

# T-INSPECT: A Vision-based Tunnel Structural Health Monitoring Solution using Deep Learning and Data Fusion

Summary Report, 19<sup>th</sup> March 2021

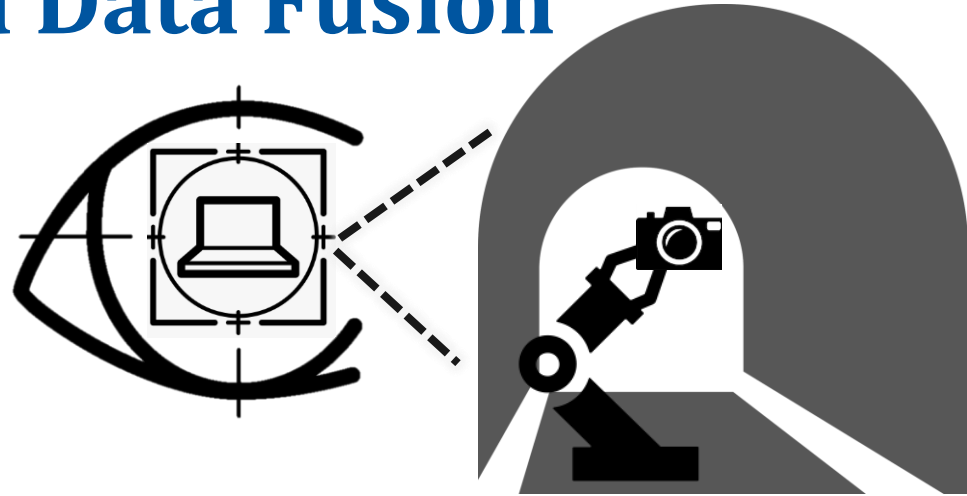
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**Mario di Castro**

**Luca Buonocore**

**Eloise Matheson**

**BE-CEM**



# Outline

- Motivation
- Robotics at CERN
- Monitoring solution
  - Data Acquisition
  - Anomaly Defect Detection
  - Change Detection
  - Visualization for surface documentation
- Ongoing and future work
- Conclusion

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  - Change Detection
  - Visualization for surface documentation
- Ongoing and future work
- Future work

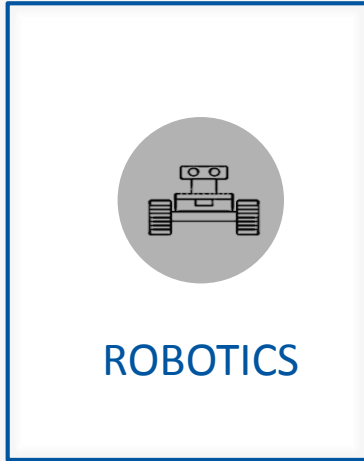
# Needs from SCE department



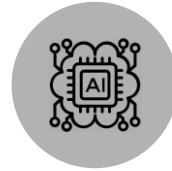
- ❑ Reduce inspection time
- ❑ Reduce personnel presence in tunnels
- ❑ Objective inspection, to reduce report subjectivity
- ❑ Change monitoring
- ❑ Visualization to aid tunnel surface documentation and analysis

# SHM

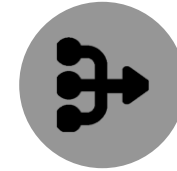
## Structural Health Monitoring



COMPUTER  
VISION



DEEP  
LEARNING



DATA FUSION

**mechatronics and robotics for a remotely  
operated automatic inspection system**

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# Robotics at CERN

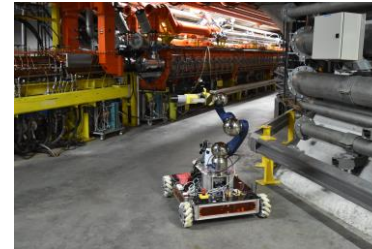
- improved personnel safety and machine availability



Telemax



TIM (in-house)



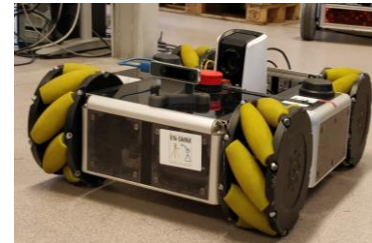
CERNbot (in-house)



Teodor



EXTRM (in-house)



CHARMbot (in-house)



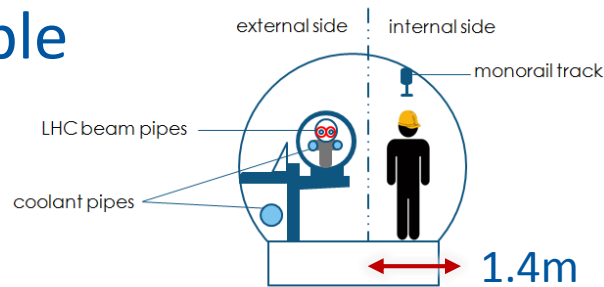
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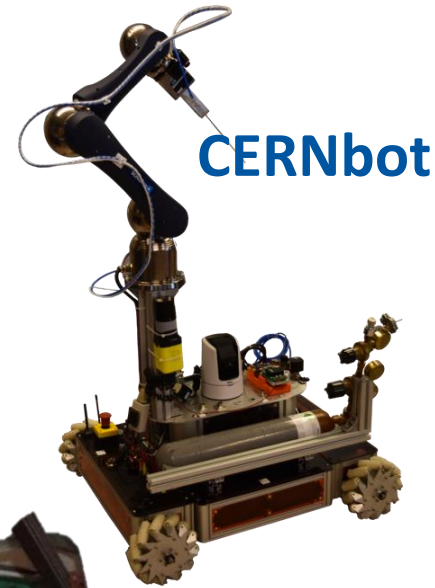
# Challenges & Constraints

- accessibility during **limited time** windows
- **difficult conditions** (radiation, dust etc.)
- long distances, capture from **moving robots**
- low and non-uniform **lighting conditions**
- **limited space** available



# Data Acquisition Setup

- **Phase 1 – Investigation**
  - study of possible sensors for inspection **CAMERAS**
  - continuous market research on inspection systems
- **Phase 2 – Implementation and testing**
  - In-house setups
    - ❑ data acquisition from a camera on TIM
    - ❑ multiple camera-setup on CERNbot
  - Commercial system
    - ❑ demo test in LHC tunnel



TIM

# In-house setups

## ➤ Software

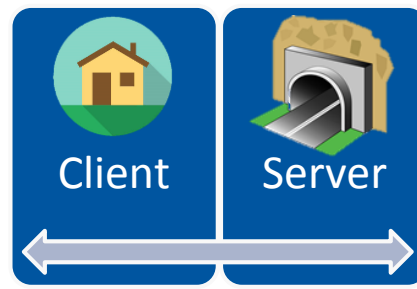
a client-server application to send commands to the camera/s

## ➤ Hardware

- ❑ Setup 1: camera on the RP arm extending from TIM
- ❑ Setup 2: multiple cameras on an adjustable vertical metal structure fixed on the CERNbot

