Drone imaging for industrial infrastructure inspection

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Version 1.1

Artificial Intelligence & Information Analysis Lab

UAV Industrial Infrastructure Inspection

UAV Industrial Infrastructure Inspection

- **Overview**
  - Pipeline Semantic Segmentation
  - Pipeline Damage Detection and Classification
  - 3D Pipeline Damage Localization
  - X-ray Pipeline Corrosion Detection
  - PEC Pipeline Corrosion Detection

Overview

- **Pipeline Semantic Segmentation**
  - Developed pipeline segmentation algorithm: *Pipeline segmentation model*.
  - Performed an extensive evaluation of the *Pipeline segmentation model*.

- **Pipeline Damage Detection and Classification**
  - Developed damage detection and classification algorithms.
    - Algorithms based on lightweight DNN detectors (YoLo, RT-DETR).
    - *Changes detection* algorithm, which works in using image patches.
  - Perfomed an extensive evaluation of the developed algorithms.

Overview

- **3D Pipeline Damage Localization**
  - Developed algorithms for creating 3D models of pipelines (cylinders) using a) 3D point cloud, b) RGB video frames.
  - Projecting the 2D detected pipeline damages on the 3D point cloud/map.
- **X-ray Pipeline Corrosion Detection**
  - Solved the task using the YoLov8 object detection algorithm.
  - Developed an image processing algorithm for corrosion detection.
  - Implemented modern anomaly detection algorithms for corrosion detection.
  - Developed an algorithm for synthetic X-ray data generation.
- **PEC Pipeline Corrosion Detection**
  - Analysed and pre-processed PEC data.

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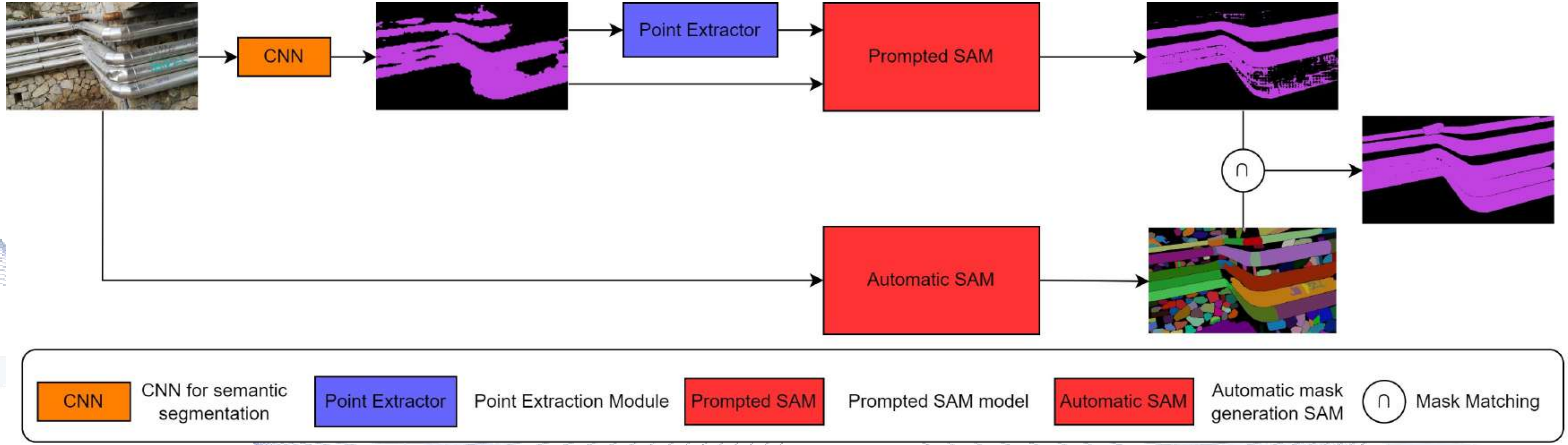
Pipeline Semantic Segmentation

- *Pipeline segmentation model*: Cooperation of a CNN segmentation model [PAP2021a] and Segment Anything Model [KIR2023].
  - The CNN model produces masks of the pipes.
  - A prompted SAM goal is used to refine the segmentation masks produced by CNN model.
  - SAM also runs on automatic mode to produce masks for all objects.
  - The final segmentation mask is produced by fusing the two intermediate outputs.

Pipeline Semantic Segmentation



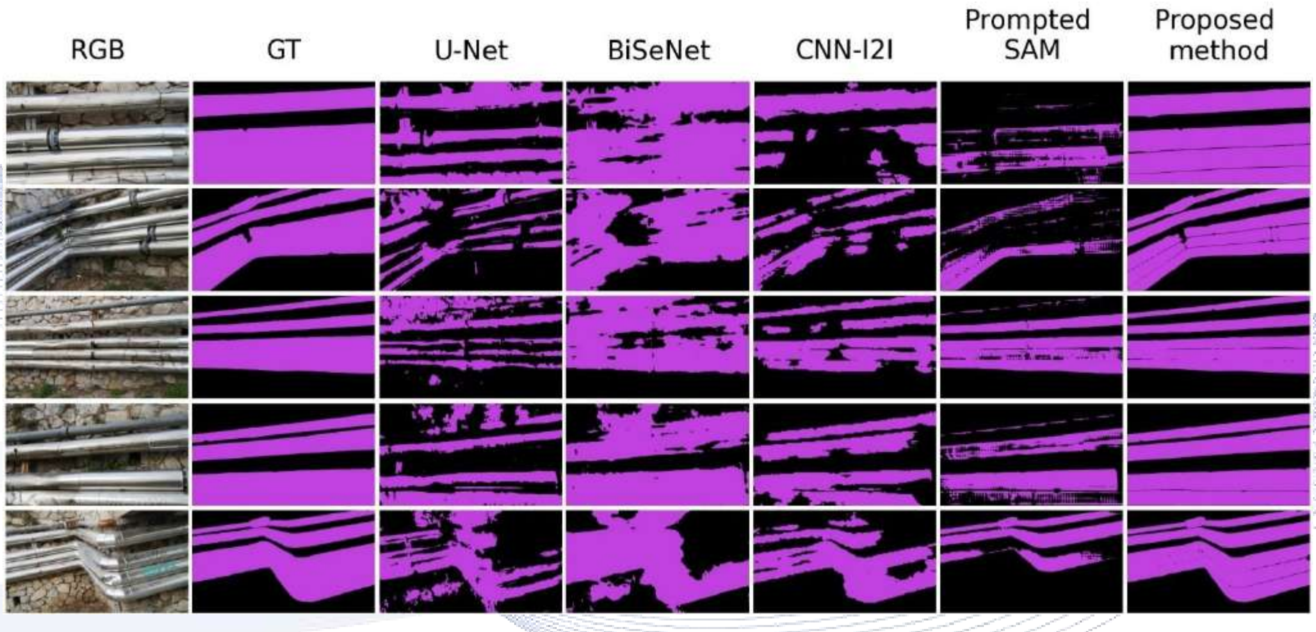
Pipeline Semantic Segmentation

- *Training dataset*: 901 annotated RGB images collected from the CHEVRON site (initial data collection).
- *Validation dataset*: 77 annotated RGB images collected from the AUTH site.
- *Test Dataset*: RGB images collected from CHEVRON on September 21st 2023 using UAV.

Validation dataset example. (AUTH site)

Pipeline Semantic Segmentation

- The performance of the model was evaluated using the *Intersection-over-Union (IoU)* metric.



	IoU (%)			
	non-pipe	**pipe**	**mIoU**	**mPA(%)**
U-Net [7]	52.0	46.1	49.0	66.0
BiSeNet [8]	54.2	65.4	59.8	75.4
I2I-CNN [9]	68.5	63.7	66.1	79.7
prompted SAM	78.9	79.3	79.1	88.3
Proposed System	**89.0**	**90.9**	**89.9**	**94.8**

D. Psarras, C. Papaioannidis, V. Mygdalis, and I. Pitas, "A Unified DNN-Based System for Industrial Pipeline Segmentation", ICASSP 2024.

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Pipeline Semantic Segmentation

Pipeline semantic segmentation image example.

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Pipeline Damage Detection and Classification

- **Detection/classification:**
  - YOLO-based algorithm [CHU2022] :
    - Extract features from CNN-based backbone.
    - Integrate features at multiple scales.
  - RT-Detr-based algorithm [WEN2023] :
    - Transformer based detector.
- **Changes detection:**
  - Deep autoencoder model:
    - Learns the distribution of non-damaged pipe from image patches.
    - Detects the image patches that differ from learned distribution and classifies them as abnormal.

Pipeline Damage Detection and Classification

Pipe damage in a Greek factory.

