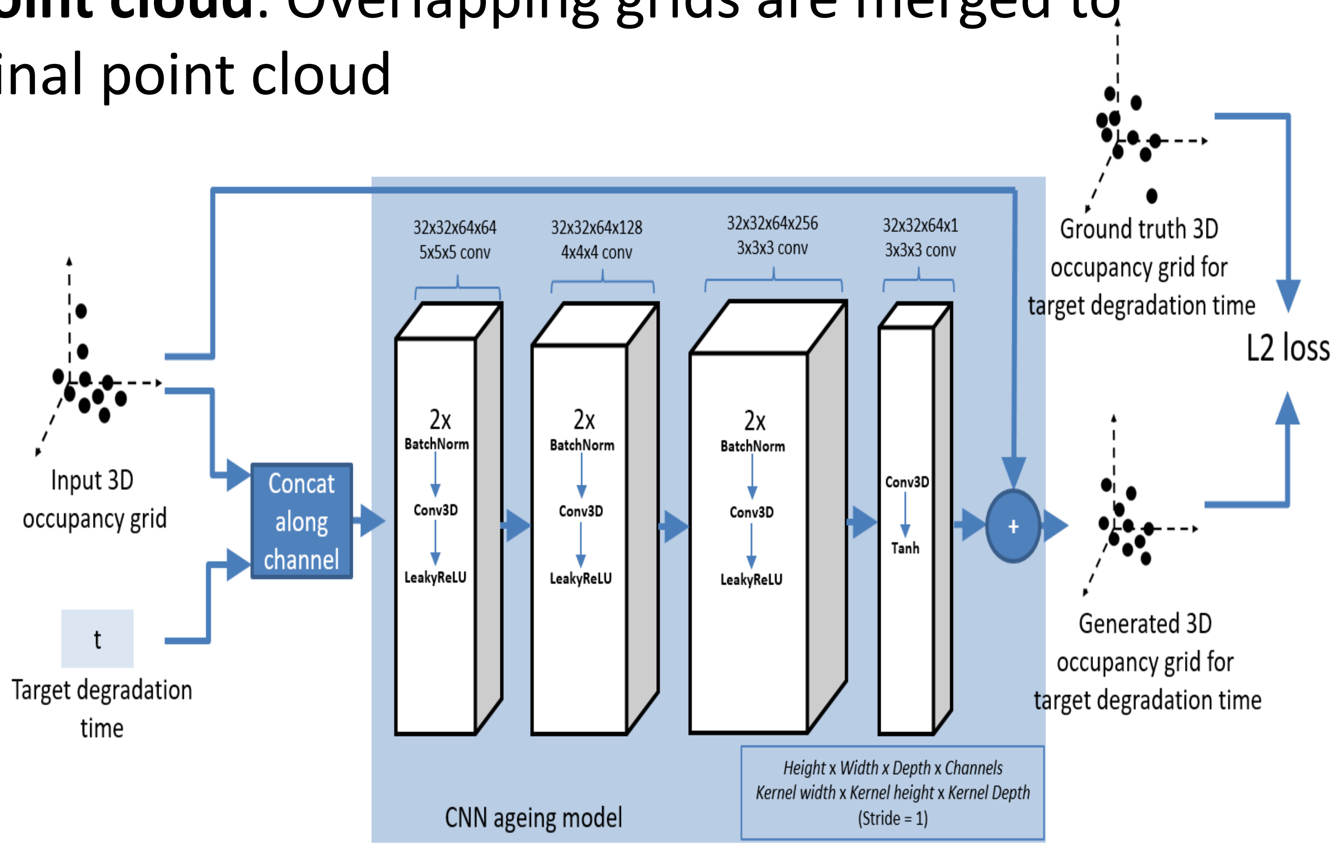


Proposed method 2/4

Architecture of 3D-CNN

- **Input**: Occupancy grid to be degraded, target time
- **Output**: Degraded occupancy grid
- **Synthesized point cloud**: Overlapping grids are merged to generate the final point cloud

Deep Learning: 20 layers including convolutions, batch normalizations, and activations (leaky relu, tanh)



Proposed method 3/4

Optimization

- **3D-CNN Loss:**

$$L = \mathbb{E}_{I,t}[|\boxed{G(I,t)} - \boxed{I_t}|^2]$$

Generated Occupancy Grid

Target time

Ground-truth Occupancy Grid

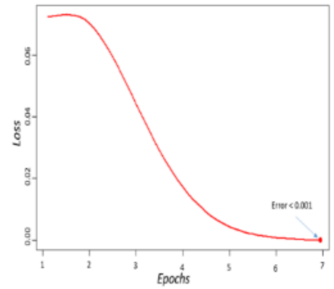
- **Optimization algorithm:** For each mini-batch, compute the loss L and perform one gradient update using the Stochastic Gradient Descent (SGD) method.