## ➤ Dataset

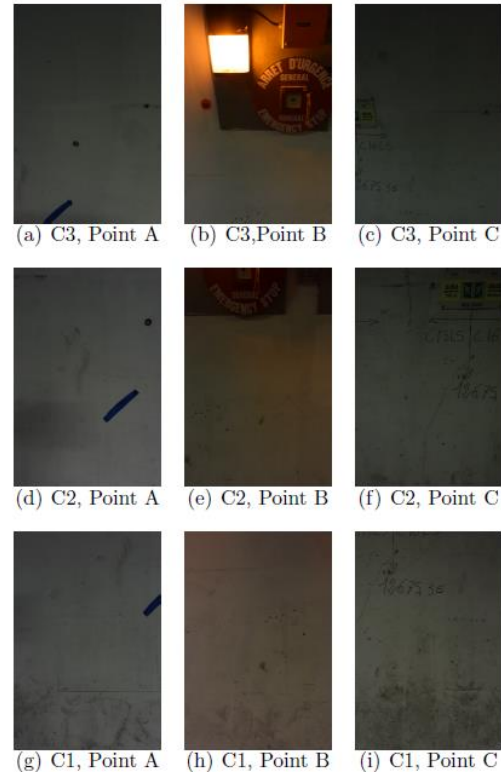
high-definition pictures in LHC, TT1, SPS



**TIM**

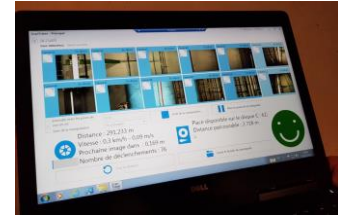
**CERNbot**

# Images from the 3-camera setup



# Commercial system

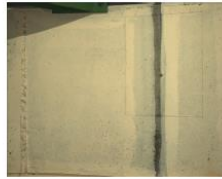
- during continuous market research, we identified commercial camera system purposely built for inspections
- this system's package features:
  - larger field of view (ideally full-tunnel cross-section)
  - synchronisation of multiple cameras and flash lights via hardware
  - better 3D reconstruction (automating 3D reconstruction)



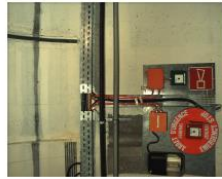
# Images from the demo test in the LHC Tunnel



(a) Camera 1



(b) Camera 2



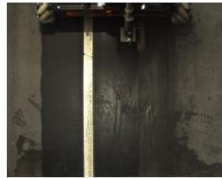
(c) Camera 3



(d) Camera 4



(e) Camera 5



(f) Camera 6



(g) Camera 7



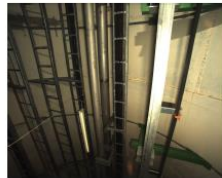
(h) Camera 8



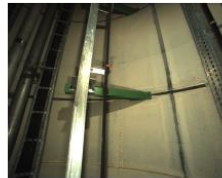
(i) Camera 9



(j) Camera 10



(k) Camera 11



(l) Camera 12



Survey at time  $T_1$



Survey at time  $T_2$

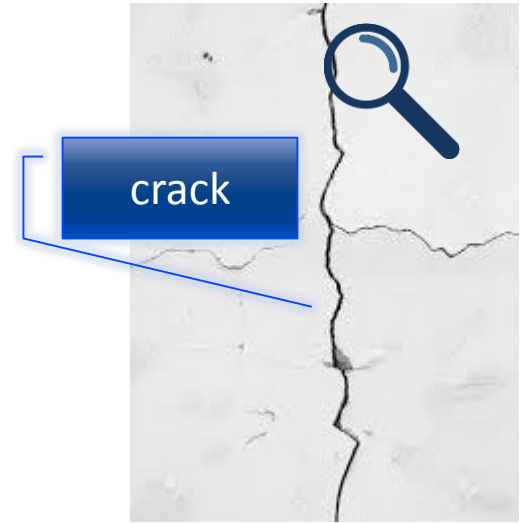
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# Anomaly Defect Detection

## example: Crack Detection

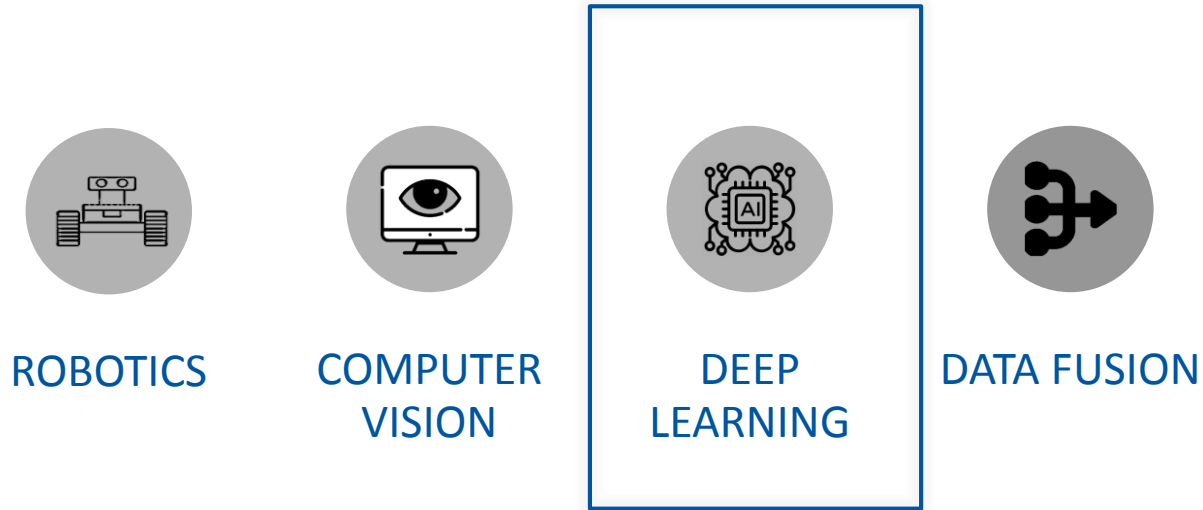
- early works use image processing techniques such as thresholding, mathematical morphology and edge detection
- these rule-based approaches cannot overcome inherent challenges associated with crack images :
  - difficult topology of cracks
  - diversity of surface texture
  - inhomogeneity of cracks
  - background complexity and inference of objects with similar shape/texture to cracks such as joints
- a better approach is to use pattern recognition and/or machine learning techniques





# SHM

## Structural Health Monitoring



**an even better approach !**

# Crack localisation using deep learning

- this work uses **state of the art deep learning models**
- built a **ground-truth datasets**

- from a standard dataset (SDNET)

[https://digitalcommons.usu.edu/all\\_datasets/48/](https://digitalcommons.usu.edu/all_datasets/48/)

- from images captured in the LHC tunnel

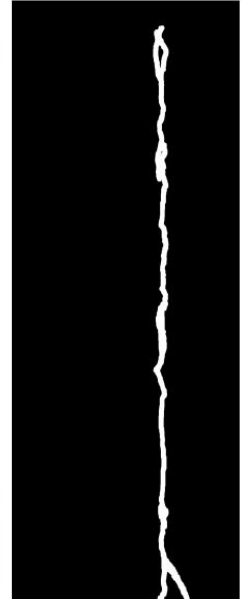
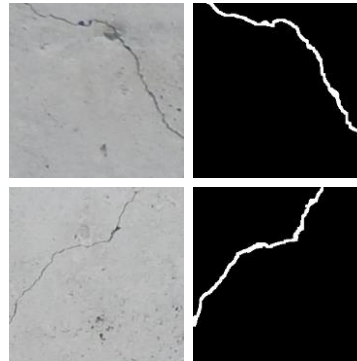
- Instance Segmentation
- Mask R-CNN
- Semantic segmentation

