

Contact sensors and computer vision systems

RESIST Workshop - Pilot Demonstration,
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Introduction

1. Contact inspection suite:

- Crack depth measurement tool
- Crack width measurement tool
- Vibration measurement tool

CNR

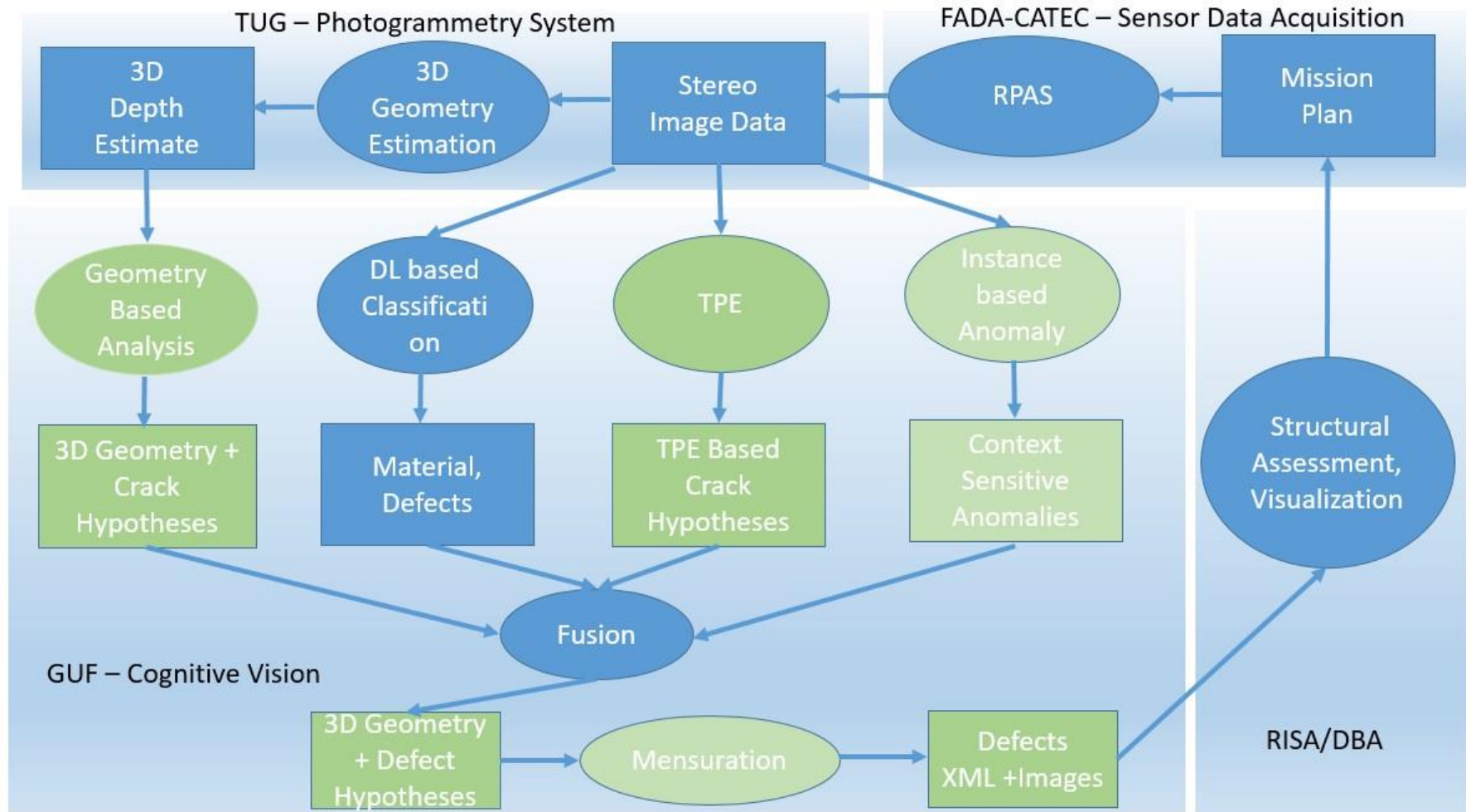
2. Vision inspection suite:

- photogrammetric computer vision systems
- cognitive computer vision systems

GUF
TUG

Cognitive Computer Vision System

Composable Computer Vision System Toolbox : Parallel Defect Hypotheses Generation based on Geometry, Color/Texture, Topology, Fusion, Mensuration



Visual Inspection Toolbox Design

- Systems engineering methodology to design application specific cognitive architecture, modules

Key Innovations:

- A human-like, composable and flexible architecture that incorporates stereo data , Modules that leverage context and is transparent by design.
- Model-based and data-driven hypotheses generators to address both small sample and large data scenarios.
- Fusion of parallel hypotheses threads for defect detection: Geometric data analysis, Topology based analysis, instance based anomalies and deep learning.
- Parallel hypotheses and voting allows for robustness - false alarm reduction while maintaining high sensitivity / detection rates
- Builds on AEROBI results and adapts architecture due to availability of Stereo sensor. Simplifies mensuration with potential for auxiliary false alarm reduction based on 3D geometry depending on the drone distance to the surface data during acquisition.
- Flexible Software composition and Overall System integration



Resist Visual Inspection Toolbox

- Composable and flexible Toolbox built on context specific inspection.
- Different modules can be leveraged for different application contexts.
- Human and AI interaction in the loop.
- Toolbox addresses small sample and large sample application scenarios.