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Pipeline Damage Detection and Classification

Performance of damage detection and classification algorithms

Model	Dataset	Mean Average Precision	Mean Average Recall
YOLO-NAS	D2023-07-01	0.39	0.776
YOLOv6L6	D2023-07-01	0.519	0.705
YOLOv6L6+SAHI	D2023-07-01	0.521	0.730
Rt-Detr	D2023-07-01	0.472	0.77
Rt-Detr+SAHI	D2023-07-01	0.45	0.54
YOLOv6L6	D2023-09-30	0.52	0.78
Rt-Detr	D2023-09-30	0.45	0.77
Rt-Detr+YOLOv6-Backbone	D2023-09-30	0.40	0.65
YOLOv6L6	**D2023-10-20**	**0.52**	**0.82**
Rt-Detr	D2023-10-20	0.46	0.78

Performance of *changes detection* algorithm

Methods	Precision	Recall
Autoencoders	0.55	0.91
Autoencoders with one-class SVM	0.56	0.89
ResNet-50 with Local Outlier Factor	0.36	0.86

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Pipeline Damage Detection and Classification

Overall pipe damage detection and visualization.

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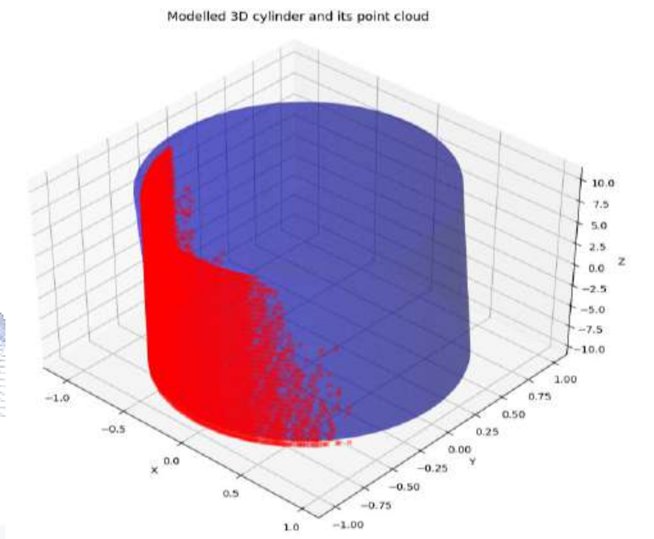
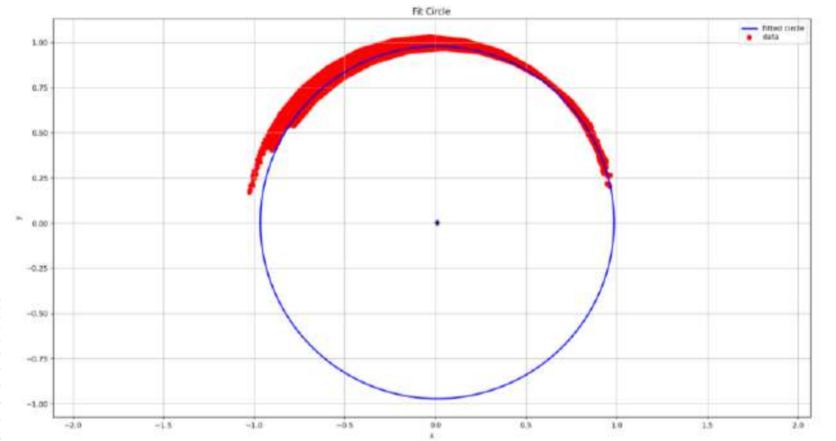
3D Pipeline Damage Localization

- **Goal**: Improve accuracy of damage localization on the 3D point cloud.
- Developed algorithm for 3D pipeline model construction from 3D point clouds.
    - *Input*: 3D point cloud from simulation.
    - *Methodology:*
        - Principal Component Analysis (PCA) to the 3D point cloud. [BRO2014]
        - Fit a circle by projecting the 3D point cloud onto the plane of the eigenvectors.
        - Compute the orientation and height of cylinder.

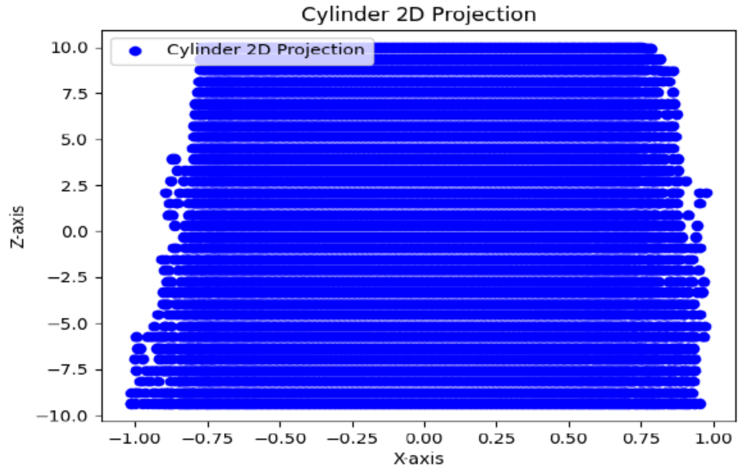
3D Pipeline Damage Localization



PCA on the 3D point cloud



Projection of the point cloud onto the plane of eigenvectors. The blue line is the circle fitted.



2D projection of cylinder to compute orientation and height

3D Pipeline Damage Localization

- 3D pipe model construction from RGB video frames.
- Structure from Motion software
    - Apply masks to point cloud mainly to reduce outliers.
    - Utilizes segmentation masks + confidence masks.
    - Better cylinder parameter computation.
    - Reduced processing time.

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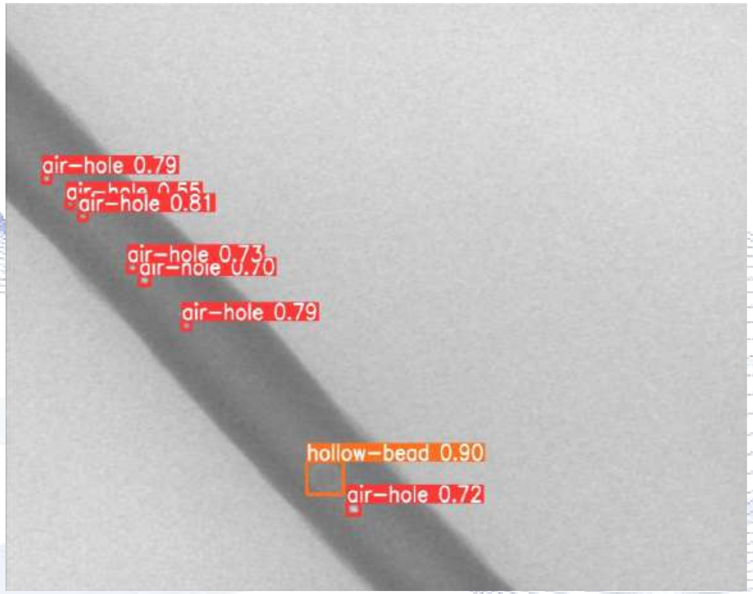
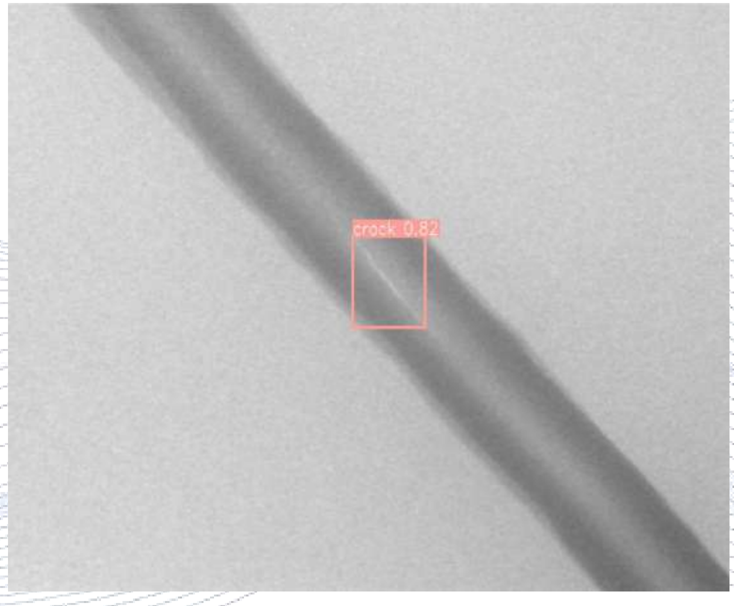
X-Ray Pipeline Corrosion Detection

- Regarding X-rays, we have three types of datasets.
  - D_{XR1}: The X-rays are powerful, and able to penetrate the metal pipelines [YAN2021]. (This dataset was captured at the manufacturing stage)
  - D_{XR2}: The X-rays are only able to penetrate the insulation. This is the type of dataset that we deal with in the SIMAR project.
  - $D_{syntethic}$: The X-ray data have been synthetically created to look similar to D_{XR2}.

X-Ray Pipeline Corrosion Detection

- Similarly to [YAN2021], solved this as an object detection task.
- Trained baseline models based on YOLO object detector [CHU2022].