- U-Net
- SegNet

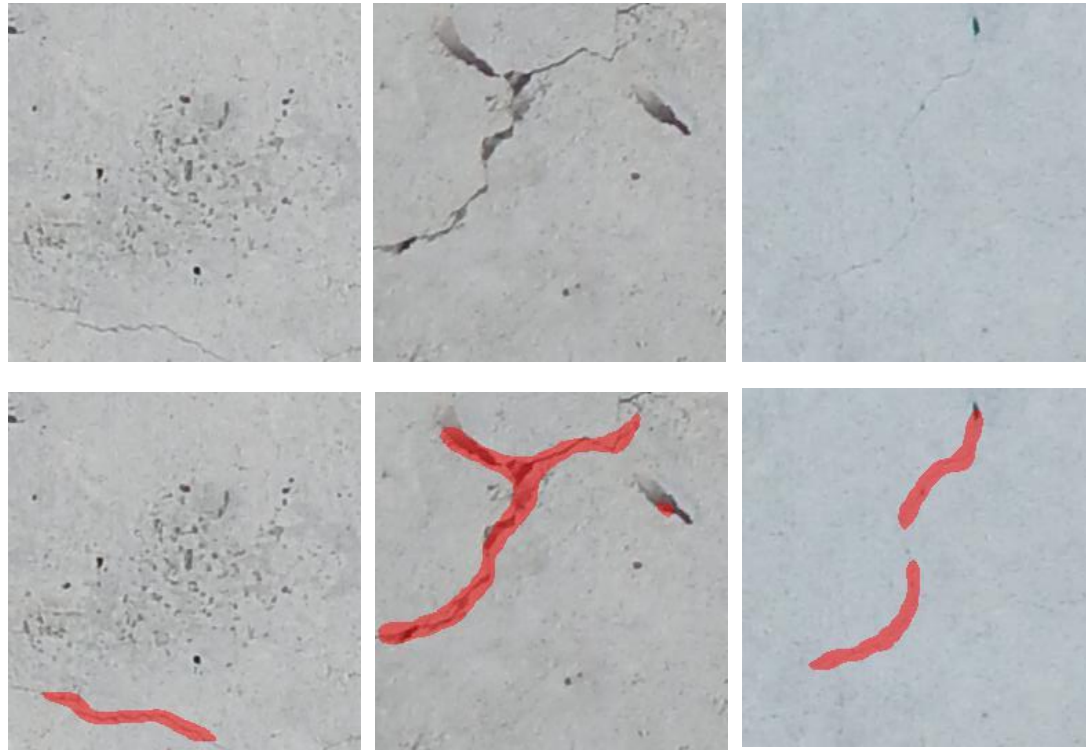


*better*

*due to limited training datasets*



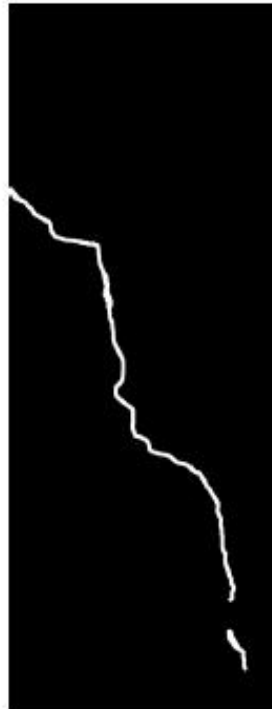
# Detection results on images from **SDNET** dataset



# Detection results on images from **LHC** dataset



(a) Crack image



(b) GT



(c) U-Net



(d) SegNet



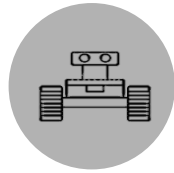
(e) Mask R-CNN

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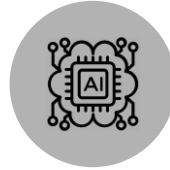
## Structural Health Monitoring



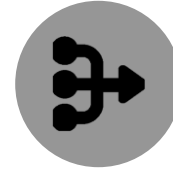
ROBOTICS



COMPUTER  
VISION

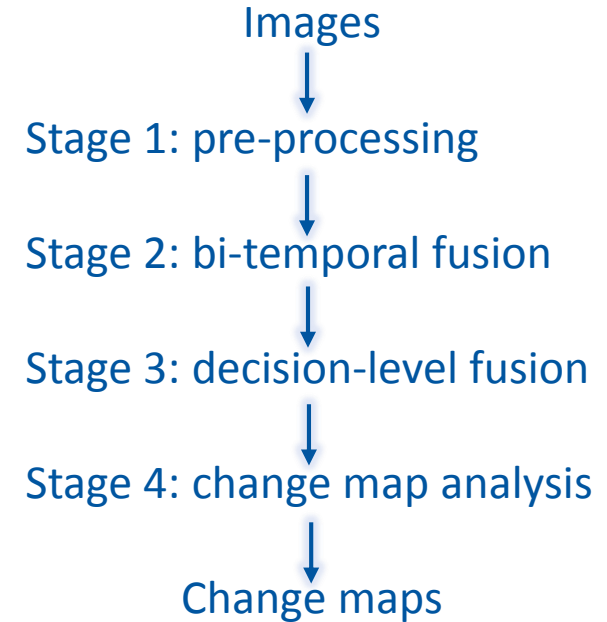
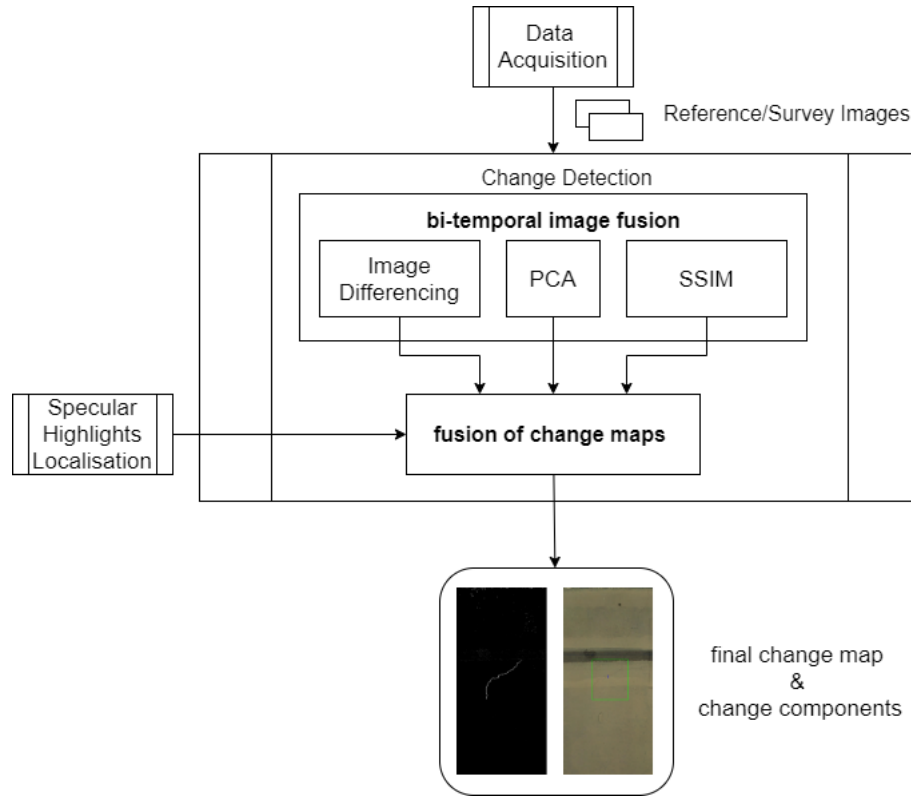