Topological
pit extractor
(TPE)

Multi-Task
Unet

Deep Image
Prior

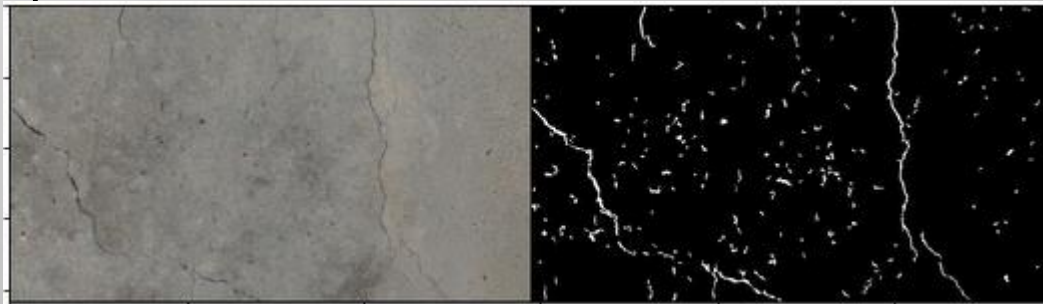
Multi-Target
Variational
Inspection

3D TPE

Steel
corrosion
Inspection

Crack Hypotheses Generation as Anomalies in Texture: TPE Algorithm

- A model-based designs have the advantage of incorporating specific contextual knowledge in the form of physics-based and statistical models.
- These appearance and geometric characteristics of cracks were leveraged in TPE algorithm to detect if a pixel belongs to a crack.
- Cracks have an intensity profile of pit-like structure on texture level and that the 2D geometry of cracks tend to be fractal like, connected and anisotropic.



Deep Image Prior to Solve Image Inpainting

- To improve the outputs generated by TPE, we use a Deep Image Prior module.
- Deep Image Prior module tries to reconstruct the image and fill out the masked parts.
- Since defects represent texture anomalies, the reconstruction will help us detect defects and specifically cracks.