Proposed method 4/4

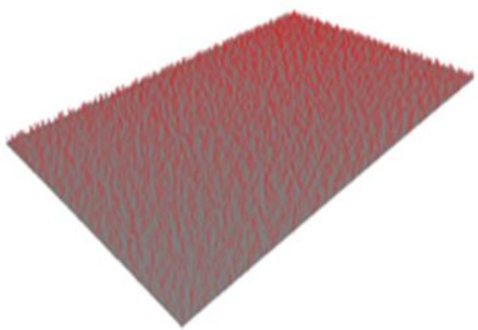
Examining convergence

- **Training process convergence verified by**

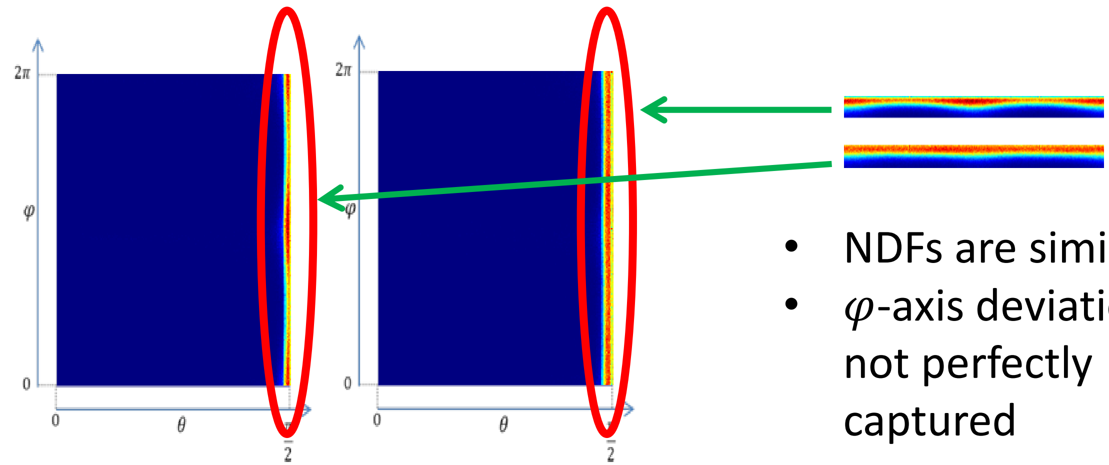
  1. **Monitoring training error:**



  2. **Comparing the distribution of normal vectors (NDF) against ground truth:**



Normal vectors quantized using spherical coordinates



NDF for ground truth

NDF for generated cloud

- NDFs are similar
- φ-axis deviation not perfectly captured

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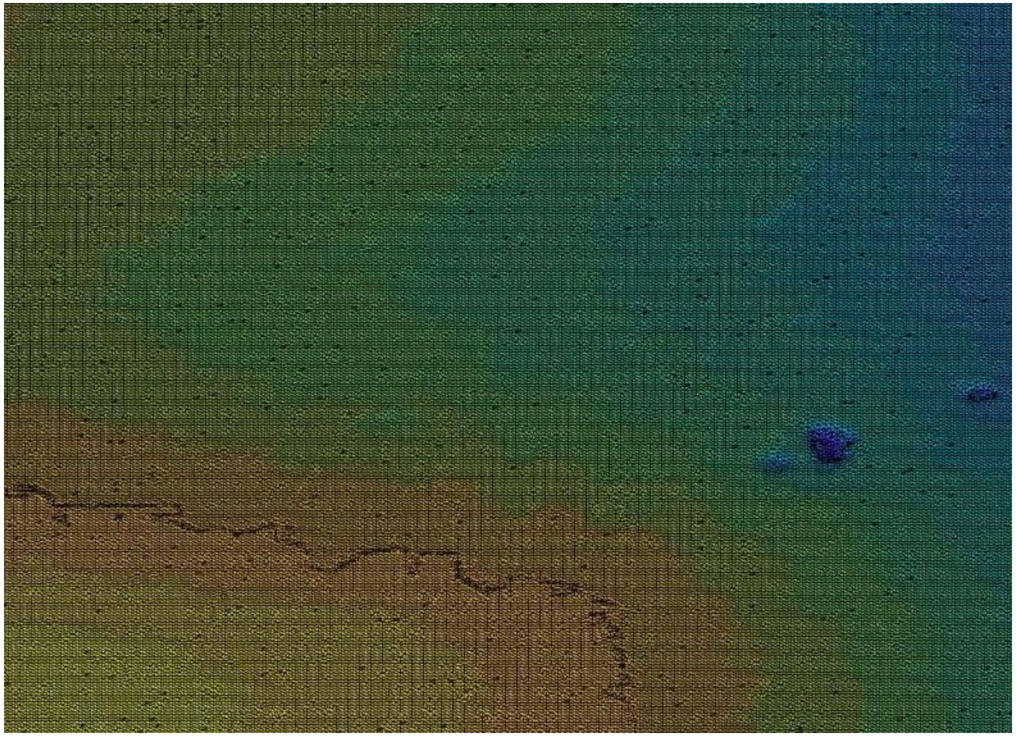
Experimental results (1/2)