Dataset D_{XR1} [YAN2021]

YOLOv8 Results	
Precision	0.97
Recall	0.96
mAP50	**0.98**
mAP50-95	0.71

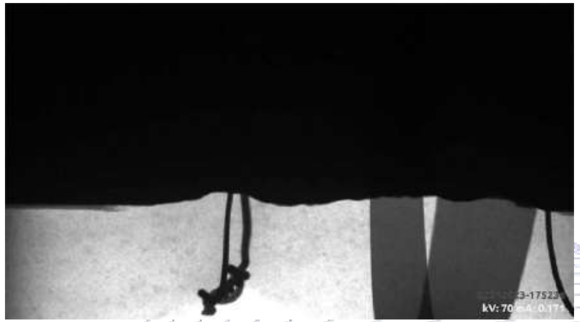
X-Ray Pipeline Corrosion Detection

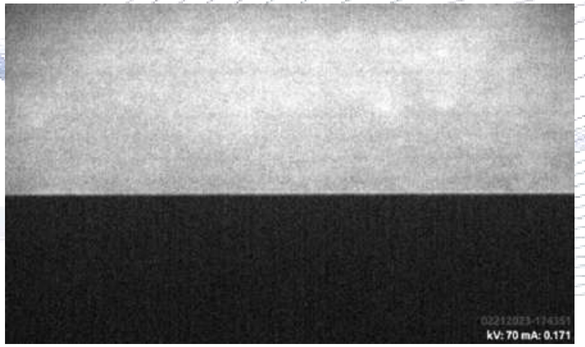
- Developed a methodology based on **traditional computer vision** and **image processing** to detect corrosion.
  - Passed a **median** and a **Gaussian** filter to deal with insulation noise.
  - Performed **Binary thresholding on** the image.
  - Made use of the well-established **Canny edge detector**.
  - Performed **Hough Line Transform** to find a suitable line that represents the ideal pipeline edge (*i.e.*, if there was no corrosion).

X-Ray Pipeline Corrosion Detection

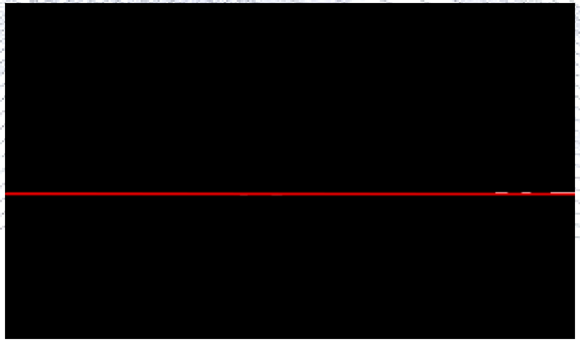
- Measured corrosion as the sum of y-axis distances from the corresponding straight line that simulates a pipeline without corrosion.

Images taken from [QSA]





Corrosion



No Corrosion

Dataset D_{XR2}

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X-Ray Pipeline Corrosion Detection

Several algorithms were implemented to solve the problem as an anomaly detection (AD) and anomaly localization (AL) task.
The algorithm with the best performance is Patchcore [PAT2022].
The results are near-perfect for some algorithms. We believe this is empowered by the simplicity of the task for modern AD/AL algorithms, as well as the low variance of dataset X-ray images.

Algorithm	*Precision*	*Recall*	*F1 Score*	*Accuracy*	*AUC*
CFA	0.788	0.850	0.818	0.790	0.849
Cflow	0.889	0.932	0.910	0.898	0.960
DFM	0.988	**0.996**	0.992	0.991	**1.000**
FastFlow	**0.996**	0.994	0.995	0.994	0.999
GANomaly	0.561	0.990	0.716	0.563	0.672
PaDiM	0.810	0.944	0.872	0.845	0.913
Patchcore	**0.996**	**0.996**	**0.996**	**0.996**	**1.000**
STFPM	0.994	0.980	0.987	0.986	0.999
CSFlow	0.951	0.974	0.962	0.958	0.992

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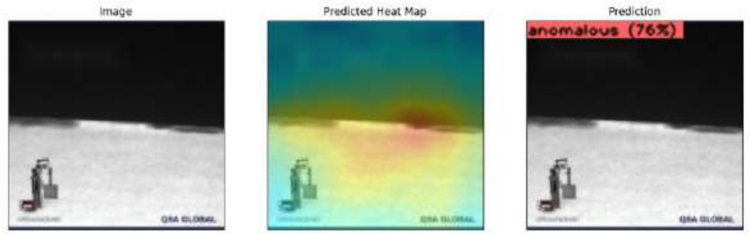
X-Ray Pipeline
Corrosion Detection

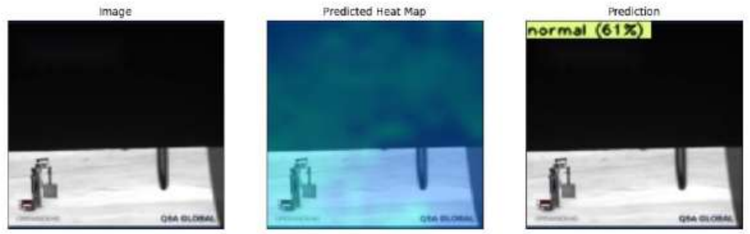
Patchcore [PAT2022] works in the following steps:

- Image patch features are extracted from a pre-trained encoder.
- The features are greedily sub-sampled into a coreset and stored in a memory bank.
- Nearest neighbor search is performed in the memory bank and patch-feature distances are calculated to perform anomaly detection and anomaly localization.

<u>Patchcore Abnormal Inference Example:</u>



<u>Patchcore Normal Inference Example:</u>



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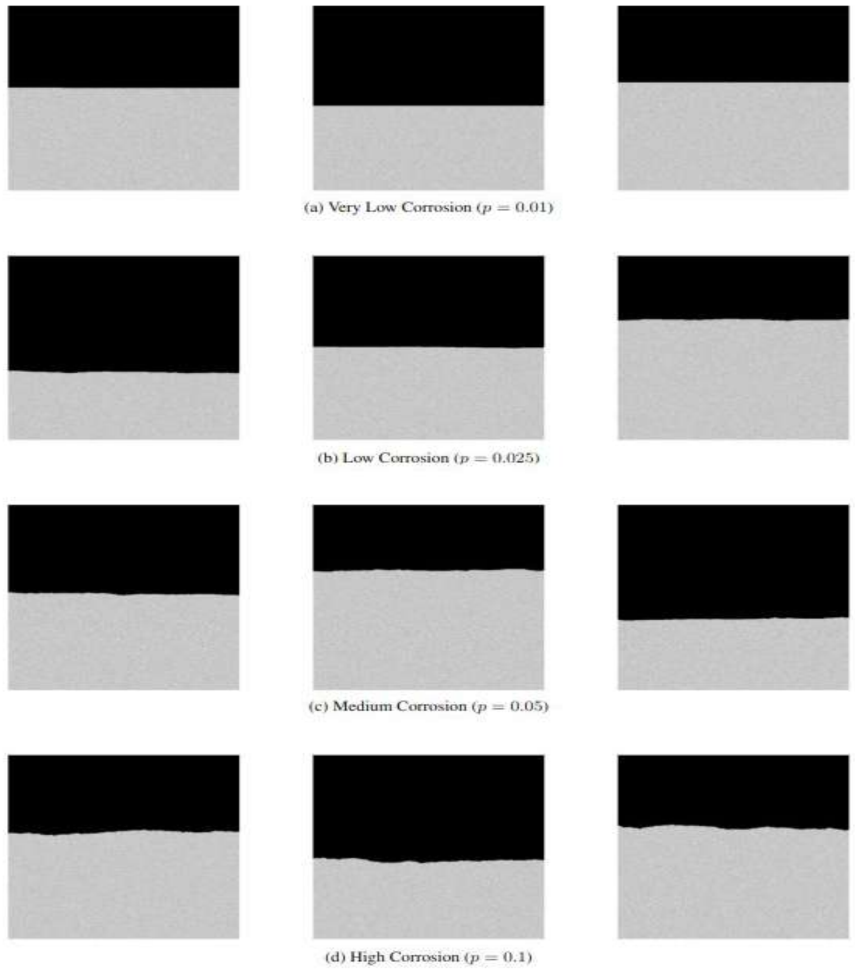
X-Ray Pipeline Corrosion Detection

Developed an algorithm for synthetic data creation which can be used to augment D_{XR2}.

Did not make use of such data because the performance is already near-perfect without augmentation.