DEEP  
LEARNING

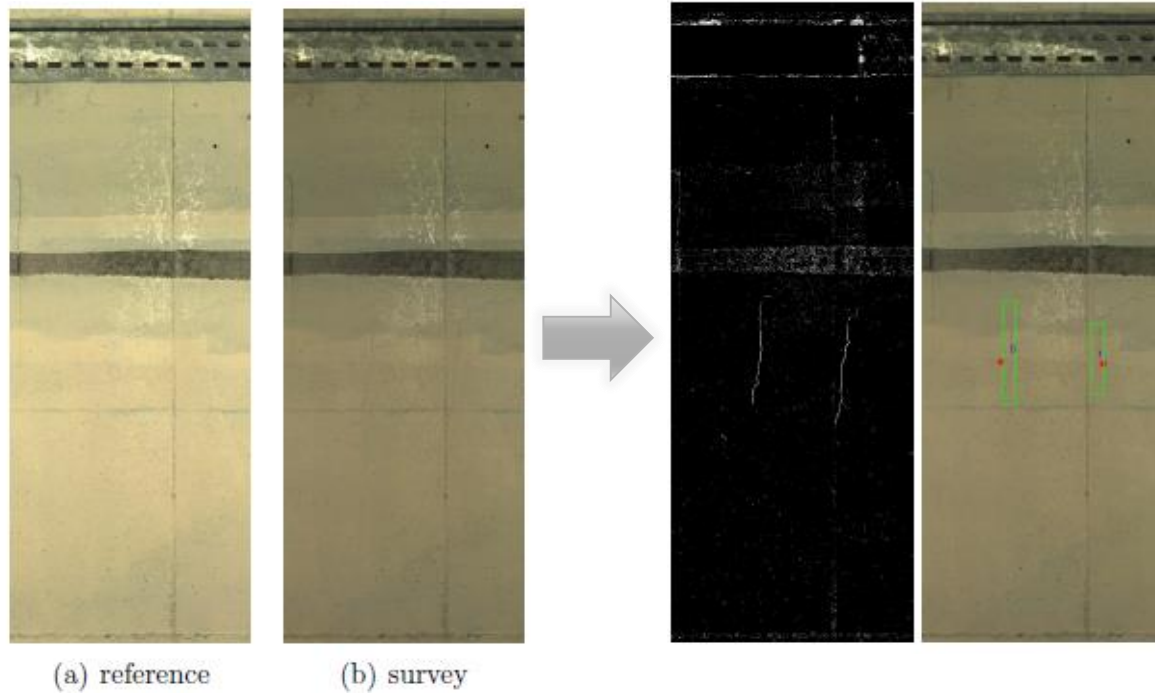


DATA FUSION

# Change detection flow diagram

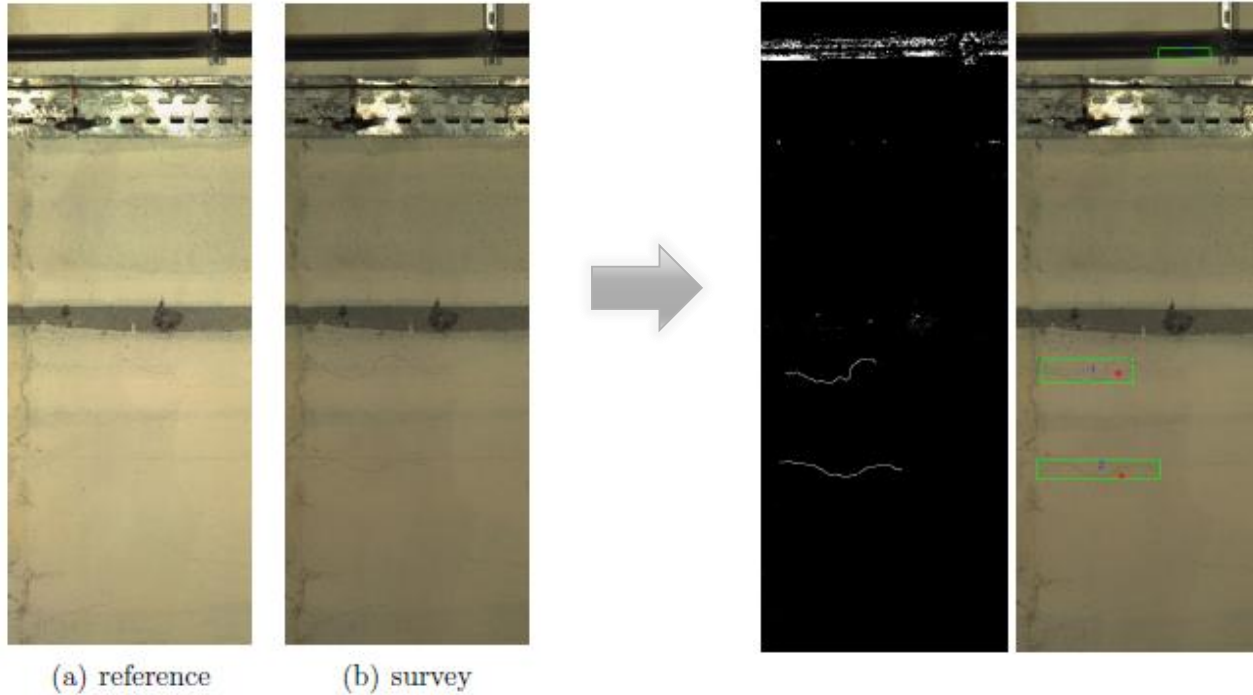


## Example 1





## Example 2



# Added benefits

- Less personnel presence in the tunnel
  - Shorter inspection times
- } -- ROBOTICS
- Objective inspection -- COMPUTER VISION & DEEP LEARNING ALGORITHMS
  - In addition to defect detection it offers a means of monitoring the structural health -- CHANGE DETECTION
  - Reliable detection -- DATA FUSION

# Application of the solution in other environments



**Subway Tunnels**



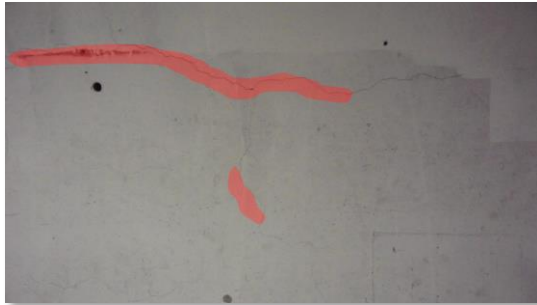
**Bridges**



# Software - Code Repositories

- **Change Detection** - CACI\_Computer\_Aided\_Change\_Identifier  
<https://gitlab.cern.ch/mro/robotics/tunnel-structure-inspection/caci>
  