- Application of the degradation model on bronze sample
- Trained model has as input the initial point cloud and the targeted time
- Dents smooth out, simulating the accumulation of surface deposits



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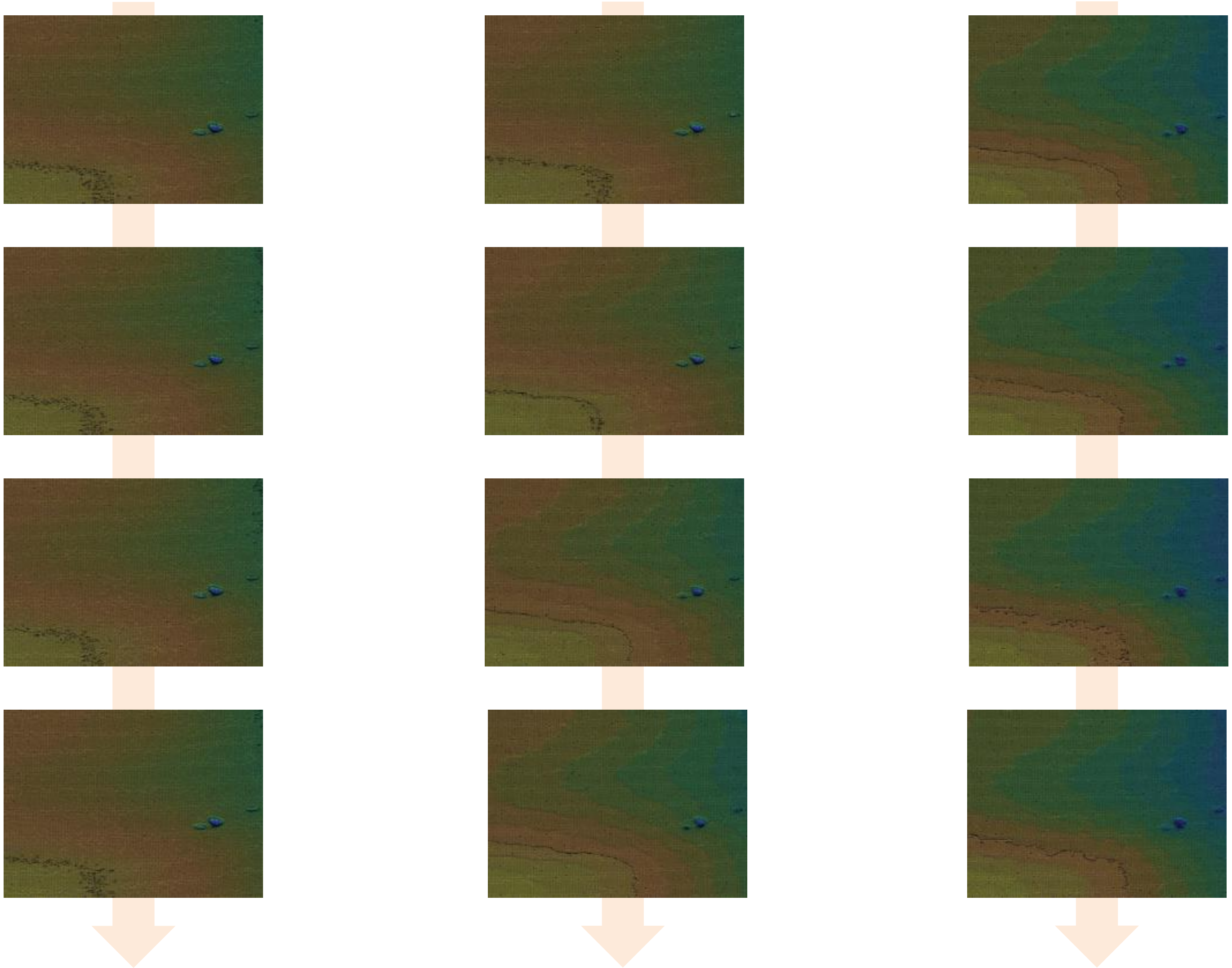
Experimental results (2/2)