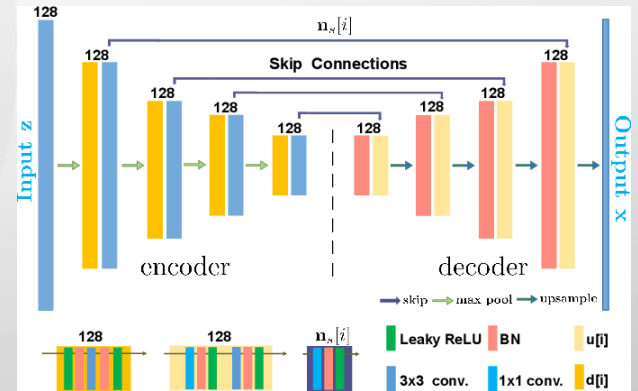


Image Inpainting Task



Masked Input



Ground Truth

Deep Image Prior is used to Reconstruct the Background Texture without Defects

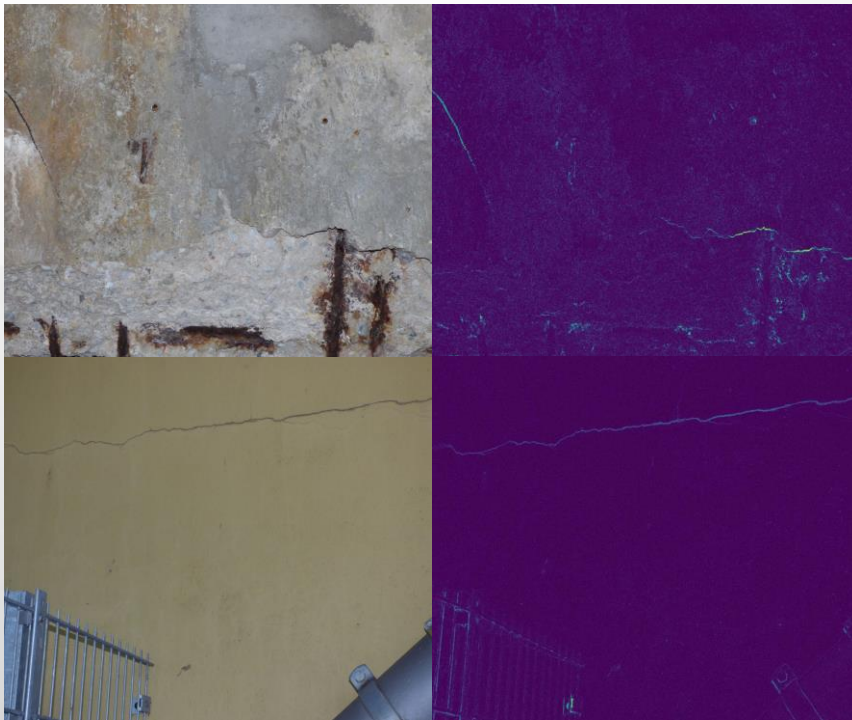


Original Image

Deep Prior
Reconstruction

Difference

Examples on Real Concrete Surface Images



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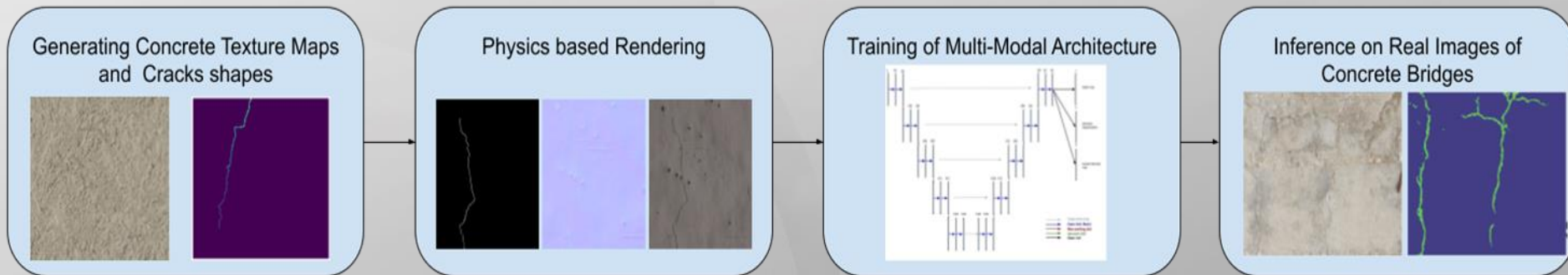
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Leveraging Simulations and multi-modal data to train Deep learning models

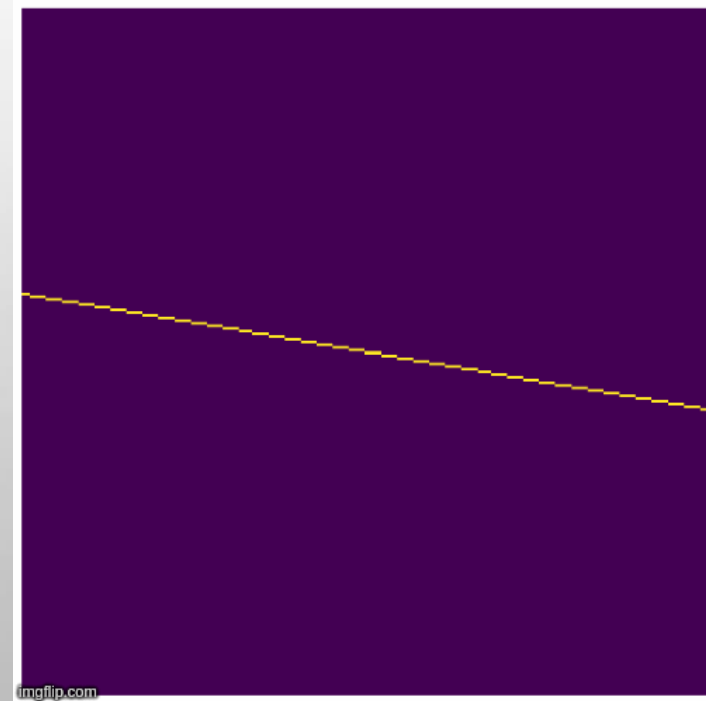
- A simulator for physically based rendering of concrete structures was designed.
- The generated images are used to train Deep learning models for crack detection.



Workflow

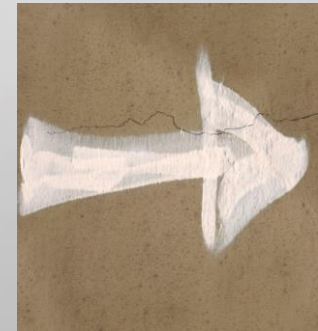
Crack Generation

- To simulate cracks on concrete surfaces, a physically grounded generative model was used.
- Similar to many effects that occur in nature, cracks can be described with irregular fractals.