- **Crack Detection**
  - Mask R-CNN - general\_mrcnn <https://gitlab.cern.ch/mro/robotics/tunnel-structure-inspection/generalmaskrcnn>
  - Semantic segmentation - keras\_segmentation  
<https://gitlab.cern.ch/mro/robotics/tunnel-structure-inspection/kerassegmentation>
  
- **Specular highlights detection**
  - (experimental, no final results) using deeplab  
<https://gitlab.cern.ch/mro/robotics/tunnel-structure-inspection/specularhighlightsdetection>
  - Semantic segmentation (same as crack detection) - keras\_segmentation  
<https://gitlab.cern.ch/mro/robotics/tunnel-structure-inspection/kerassegmentation>
  
- **Thermal camera interface** – ThermoVis (also a class in the CRF)  
<https://gitlab.cern.ch/mro/robotics/libraries/thermovis>
  
- **Nikon camera control (using Nikon SDK and their sample code)** –  
<https://gitlab.cern.ch/mro/robotics/libraries/nikoncamerascontrol>

# Example of anomaly detected



Example of crack found using vision based machine learning techniques



Example of water leak found by TIM2 during TS3 2018

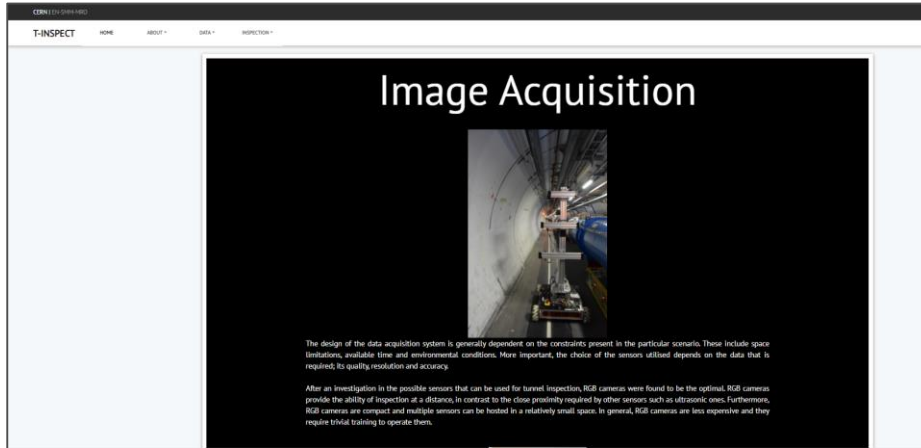
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# Webpage

<http://test-tinspect.web.cern.ch/>

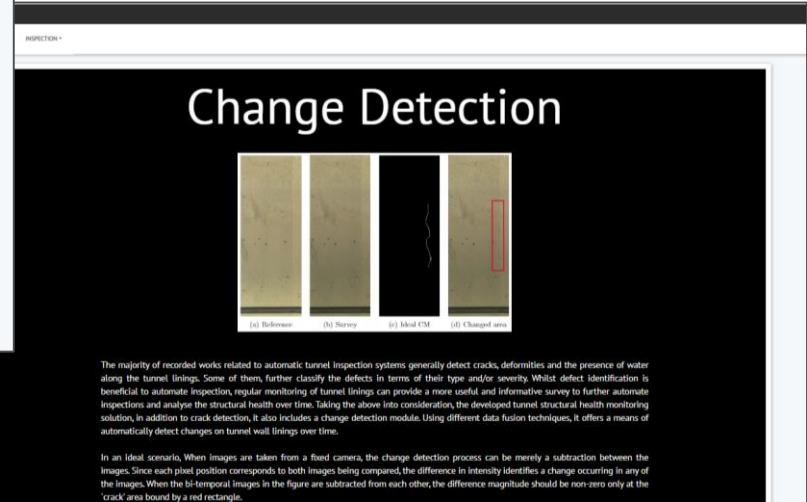
# General information pages



The screenshot shows the 'Image Acquisition' page of the T-Inspect website. The page features a navigation bar with 'HOME', 'ABOUT', 'SERVICES', and 'INSPECTION'. The main content area has a large heading 'Image Acquisition' and a central image of a tunnel inspection robot. Below the image, there are two paragraphs of text.

The design of the data acquisition system is generally dependent on the constraints present in the particular scenario. These include space limitations, available time and environmental conditions. More important, the choice of the sensors utilized depends on the data that is required, its quality, resolution and accuracy.

After an investigation in the possible sensors that can be used for tunnel inspection, RGB cameras were found to be the optimal. RGB cameras provide the ability of inspection at a distance, in contrast to the close proximity required by other sensors such as ultrasonic ones. Furthermore, RGB cameras are compact and multiple sensors can be hosted in a relatively small space. In general, RGB cameras are less expensive and they require minimal training to operate them.



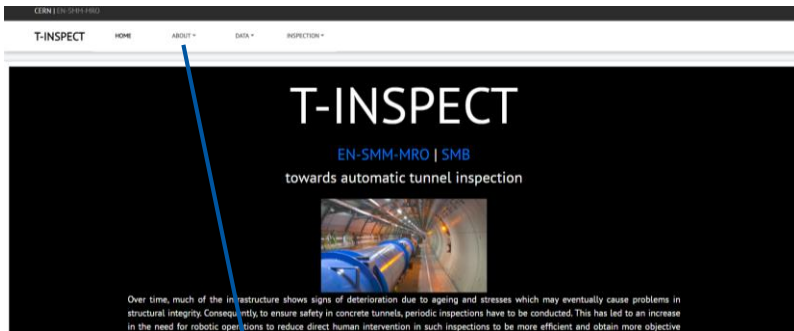
The screenshot shows the 'Change Detection' page of the T-Inspect website. The page features a navigation bar with 'INSPECTION'. The main content area has a large heading 'Change Detection' and a central image showing four panels: (a) Reference, (b) Noisy, (c) Ideal CM, and (d) Changed area. Below the image, there are two paragraphs of text.

The majority of recorded works related to automatic tunnel inspection systems generally detect cracks, deformities, and the presence of water along the tunnel linings. Some of them, further classify the defects in terms of their type and/or severity. Whilst defect identification is beneficial to automate inspection, regular monitoring of tunnel linings can provide a more useful and informative survey to further automate inspections and analyse the structural health over time. Taking the above into consideration, the developed tunnel structural health monitoring solution, in addition to crack detection, it also includes a change detection module. Using different data fusion techniques, it offers a means of automatically detect changes on tunnel wall linings over time.

In an ideal scenario, when images are taken from a fixed camera, the change detection process can be merely a subtraction between the images. Since each pixel position corresponds to both images being compared, the difference in intensity identifies a change occurring in any of the images. When the bi-temporal images in the figure are subtracted from each other, the difference magnitude should be non-zero only at the 'crack' area bound by a red rectangle.