Aggregated view



Conservation Oriented DSS

Architecture

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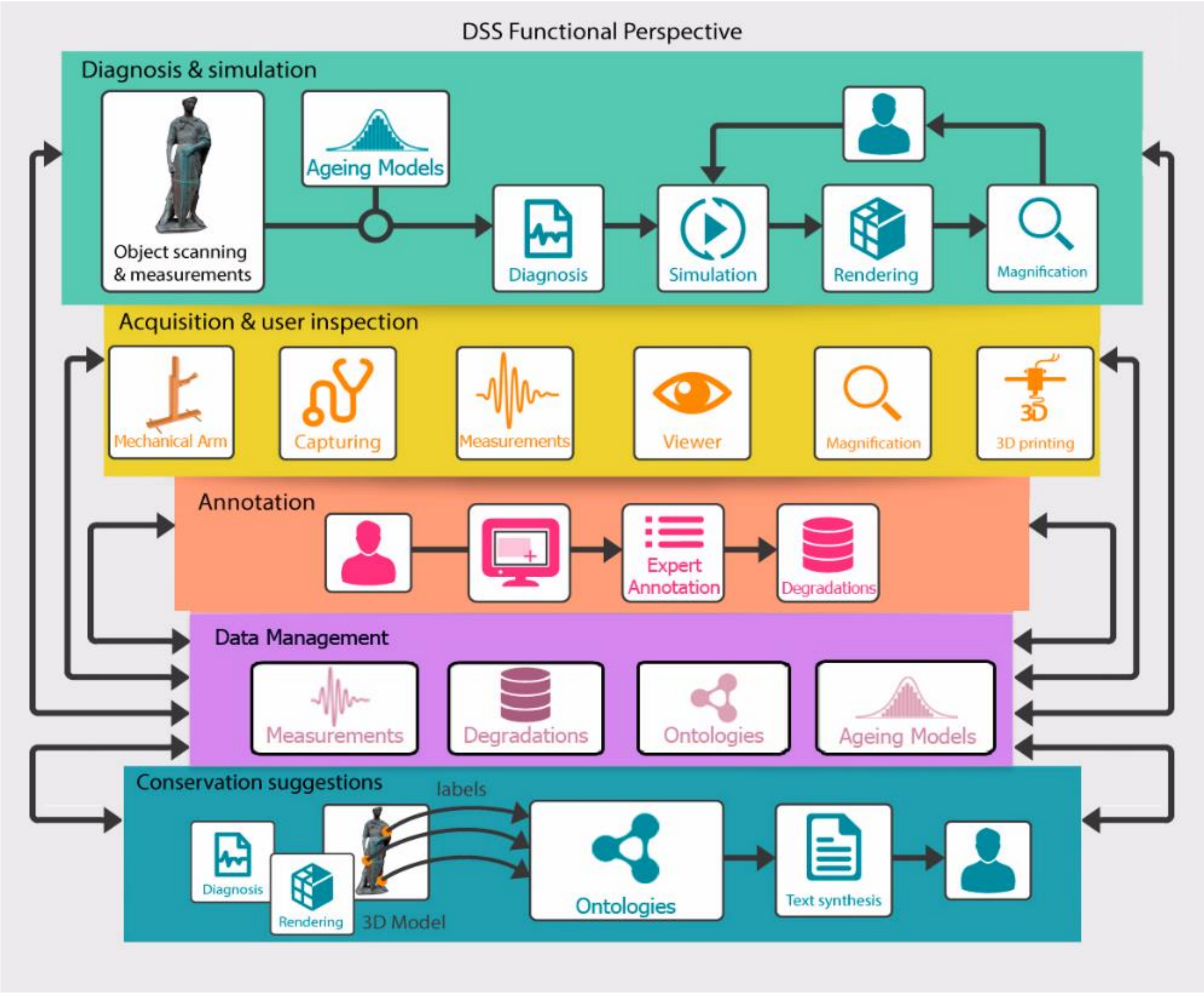
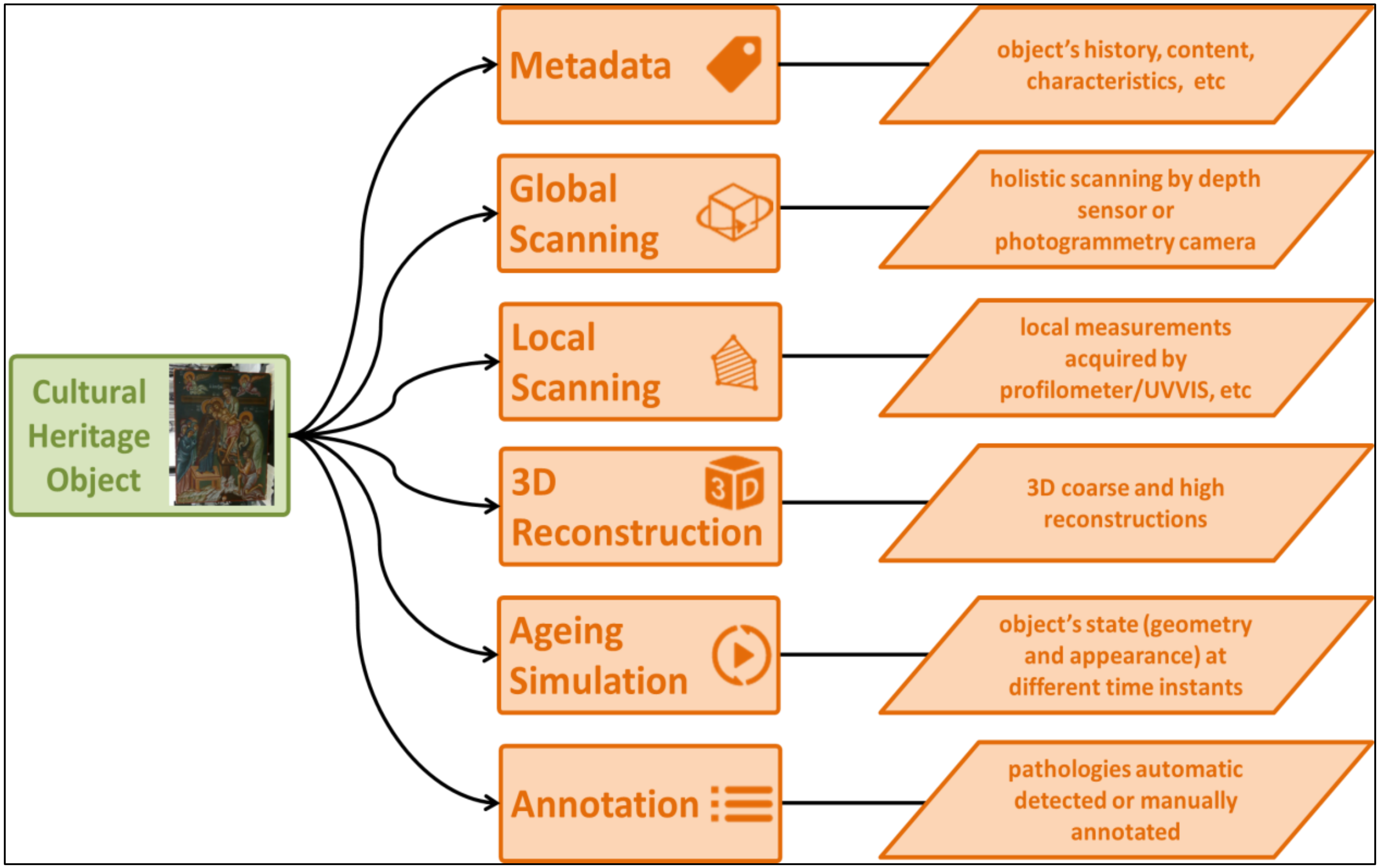
Main blocks of Scan4Reco DSS:

- Acquisition & User inspection
- Annotation
- Data Management
- Diagnosis & Simulation
- Conservation Suggestions



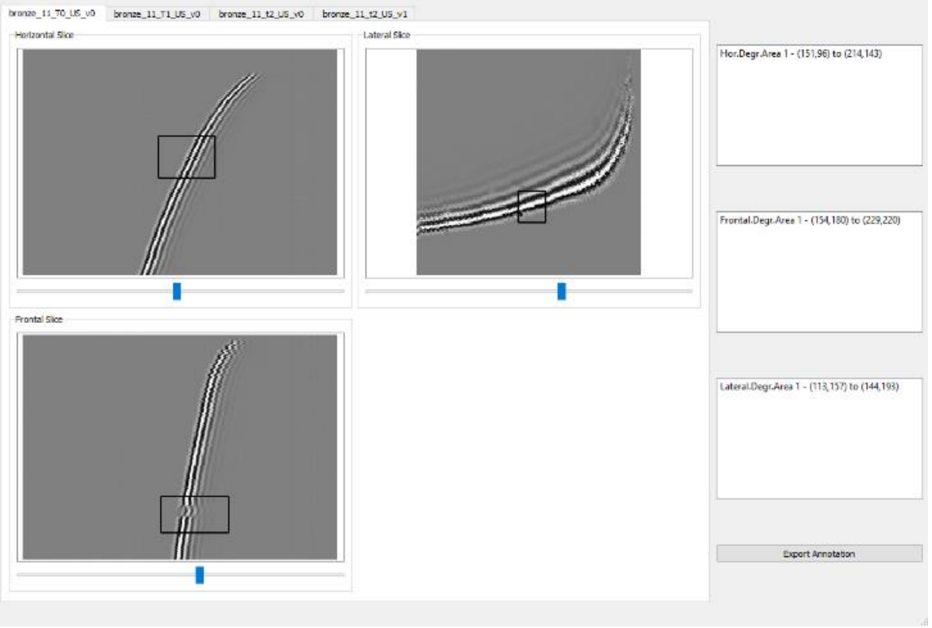
Conservation Oriented DSS

Diagnosis

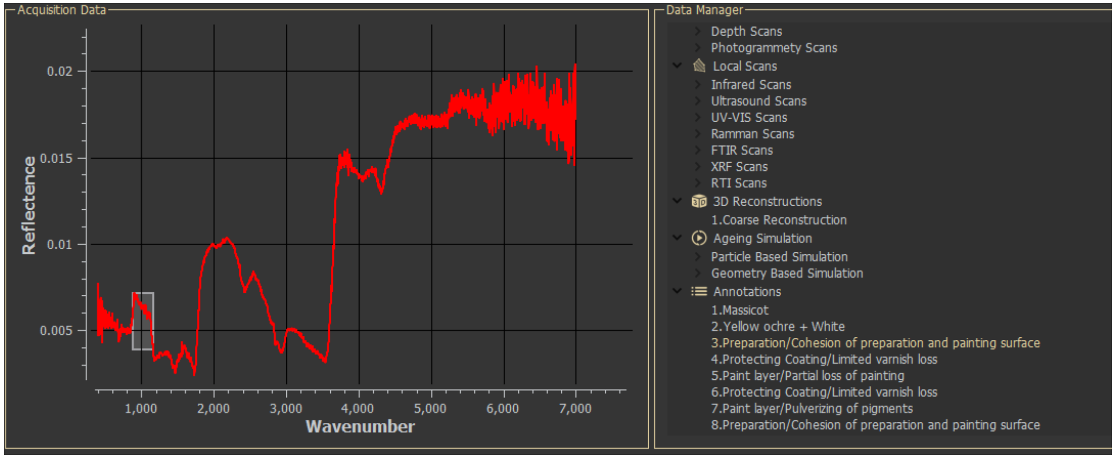


Conservation Oriented DSS