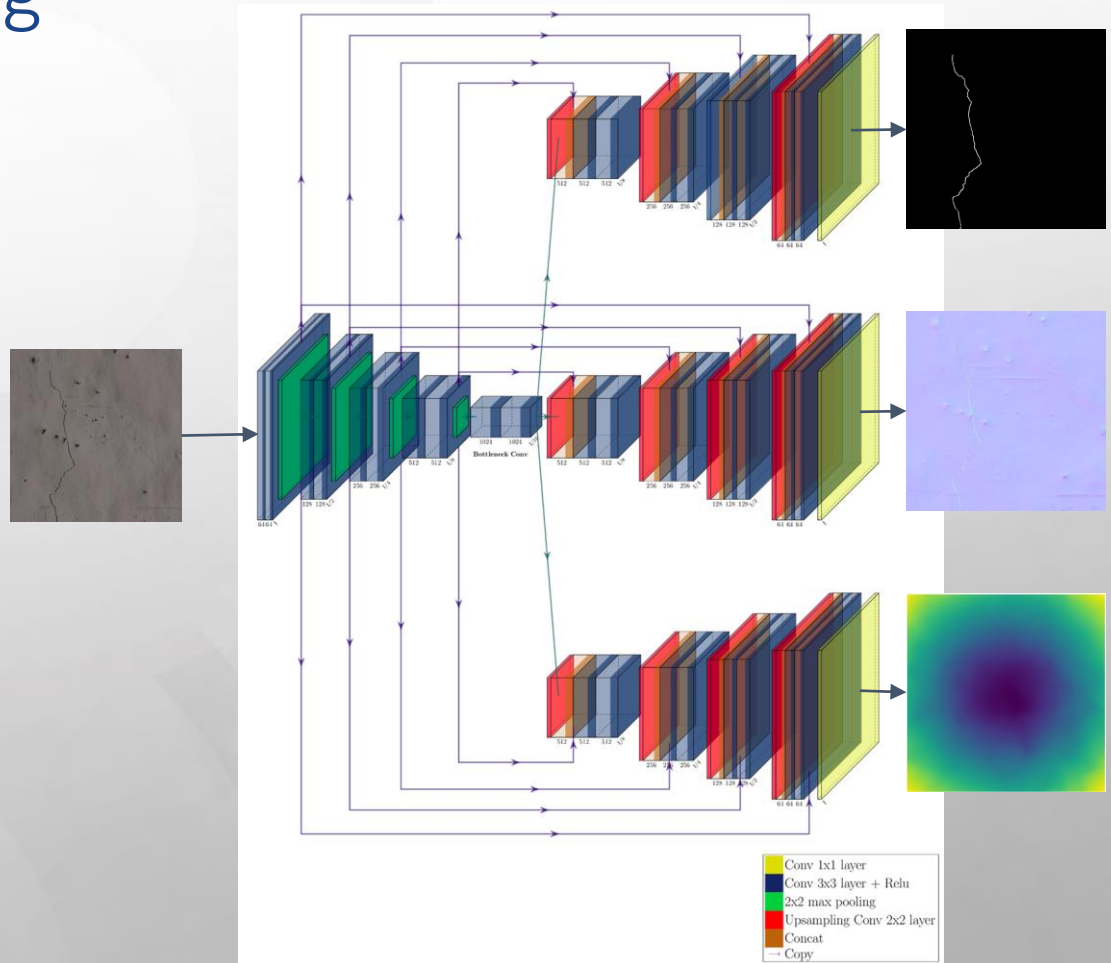
Physics Based Rendering

- We combine the generated Crack shapes with concrete texture and visual perturbations like Moss or Graffiti to improve the model invariance.



Multi-Task Training

- Using simulations allow us to obtain accurate annotations without human effort.
- The obtained Dataset was used to train deep learning models on various tasks simultaneously.
- Our experiments show that multi-task training improves the generalization on real images.



Examples of real images & Results



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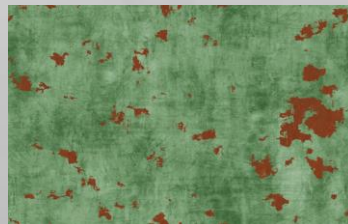
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3D TPE

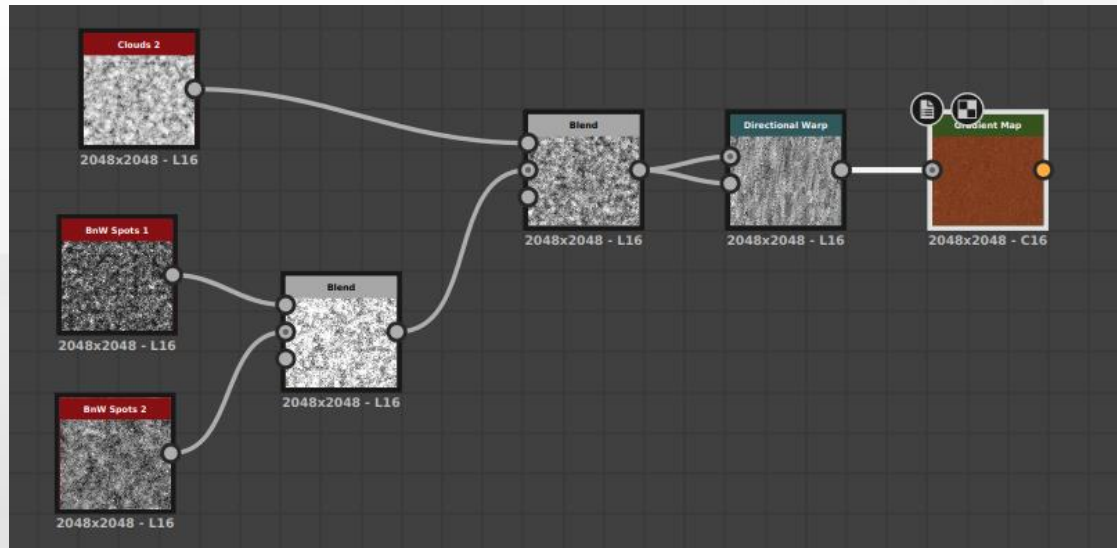
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Texture Generation in Substance Designer

- Corroded steel textures were generated in Substance Designer. Substance Designer offers a wide variety of generative models for fractal noise patterns and color gradients.
- Corrosion patterns on steel can be modeled by cloud like fractal shape.
- The amount of corrosion can be controlled with a slider.
- We vary the following **parameters** to create a dataset for training neural networks: **corrosion amount**, **color pattern of the corrosion**, **steel color**, **steel dirt pattern** and **corrosion fractal parameters**.