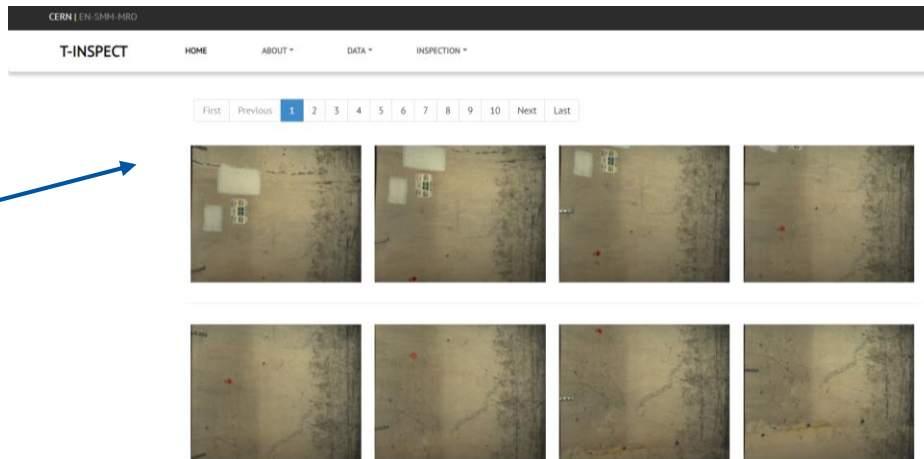


# Image datasets



📷 Datasets

Location	Date	Orientation	Dataset
LHC-P1	31-10-2018	/	📷 ONSITE-VISIT
LHC-P1	July-2019	/	📷 SITES-aller-cam2
LHC-P1	July-2019	/	📷 SITES-aller-cam3
LHC-P1	July-2019	/	📷 SITES-aller-cam4
LHC-P1	July-2019	/	📷 SITES-aller-cam5
LHC-P1	July-2019	/	📷 SITES-aller-cam6
LHC-P1	July-2019	/	📷 SITES-retour-cam2
LHC-P1	July-2019	/	📷 SITES-retour-cam3



# Change Detection results

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T-INSPECT HOME ABOUT ▾ DATA ▾ INSPECTION ▾

📷 Change Detection Samples

Location	Date 1	Date 2	Dataset
LHC-P1	July-2019	July-2019	📷 SIMULATION-SITES

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T-INSPECT HOME ABOUT ▾ DATA ▾ INSPECTION ▾

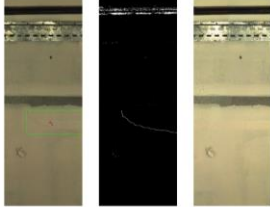
📷 Change Detection Results by DCUM

Orthophoto segment	DCUM start	DCUM end	Images
Section-6	268.66	269.16	📷
Section-6	269.16	269.66	📷
Section-6	269.66	270.16	📷
Section-6	270.16	270.66	📷
Section-6	270.66	271.16	📷

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First Previous 1 Next Last



# Thermal and RDGB-D images

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T-INSPECT HOME ABOUT ▾ DATA ▾ INSPECTION ▾

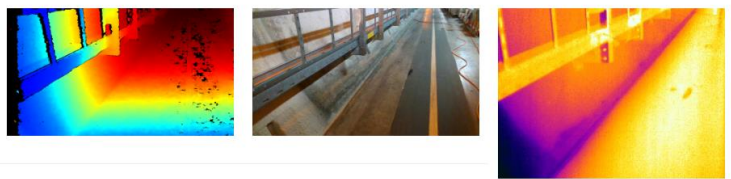
📷 RGB-D Thermal Datasets

Name	Location	Dataset
PT3_JULY_2019	LHC	📷
TS_JUNE_2018	LHC	📷
TT1_JULY_2019	LHC	📷

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T-INSPECT HOME ABOUT ▾ DATA ▾ INSPECTION ▾

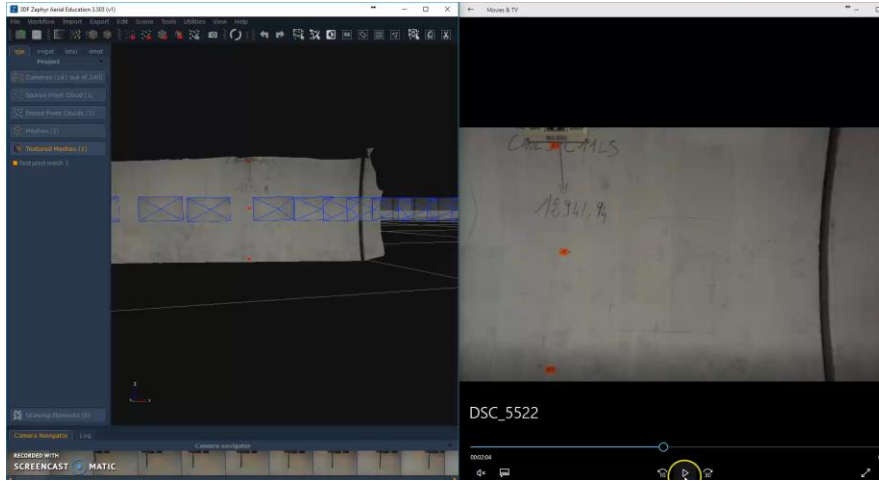
First Previous 1 2 3 4 5 6 7 8 9 10 Next Last



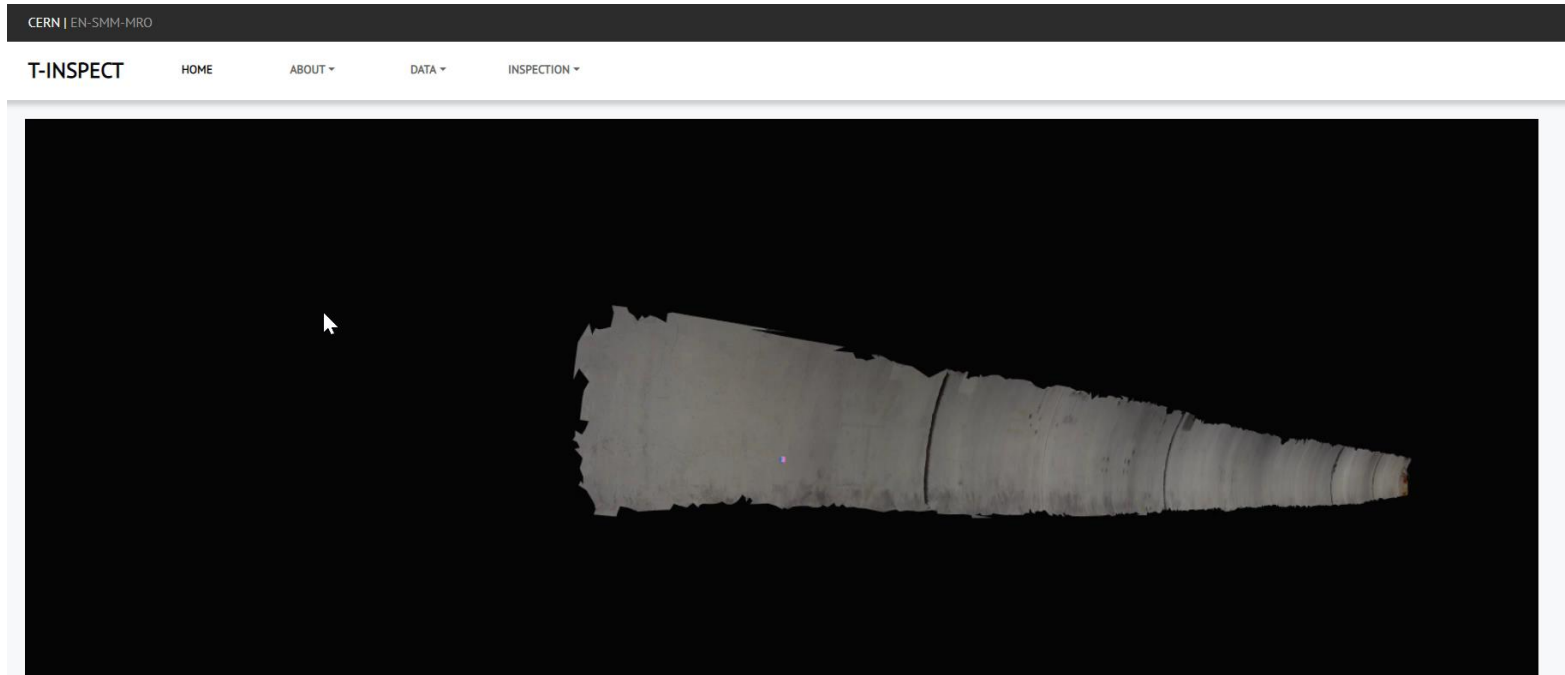
The second screenshot shows the same application interface but with a pagination control and a gallery of three images. A blue arrow points from the camera icon in the first screenshot to the '4' button in the pagination control. The gallery contains three images: a thermal image of a tunnel floor, a standard RGB image of the same tunnel floor, and a combined thermal/RGB-D image.