Dataset $D_{synthetic}$

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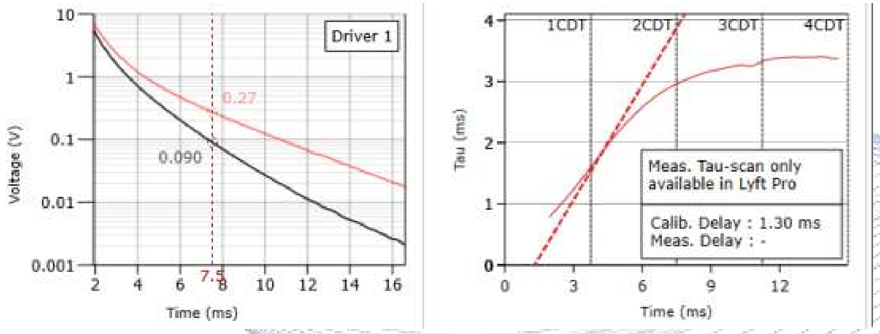
PEC Pipe Corrosion Detection

- A literature review is needed to identify deep learning methods and baselines for analysing PEC signals.
- A sample of demo data provided by USE:



Wall thickness percentage values

Color palette legend

40,0	43,7	47,4	51,1	54,7	58,4	62,1	65,8	69,5	73,2	76,8	80,5	84,2	87,9	91,6	95,3	98,9	102,6	106,3

	353,4	344,8	336,2	327,6	319,0	310,3	301,7	293,1	284,5	275,9	267,2	258,6	250,0	241,4	232,8	224,1	215,5	206,9	198,3	189,7	181,0
0,0		98,0	98,0	97,8	97,7	97,4	96,8	95,9	95,3	94,9	95,6	95,9	96,7	97,4	98,0	98,4	98,7	98,8	99,2	99,3	99,2
20,0		98,2	97,3	96,5	95,7	93,8	90,9	88,0	86,1	85,5	85,9	87,9	90,3	93,2	95,4	97,1	98,0	98,6	99,0	98,8	98,9
40,0			98,8	99,8	96,8	90,2	80,5	72,8	69,3	68,2	68,4	70,0	75,5	84,7	94,2	98,9	99,9	100,0	99,2	99,3	99,4
60,0			99,6	98,5	95,3	88,9	79,9	73,7	71,0	70,2	70,5	72,5	78,2	87,9	96,5	99,0	100,3	100,3	99,7	99,9	100,0
80,0			97,8	96,8	96,4	95,4	94,8	93,2	91,6	90,6	90,3	90,9	92,1	94,8	97,1	97,8	98,7	99,2	99,6	99,8	99,8
100,0		99,1	98,6	98,0	98,2	97,6	97,4	97,6	97,5	97,3	97,5	97,7	97,8	98,1	98,7	99,2	99,0	99,5	99,8	99,8	99,8
120,0	98,6	98,5	98,1	97,3	98,2	98,0	98,5	98,7	98,6	98,7	98,9	99,0	98,9	99,3	99,5	99,4	99,7	100,0	99,6	99,7	98,9

Electrical Infrastructure Inspection

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Infrastructure inspection applications

- Aerial robots with different characteristics must be integrated for:
  1. Long range and local very accurate inspection of the infrastructure.
  2. Maintenance activities based on aerial manipulation involving force interactions.
  3. Aerial co-working safely and efficiently helping human workers in inspection and maintenance.

Electrical Infrastructure Inspection

- **Overview**
- Sensors
- Visual analysis
- Drone operations

Technical objectives

- Cognitive functionalities for aerial robots including ***perception based on novel sensors*** such as event cameras and data fusion techniques, learning, reactivity, fast on-line planning, and teaming.
- Cognitive safe aerial robotic co-workers capable of ***physical interaction with people***.
- ***Cognitive aerial manipulation*** capabilities, including manipulation while flying, while holding with one limb, and while hanging or perching to improve accuracy and develop greater forces.
- Aerial platforms with ***morphing capabilities***, including morphing between flight configurations, and between flying and ground locomotion, to save energy and perform a very accurate inspection.

Long range inspection of power lines

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Helicopter inspection of power lines

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Helicopter inspection of power lines

- Complete manned helicopter flight:
  - The helicopter has on-board a pilot and a camera operator.
  - Manned helicopter is flying at low altitude and stopping at each electrical tower.
  - High quality visual, thermography and LIDAR data are obtained at the same time.
  - LIDAR is disconnected in each electrical tower since it gets bad results when it is a long time in the same spot.

Types of flights with manned helicopter

- Fast manned helicopter flight:

  - Thermography and LIDAR acquisition at the same time.
  - Helicopter does not stop at each electrical tower, but the flight is at low altitude (due to the thermography camera resolution).

  - ***Speed limited to 50-60 km/h because of the thermography.***

Disadvantages of current approach

Main disadvantages of current inspections with manned helicopters:

- Costs: 40,5 €/km.
- Difficulties to detect some devices, like connecting cable from the tower to ground.
- Safety.

- ***200 km report is ready in two weeks.***

Safe local manipulation interventions

- Examples:
  - Installing anti-birds systems.
  - Cleaning isolator in power lines.

Installing anti-birds systems

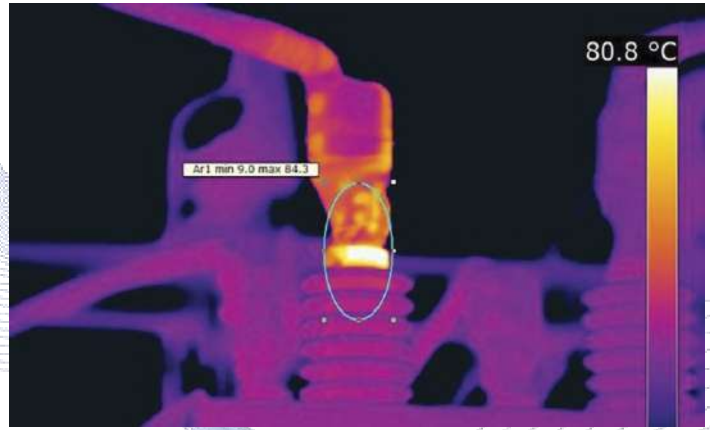
- National regulation (a few years ago) enforces their installation every 5-10 m.
- (De-)installation is performed by work at height on a basket.
- Dangerous, slow and costly.
- The electrical lines has to be without voltage, resulting in money loss.

Co-working activities

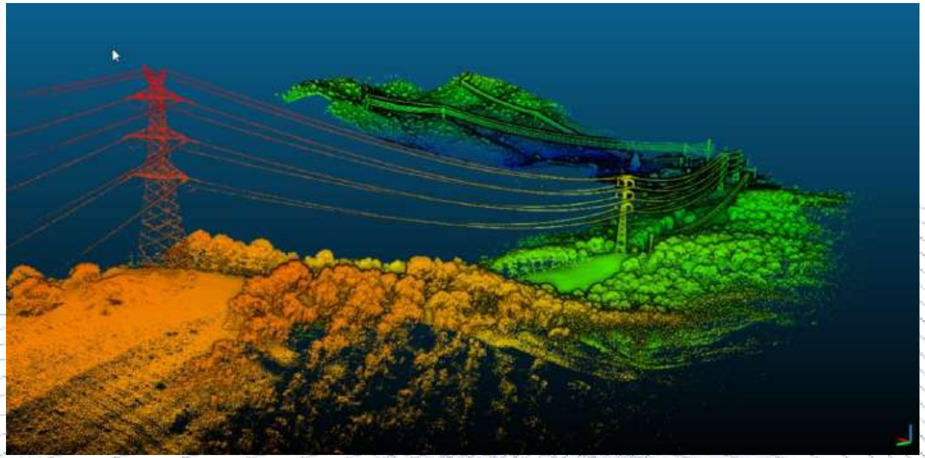
Infrastructure Inspection

- Overview
- **Sensors**
- Visual analysis
- Drone operations

Types of inspection



Thermography



3D mapping (LIDAR)

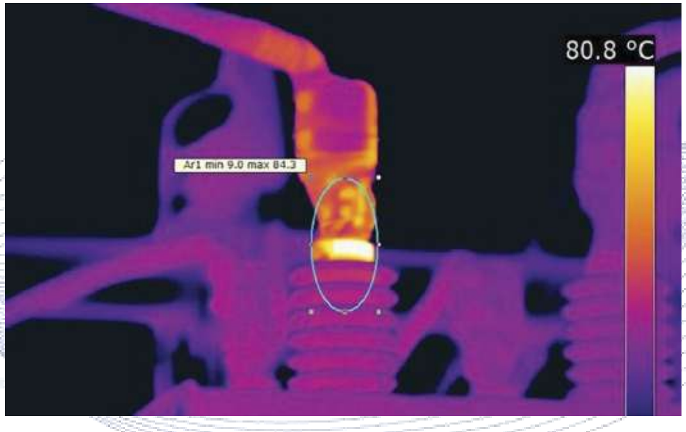
Camera & video

Inspection using camera/video

- High quality images and videos
- Detailed images of the complete electrical tower
- Requires 2 mm GSD, i.e., 1 pixel per 2 mm to be able to identify all the required details.
- For example:
  - check that the bolt on a screw is there.
- Requires that the UAV moves very slowly around the electrical tower.