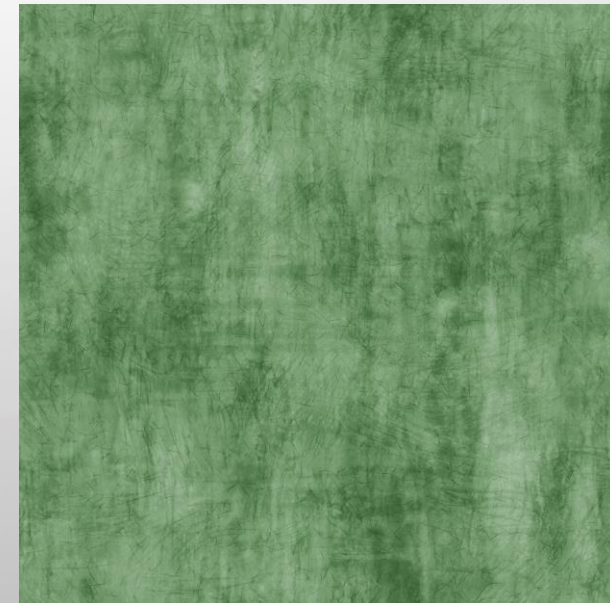
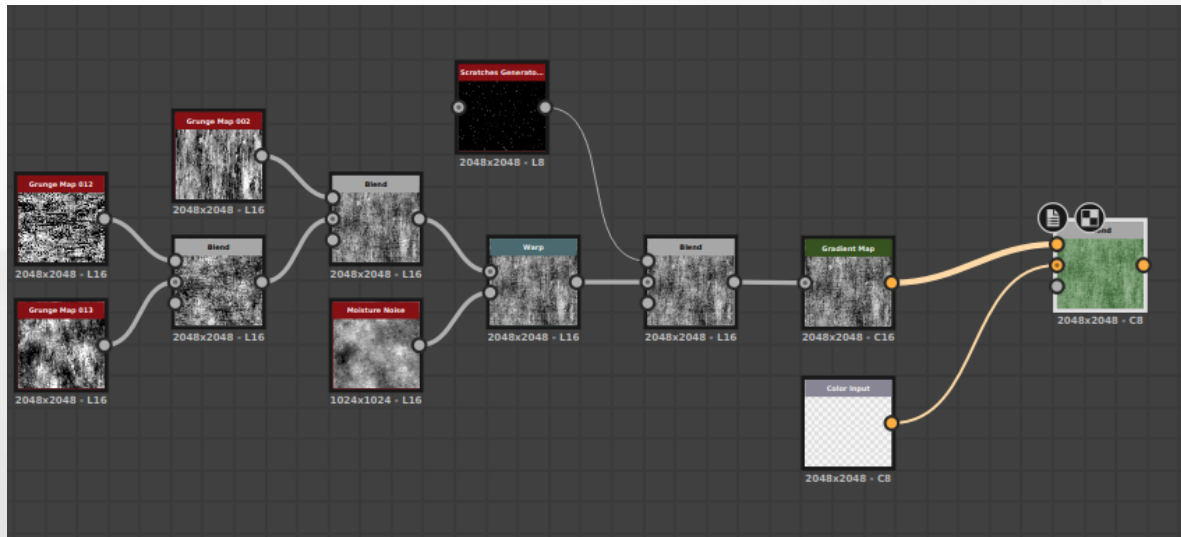


Texture Generation: Corrosion pattern



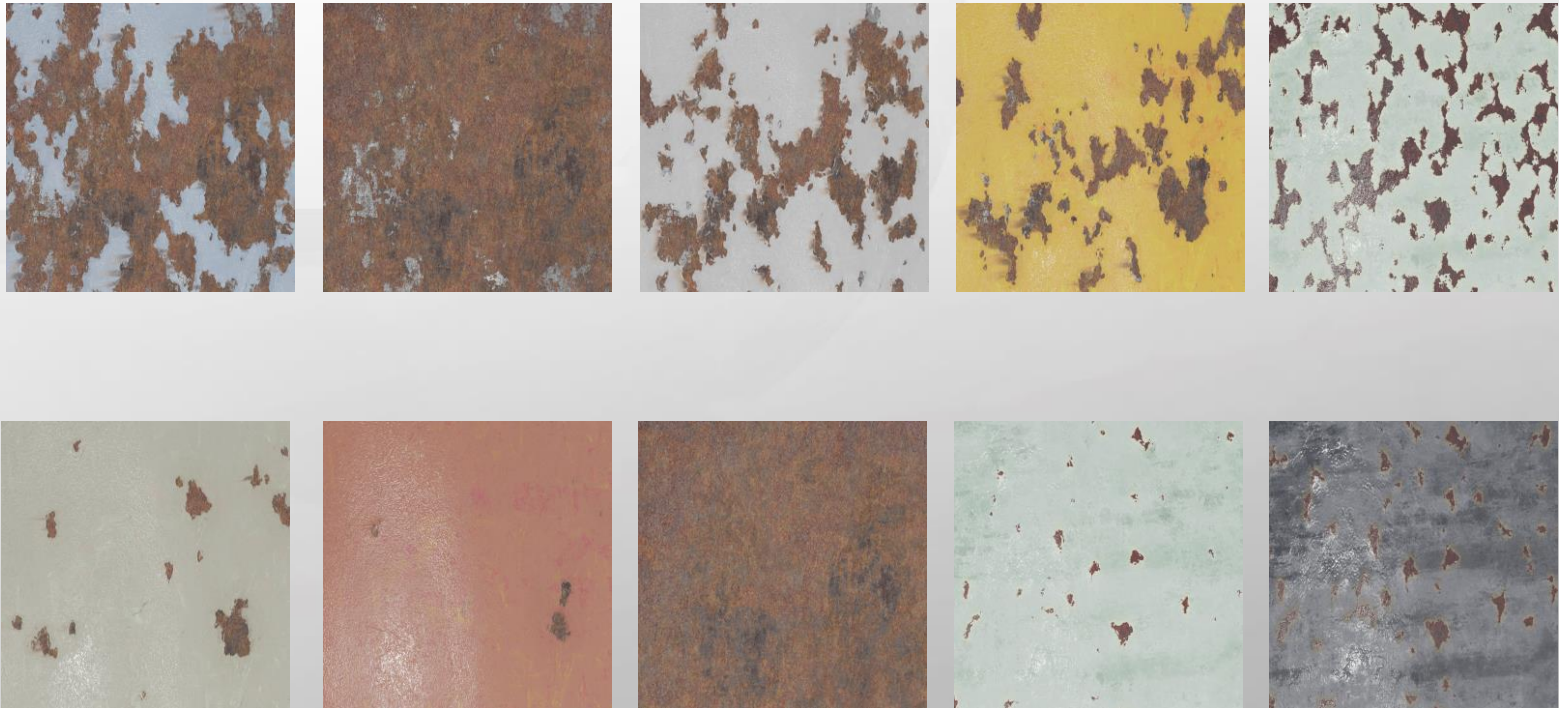
- Cloud like fractal patterns at different frequencies were combined and color graded.
- The color palette for corrosion was sampled from real images of corroded steel.