Diagnosis/Annotation & Detection



Inspecting and annotating ultrasound scans



Inspecting and annotation FTIR spectrum

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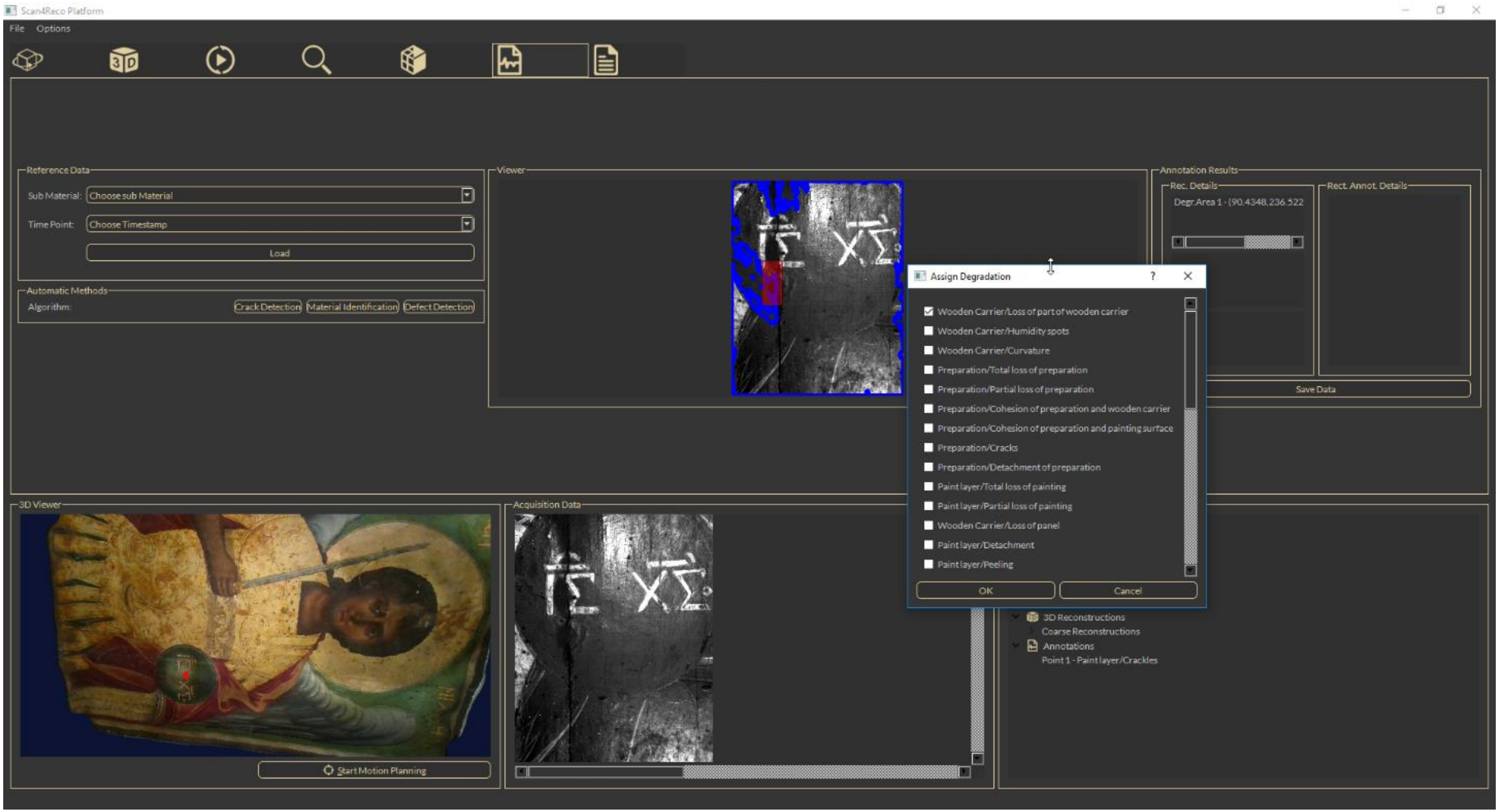
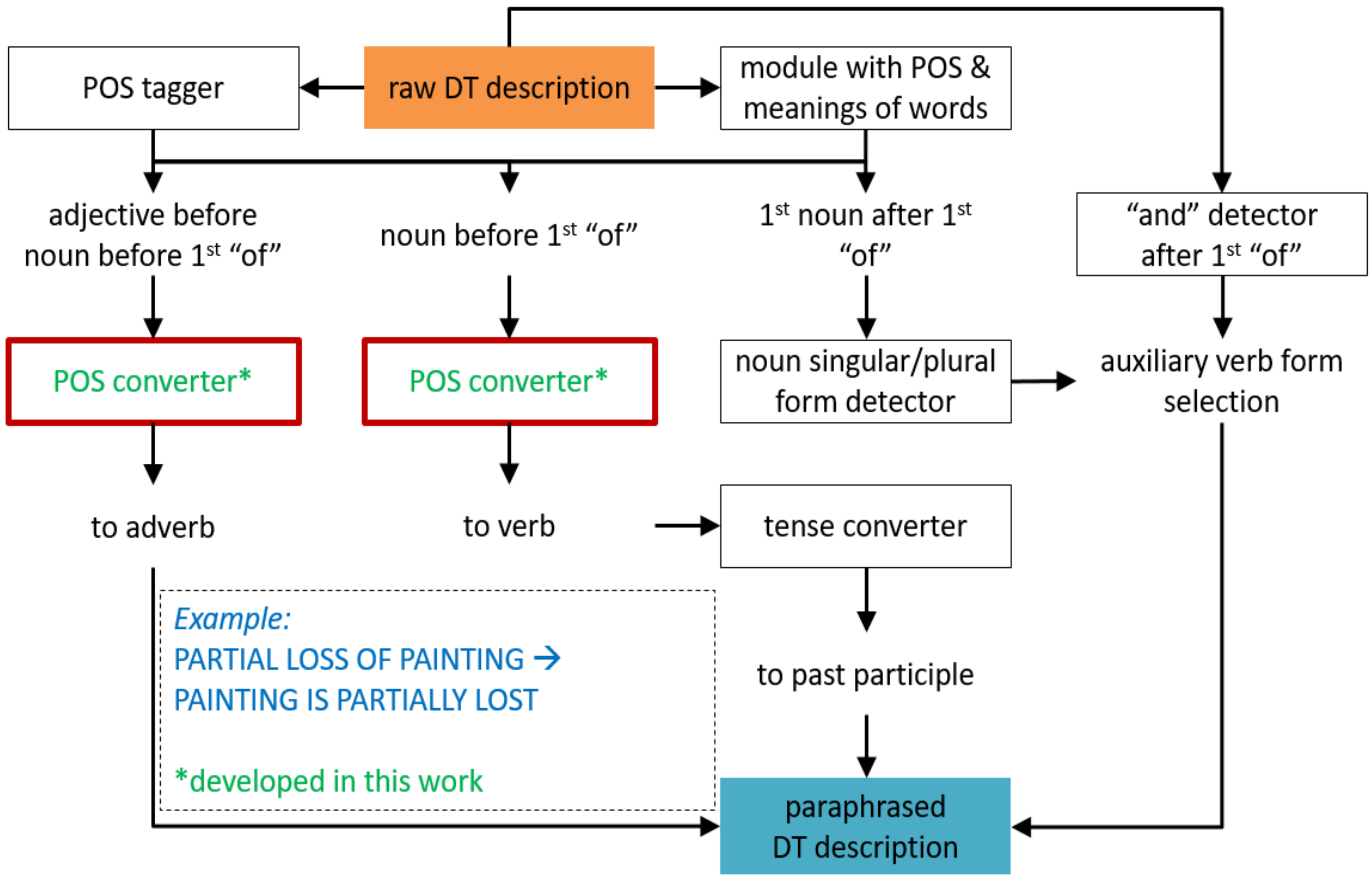
Conservation Oriented DSS