Thermography

- Detection of hot spots in the electrical tower: cramps and connections
- To perform thermography, the speed of a fixed wing UAV is limited to 50-60 km/h.

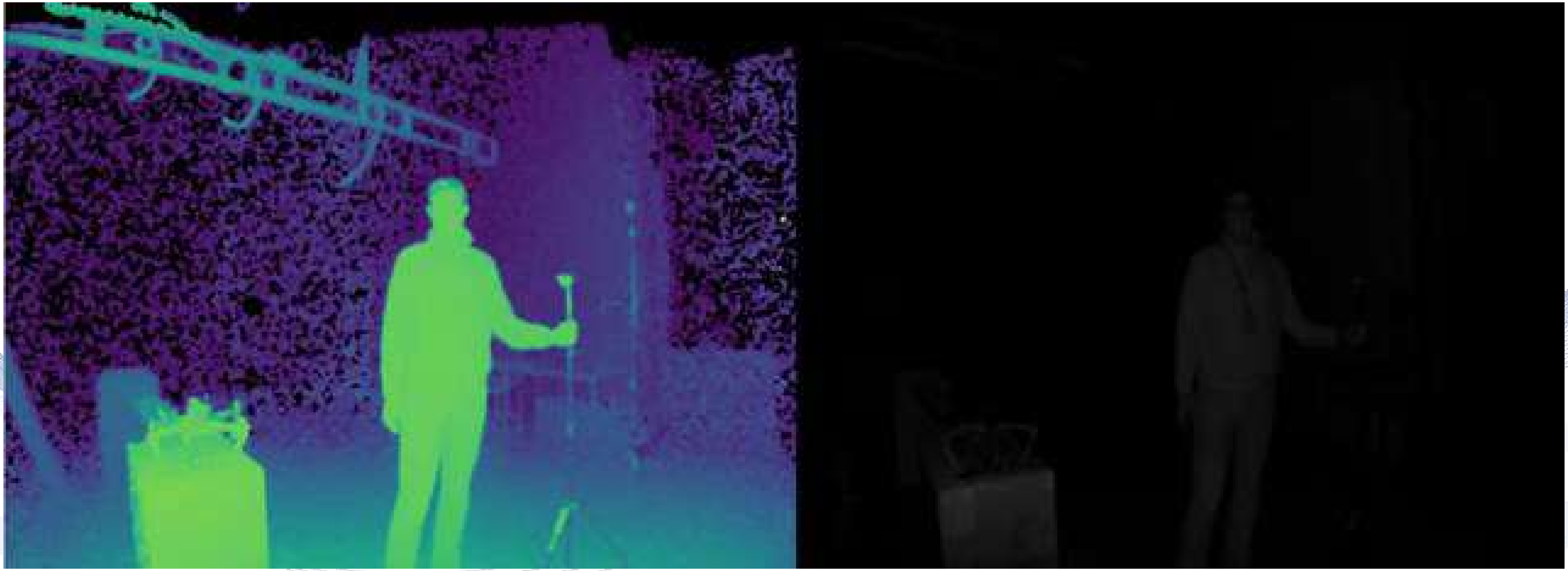


3D LIDAR

- Precise 3D mapping (with cm level accuracy and precision)
- No speed limitation on the manned helicopter
- A 3D map is constructed to:
  - Detection of obstacles close to power lines.
  - Measurement of vegetation around power lines.
  - Checking distance when crossing power lines.
  - Once the 3D map is obtained, a classifier algorithm (and also checked and adjusted by a technician) is used.
  - Afterwards, distances and other measurements are performed to develop the inspection report.

3D VGA Time-of-Flight camera

- A camera for human gesture recognition, object avoidance in close distance, landing and taking-off.



Indoor Tests, February 2021, Terabee facilities.

Event cameras - motivation

Latency & Motion blur.

Dynamic Range.

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Event cameras

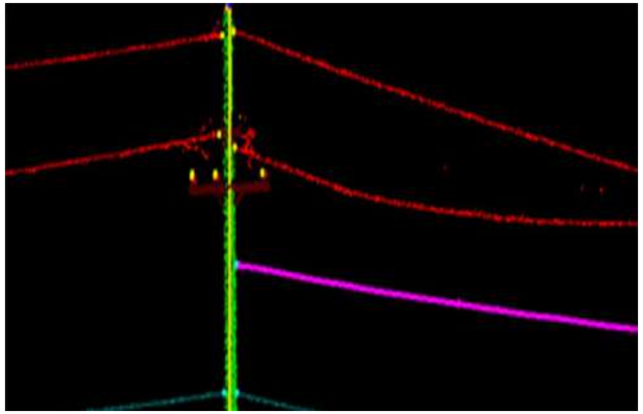
- Novel sensor that measures only motion in the scene.
- Low-latency (~ 1 μs).
- No motion blur.
- High dynamic range (140 dB instead of 60 dB).
- Ultra-low power (1 mW vs 1W).
- Traditional vision algorithms do not work all the time!

Infrastructure Inspection

- Overview
- Sensors
- **Visual analysis**
- Drone operations

Research tasks

- Semantic 3D world mapping.
- Learning methods for object detection/tracking of electric lines, rods, etc.
- Human-drone interaction:
  - Gesture drone control.
  - Body posture estimation.
  - Human action recognition.
  - Facial pose estimation.



Learning methods for aerial inspection

- Visual detection.
- Semantic segmentation of power lines to enhance robot behavior.
- Object detection for manipulation tasks.
- Focus in lightweight nets for online computing.
- Generative adversarial networks (GAN) to improve detection quality from previous learned experiences.

Semantic visual cognition

- Deep Neural Networks (DNNs) are the algorithm of choice for 2D visual object detection/tracking tasks.
- They require powerful GPU-equipped hardware platforms for real-time execution.
- E.g.: Nvidia Xavier computing board for embedded/robotics applications.
- Software execution environment: Linux + Python.

Fast 2D Convolutions

- State-of-the-art neural network architectures for visual data use convolutional layers.
- The convolution operation takes up most of the total inference and training time.
- Reducing the computational complexity of convolutions would render networks for e.g., target detection or target tracking much more efficient for deployment on embedded GPUs.

- We developed a fast convolution algorithm which splits cyclic convolution into smaller products.
- In this algorithm, cyclic convolution takes the following form:

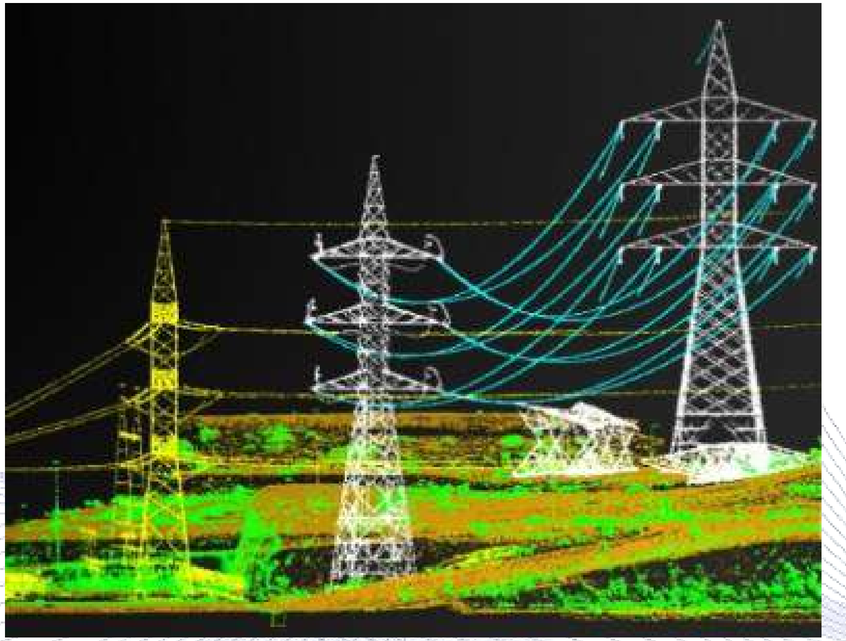
$$\mathbf{y} = \mathbf{C}(\mathbf{Ax} \otimes \mathbf{Bh}).$$

- Thus, the problem is reduced to finding matrices $\mathbf{A}, \mathbf{B}$ and $\mathbf{C}$.