Texture Generation: Dirty steel pattern

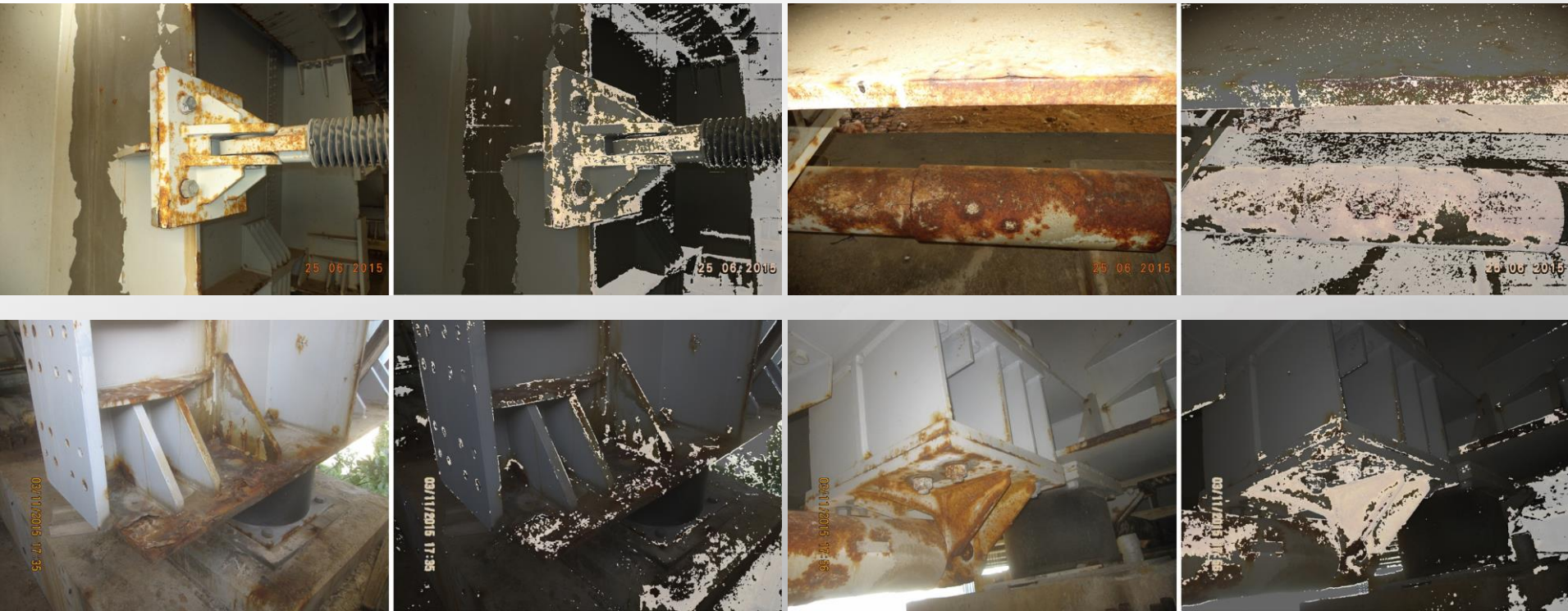


- Grunge patterns were used to create realistic looking wear and tear effect on the steel surface.
- The colors for steel surface were sampled from images of coated steel surfaces.

Examples of generated Steel Patterns



Results (Rusting) on EOAE Steel Bridges



Example Results on CODEBRIM Dataset



TPE + Depth data

Motivation: Leverage depth information for detection purposes. Instead of color input use depth information

Assumptions:

- Context and task priors: Surface depth isn't uniformly distributed, but locally planar
- Variability in the output is due to surface roughness, extrinsic orientation with respect to target surface, and noise variance due to stereo sensor

Current Challenges:

- Drone distance to the surface ($>2.5\text{m}$) results in many false positives due to high variance of depth data. So depth module not very useful for false alarm reduction for cracks.

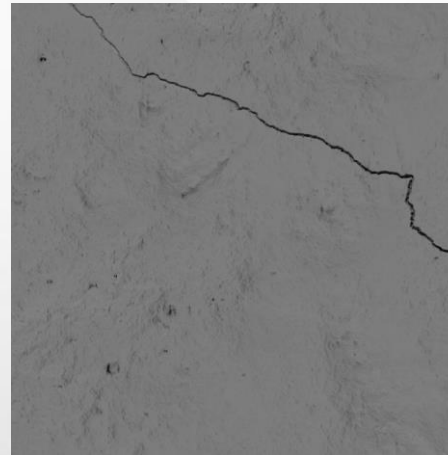


Fig 1: defect on concrete (simulated)