# 3D and VR

# 3D and VR models for better contextualization



# 3D models on the web-page



# Publication contributions

[published]

1. Tunnel inspection using photogrammetric techniques and image processing: A review, ISPRS Journal of Photogrammetry and Remote Sensing, Vol. 144, 2018.
2. A comprehensive virtual reality system for tunnel surface documentation and structural health monitoring, 2018 IEEE International Conference on Imaging Systems and Techniques (IST), Krakow, 2018.
3. Automatic Crack Detection using Mask R-CNN, 11th International Symposium on Image and Signal Processing and Analysis (ISPA), Dubrovnik, Croatia, 2019.
4. VR-SHM - A structural health monitoring tool to assist crack detection using deep learning and virtual reality, Sustainable Built Environment conference, Malta, 2019

[under review]

1. Specular highlights detection using a U-Net based deep learning architecture, 2020 IEEE International Conference on Image Processing (ICIP)
2. Automatic crack detection using deep learning models - a comparative analysis, Automation in Construction
3. Tunnel structural health monitoring using a computer vision and data fusion change detection solution, Image and Vision Computing Journal

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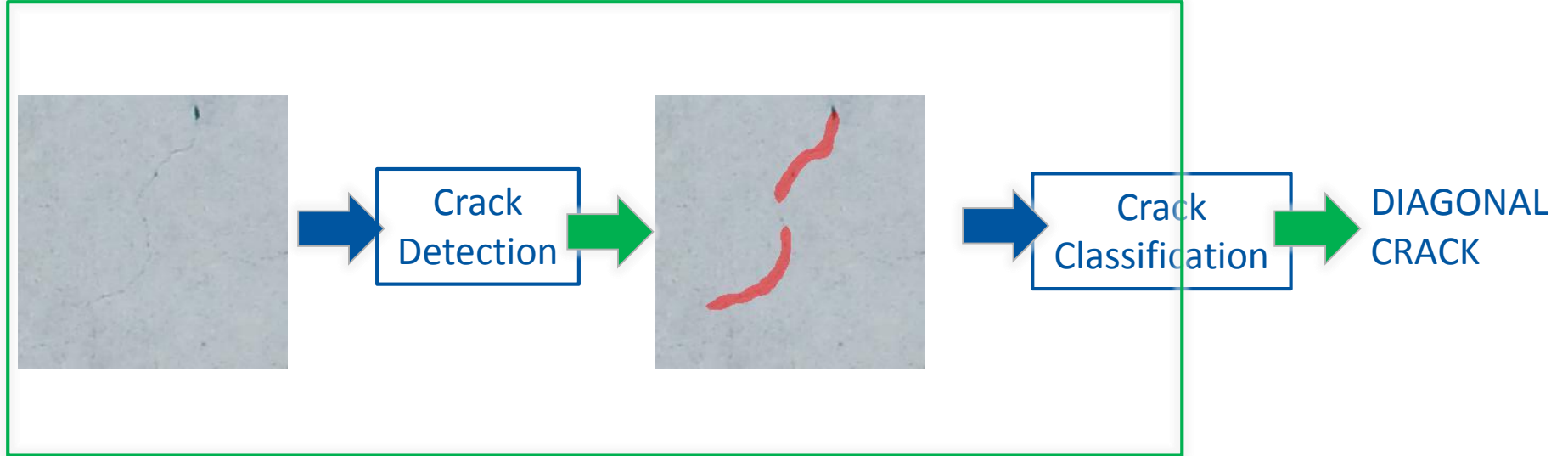


# Crack classification

# From crack detection to crack classification.....

- crack detection can be used as a pre-processing stage to crack classification
- once crack's bounding boxes are identified, properties such as, width/length/moments of the contours can be extracted to get the directionality
- these can then be used:
  - via rule-based conditions such as if length > width by a certain amount then it is a vertical crack (just as an example)
  - to implement a more accurate and generalised way of classification by using these properties as a feature vector and then use pattern recognition techniques or machine learning, through classification networks such as SVMs
- deep learning principle can also be used for classification

# From crack detection to crack classification.....



**DONE** ✓

**ONGOING**

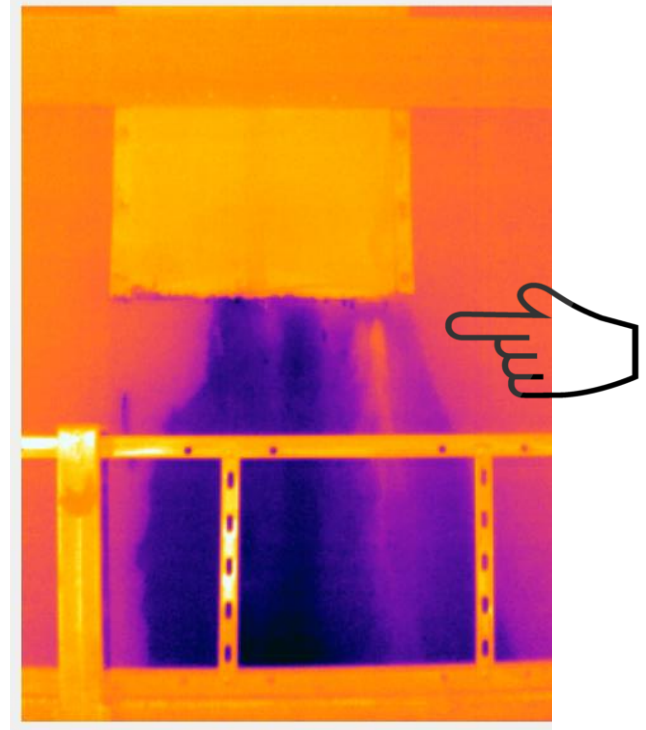
# Thermal imagery Data Fusion

# Thermal Imagery for in-depth inspection

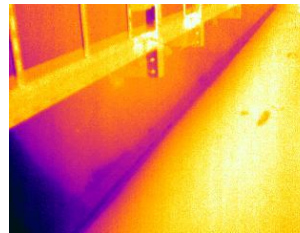
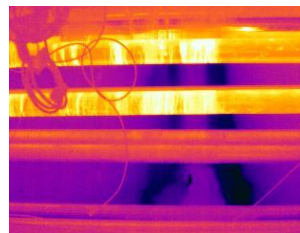
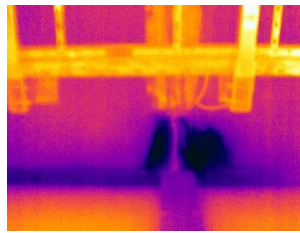
non-contact technology which measures infrared wavelengths emitted from objects