Diagnosis/Annotation & Detection



Conservation Oriented DSS

Text Synthesis / Architecture



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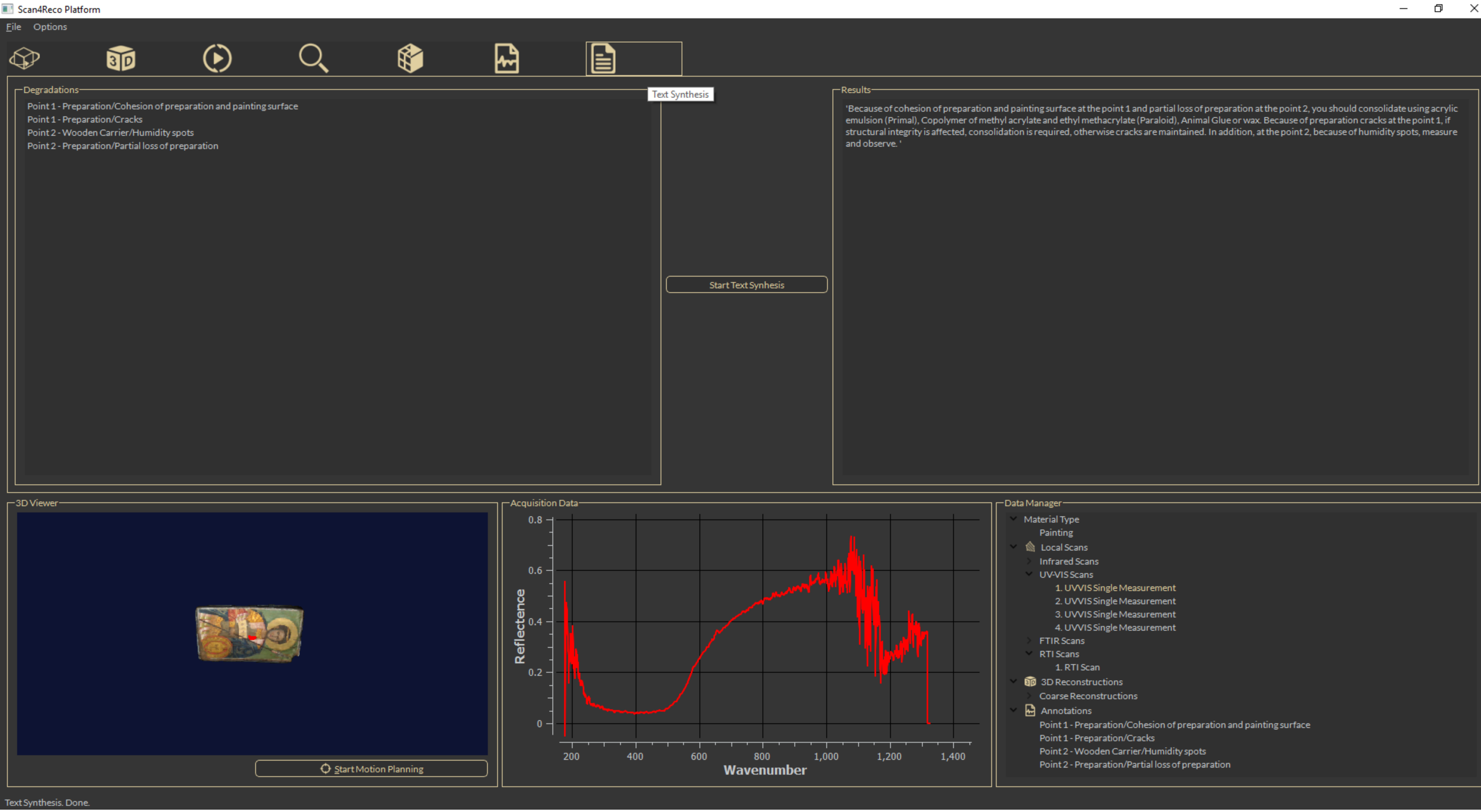
Conservation Oriented DSS

Text Synthesis



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Questions & Answers

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