Fig 2: by depth gray scaled image



Fig 3: sigma field of residual

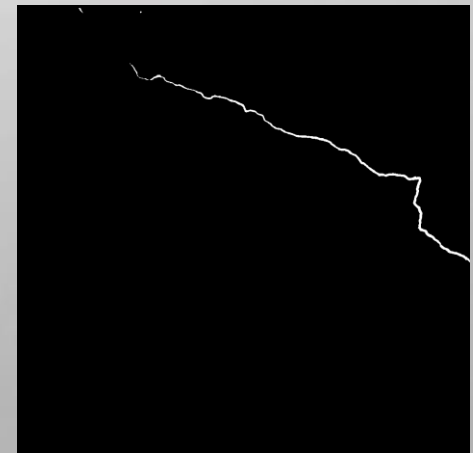
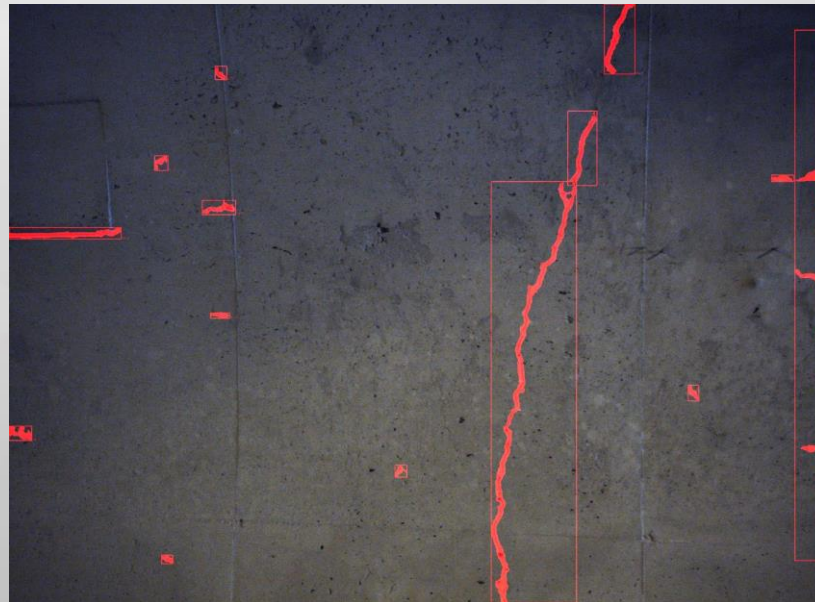


Fig 4: detection mask

Turin Pilot Data & Example Results

- Tunnel is a low light setting.
- High sensitivity of TPE and Deep Prior modules. Some false positives include surface markings, small holes, edge of concrete plates have pit like structure due to low light intensity setting.
- Simulated concrete images share similarities with the Tunnel concrete surface. => Multi-Task Unet model useful to suppress false positive.

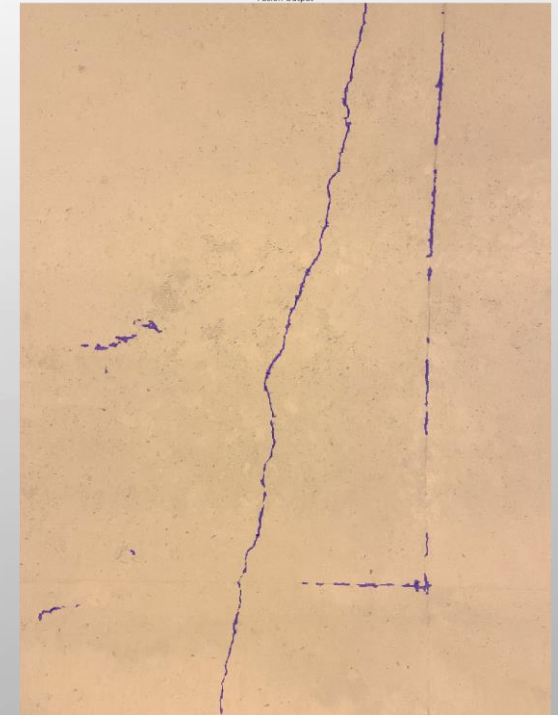
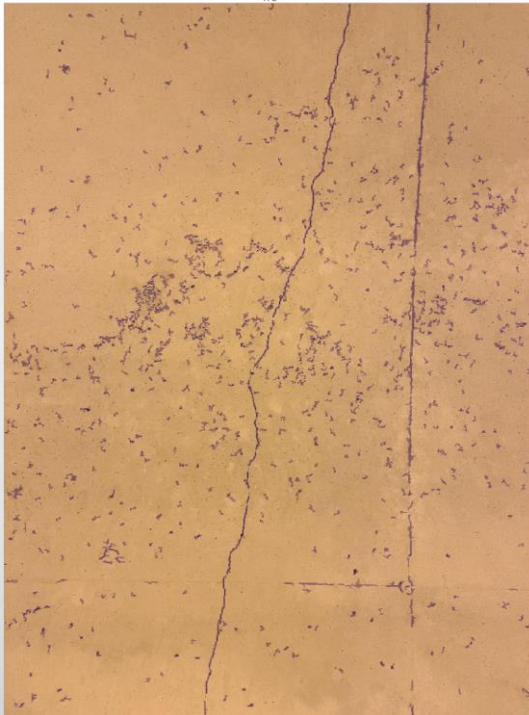