Experimental Results

Algorithm	Computation time (ms)
Winograd-6 (cuDNN Winograd linear convolution)	0.9165
GEMM-0 (fastest cuDNN convolution)	0.3858
Ours	**0.0809**

Semantic 3D World Mapping



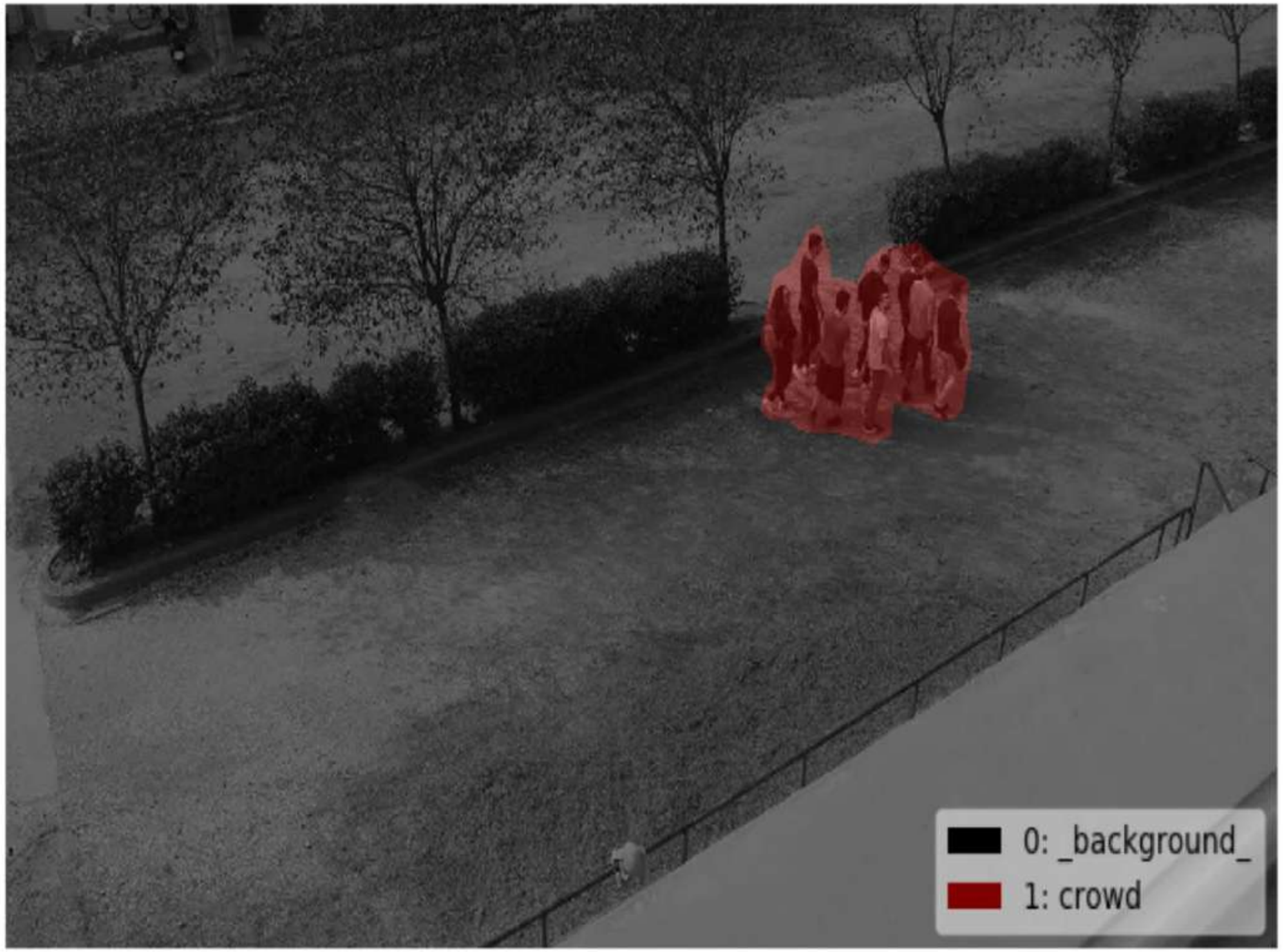
Geometric modeling of the 3D world.

Semantic 3D World Mapping

- ***Semantic image segmentation***:
  - Segment low/high vegetation regions, roads.

Semantic 3D World Mapping

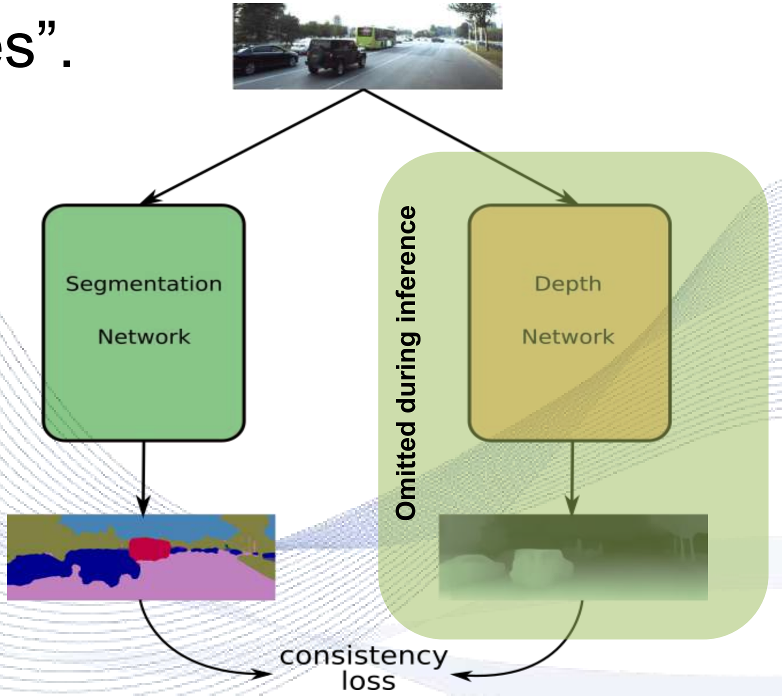
- ***Semantic image segmentation:***
  - Crowd detection and localization.



Semantic Segmentation

- Multitask CNN for semantic segmentation and self-supervised depth estimation.
- Novel consistency loss function to regularize segmentation output.
- “Do not form semantic edges, if there are no depth edges”.

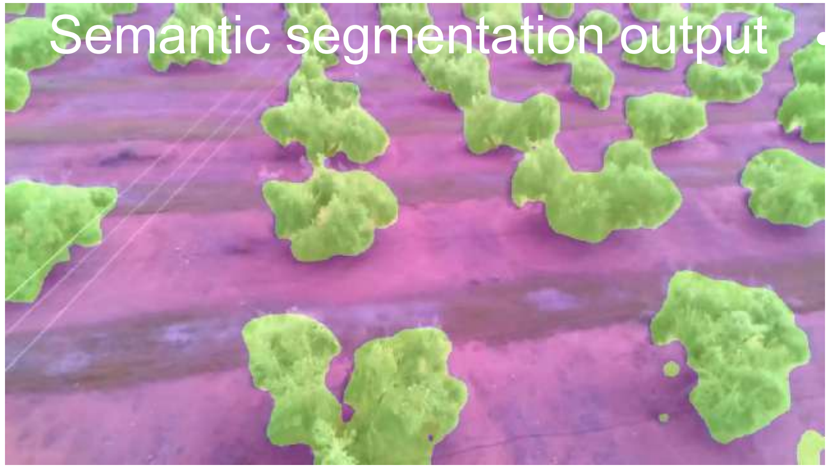
Method	Mean IoU	Inference (ms)
Yu et al.	39.557%	**6.2**
Klingner et al.	34.318%	6.4
Novosel et al.	37.683%	8.3
Chen et al. (pretrained)	39.610%	**6.2**
Chen et al. (multitask)	38.153%	9
Ours	**40.597%**	**6.2**

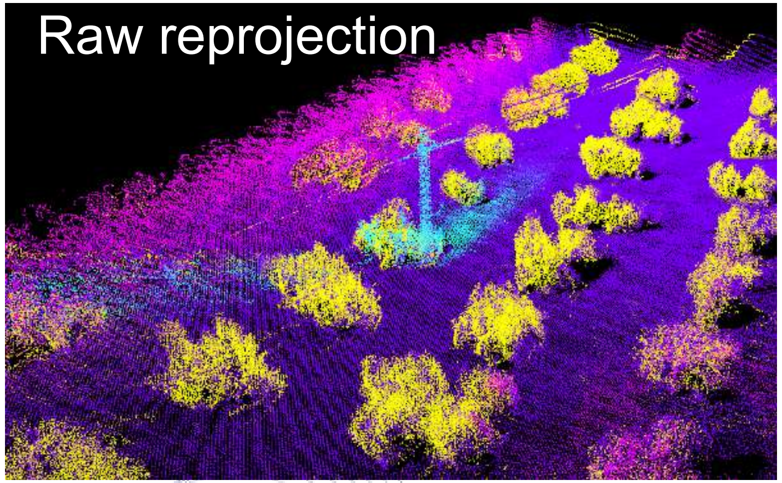


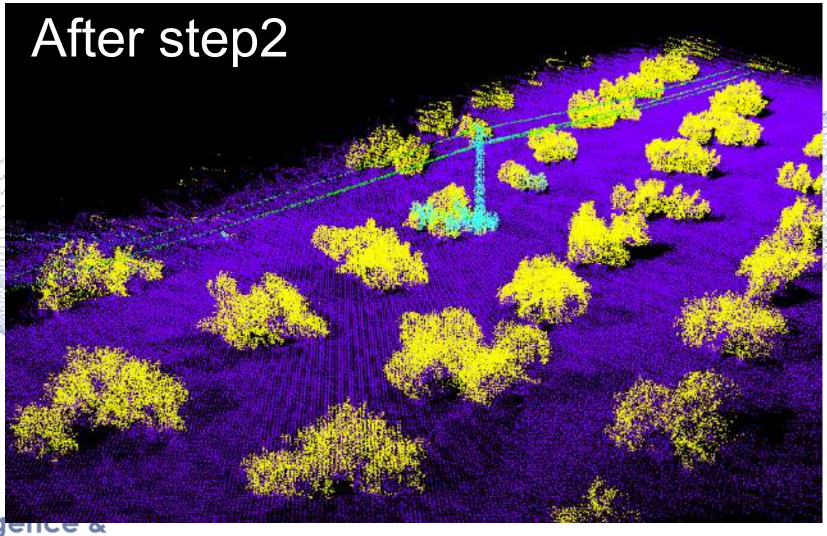
Semantic Image Segmentation Guided by Scene Geometry [PAP2021b].