## Work done

- ✓ developed an interface that:
  - captures images / videos
  - saves the temperatures in °C
- ✓ data acquisition in TT1, LHC PT3



# Thermal Imagery for in-depth inspection



# Thermal – Visible image fusion

- **TIR images** distinguish targets from their backgrounds based on the radiation difference, which works well in all-weather and all-day/night conditions
- **Visible images** provide texture details with high spatial resolution and definition in a manner consistent with the human visual system

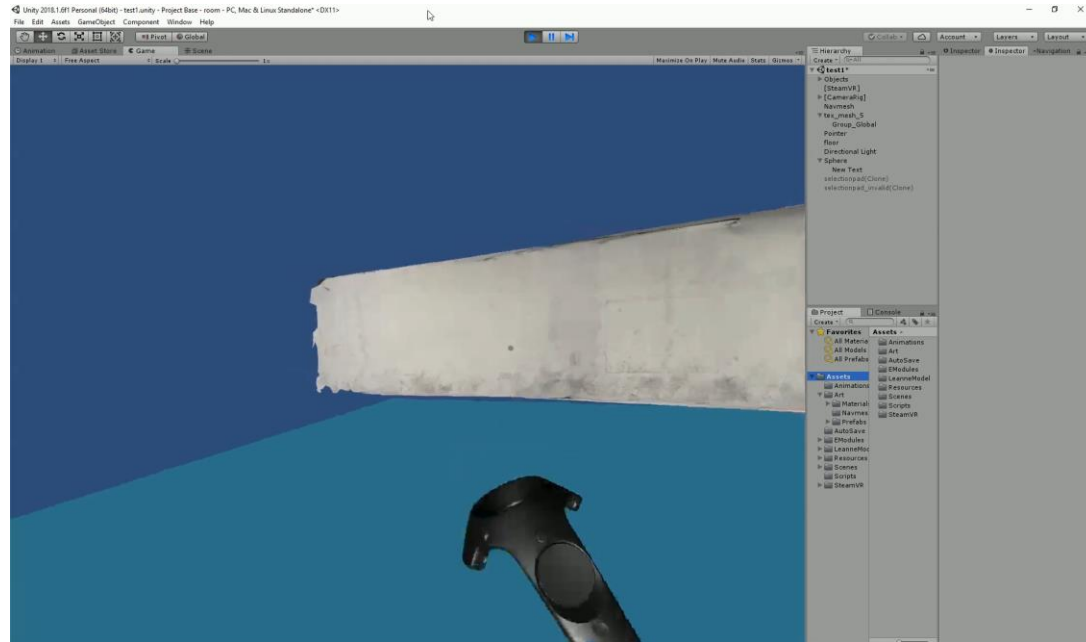


- Fusion of these two types of images combines their individual properties and can be beneficial for in-depth inspection to detect water leakages, deposition etc.

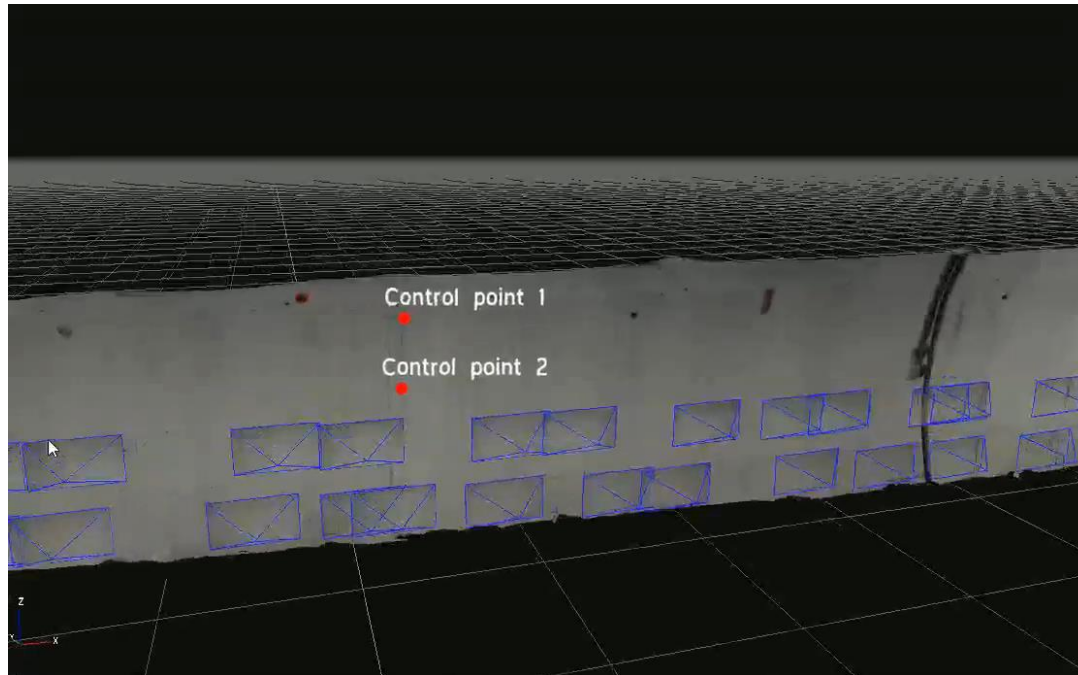
# VR



# Augment information to the VR models



# Remote measuring from VR



A yellow speech bubble with a tail pointing towards the bottom left, containing the text "THE WAY FORWARD!" in a bold, red, sans-serif font.

to monitor the **full tunnel lining** cross-section

➤ additional hardware which is currently in procurement stages

to ensure **monitoring speed and personnel safety**

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  - Crack Detection
  - Change Detection
  - Visualization for surface documentation
- Ongoing and future work
- **Conclusion**

# What has been done so far



- ❑ Reduce inspection time
- ✓ Image capture in real-time using **on-board processors** during technical stops, inspection process **executed offline on powerful computers**, to flag issues within a few hours
  
- ❑ Reduce personnel presence in tunnels
- ✓ Implementation of remote image capturing **on moving robots**
  
- ❑ Objective inspection, to reduce report subjectivity
- ✓ Anomaly defect (cracks) detection using **deep learning**

# What has been done so far



- ❑ Change monitoring
  - ✓ **Reliable** change detection using **image processing** and **data fusion**
  - ✓ Pre-processing and post-processing stages **to reduce false alarms** using image processing and deep learning techniques
- ❑ Visualization to aid tunnel surface documentation and analysis
  - ✓ Experimentation with the use of **3D and VR models** for their use in **tunnel surface documentation, inspection and analysis**
- ❑ Experimentation with the use of **thermal imagery** for in-depth inspection

# Man Power needed for the possible future work

- ❑ Future manpower needed to have a fully operational device: mainly hardware integration tasks on existing robotic platforms + testing and commissioning of the novel 360 deg camera system under procurement.
  - ✓ 2 FTE (Robotics/Integration Engineer) + 1 TECH



Thanks a lot