Turin Pilot Example Results

TPE

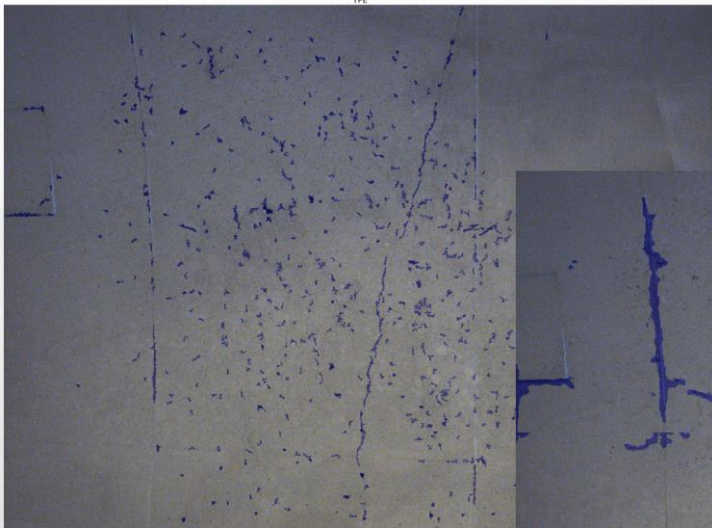
MultiUnet

Fusion



Turin Pilot Example Results

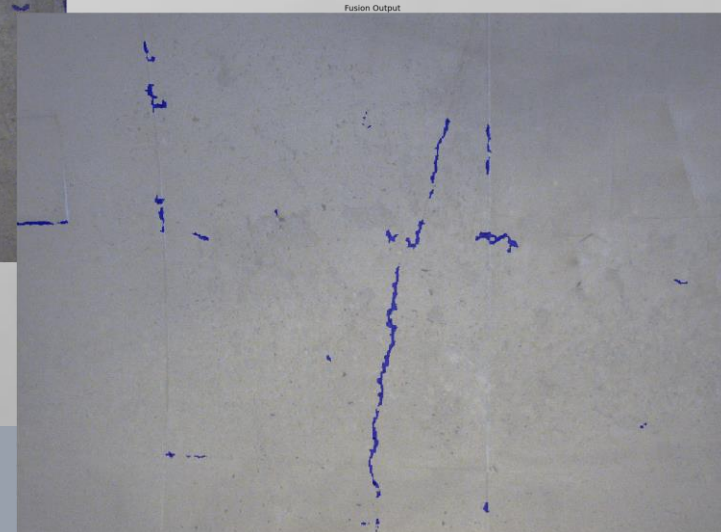
TPE



MultiUnet

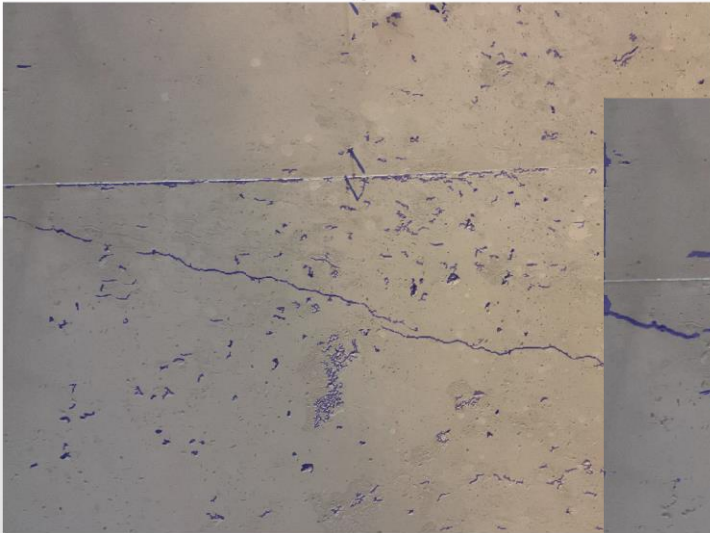


Fusion

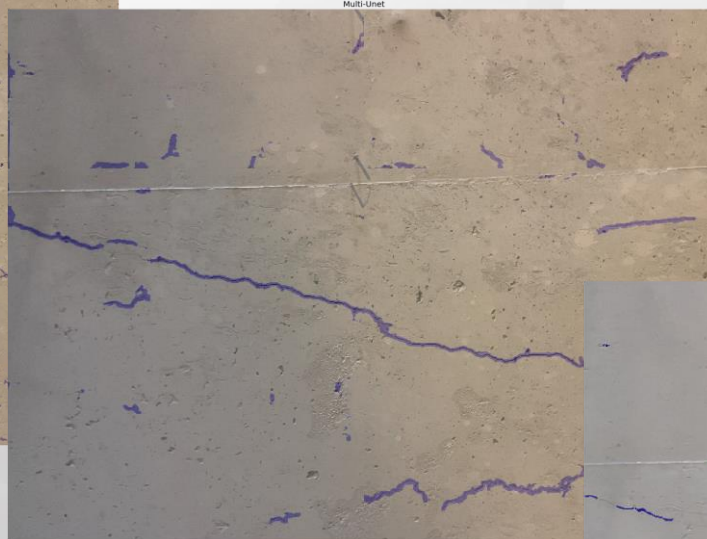


Turin Pilot Example Results

TPE



MultiUnet



Fusion



Cognitive Vision System: Key findings

- Module tests confirm strengths/limitations of each designed module. Fusion of modules improves performance adequately.
- MultiUnet Deep Learning model trained from simulations adequately transfers to tunnel setting.. Transfer learning starting from pre-trained model (from simulations) with new datasets can further enable fine-tuning of performance.
- Based on Metsovo pilot tests, 3D depth data from sensor is not sufficient for reduction of false positives of crack hypotheses (as originally hoped). Thus, stereo data mainly assists in mensuration of width and length of crack hypotheses.
- Feedback of human and DeeplImagePrior model based background estimation concept allows for adaptation of system to context. Current System is semi-automated and includes human in the loop for data selection and editing results.
- Larger data sets along with integrated end-to-end training including fusion step can further optimize system to provide value to end customers.

THANK YOU!

Any Questions?

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Backup