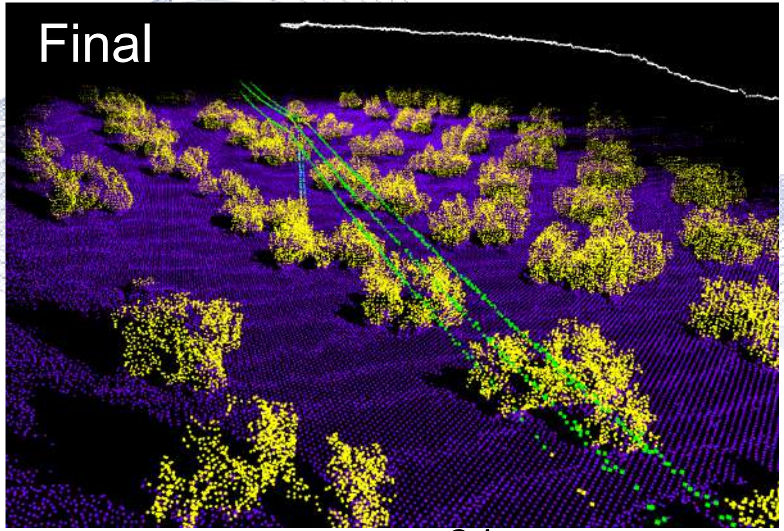
Semantic Segmentation

Semantic 3D World Mapping

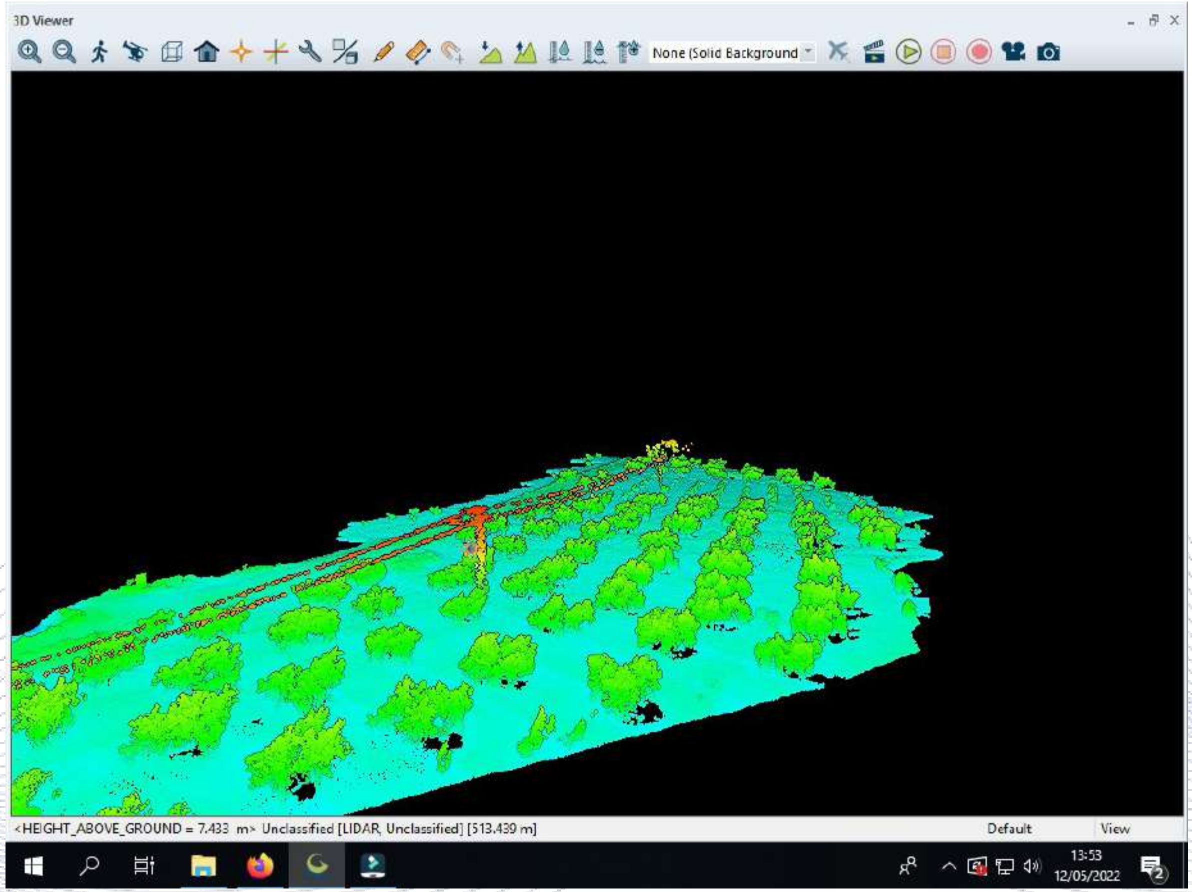




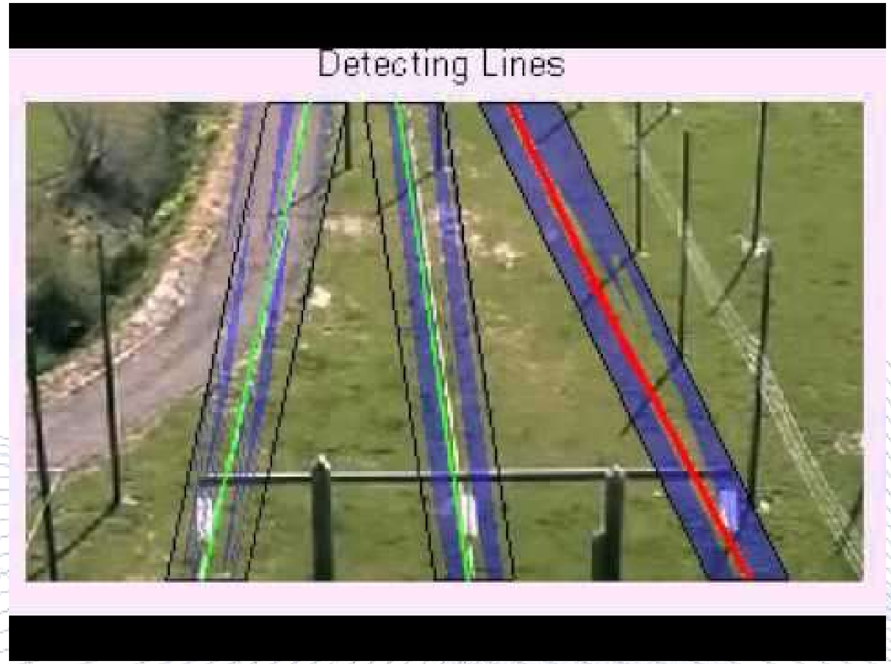




Semantic 3D World Mapping

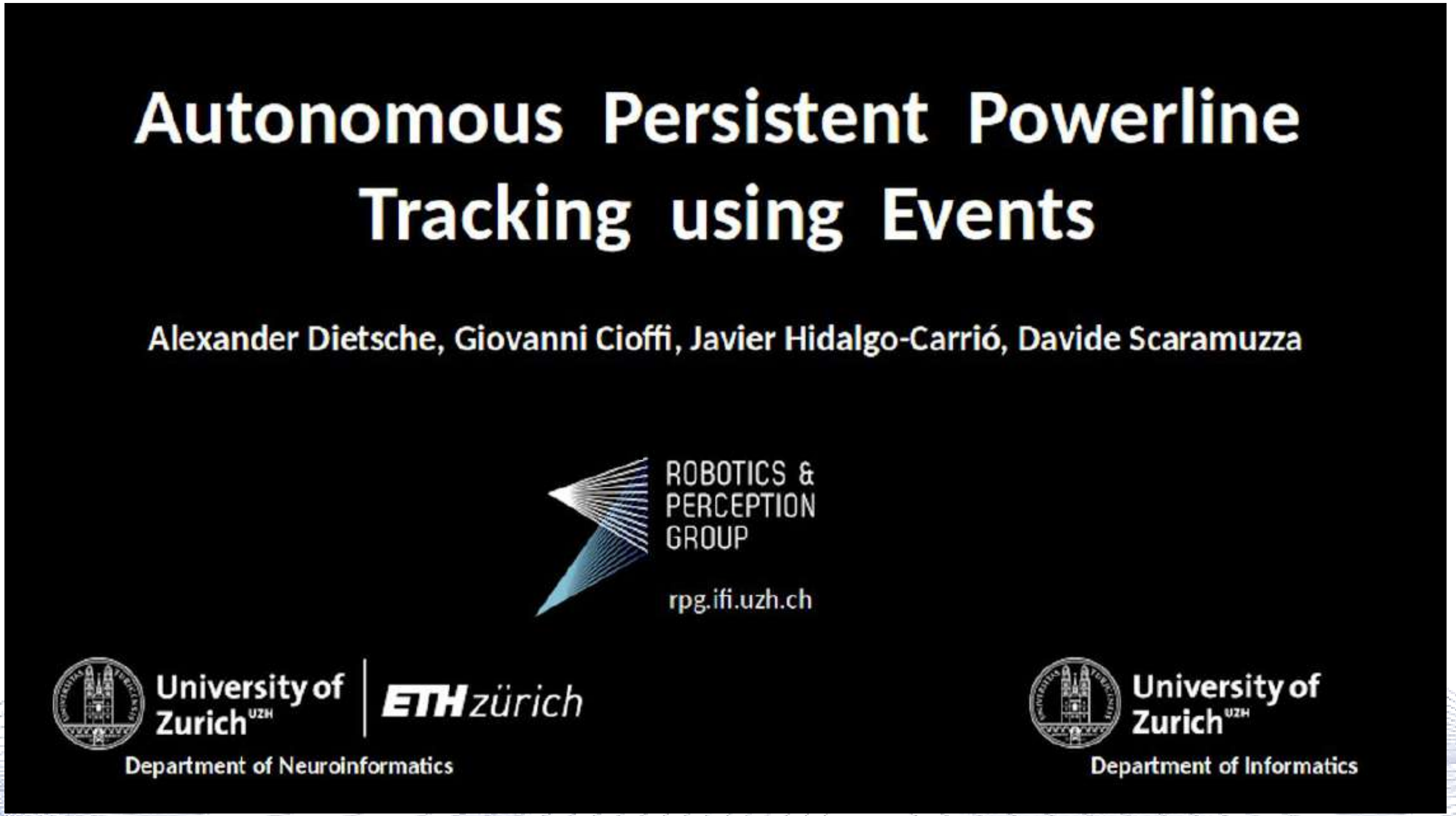


Object detection and tracking



Deep learning for power line detection and tracking.

Object detection and tracking



Event-based Powerline tracker.

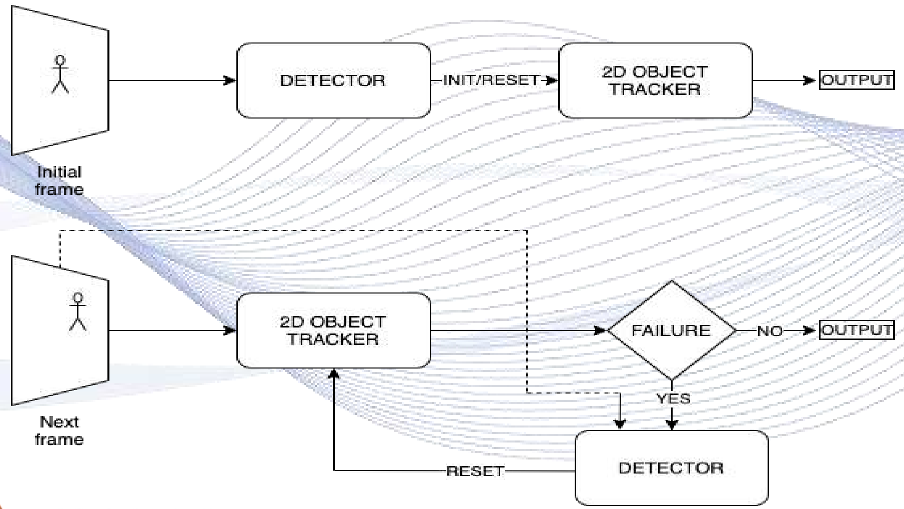
Object detection and tracking

- ENDESA dataset (17K images, insulators, dumpers, towers).
- SoA detector evaluation (Single-Shot-MultiBox-Detector (SSD), You-Only-Look-Once v4 (YOLOv4), Detection-Transformer (DETR).
- Proposed approach: Content-specific image queries (based on DETR).

Model	FPS 2080 / Jetson	AP	AP_{50}
YOLO v4 CSPDarknet53	96/26	41.6	83.5
SSD Mobilenet v2	126/17	50.1	82.1
SSD Inception v2	84/13	48.7	80.0
SSD Resnet50	40/9	52.3	79.8
DETR Resnet50	35/8	52.4	83.1
Ours Resnet50	35/8	**53.9**	**83.9**

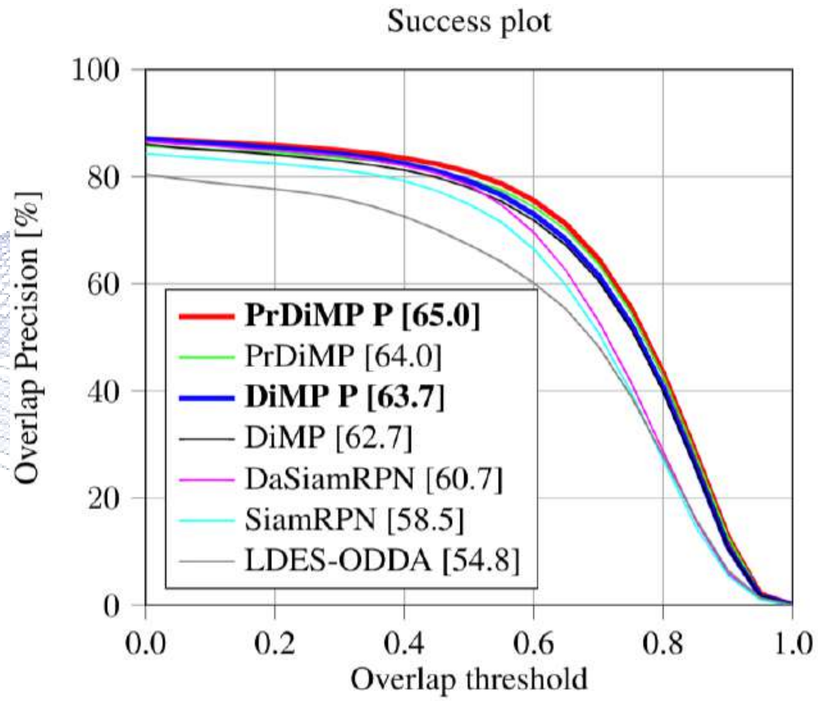
Object detection and tracking

- Combination of object detection/tracking methods.
- Object detector periodically re-initiates the tracker.



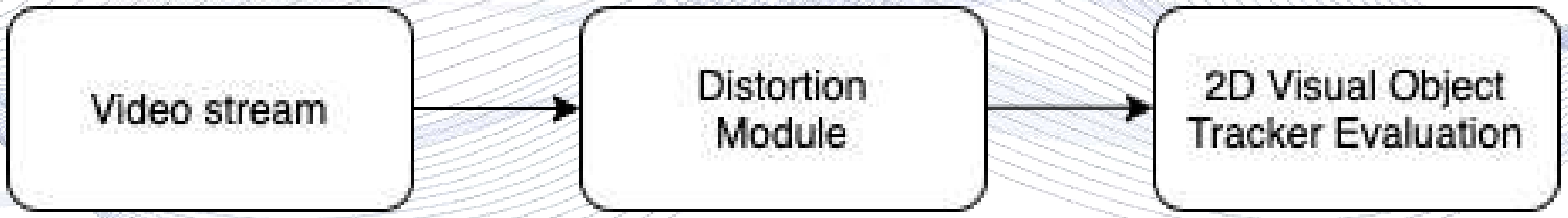
Online tracking model adaptation

- Online tracking model updating is typically addressed as a regression problem.
- An **adversarial optimization scheme**
- **Generator** is assigned to the tracking model producing response maps.
- **Discriminator** network is trained to identify if the tracker response maps produced by the generator belong to the target distribution, or not.

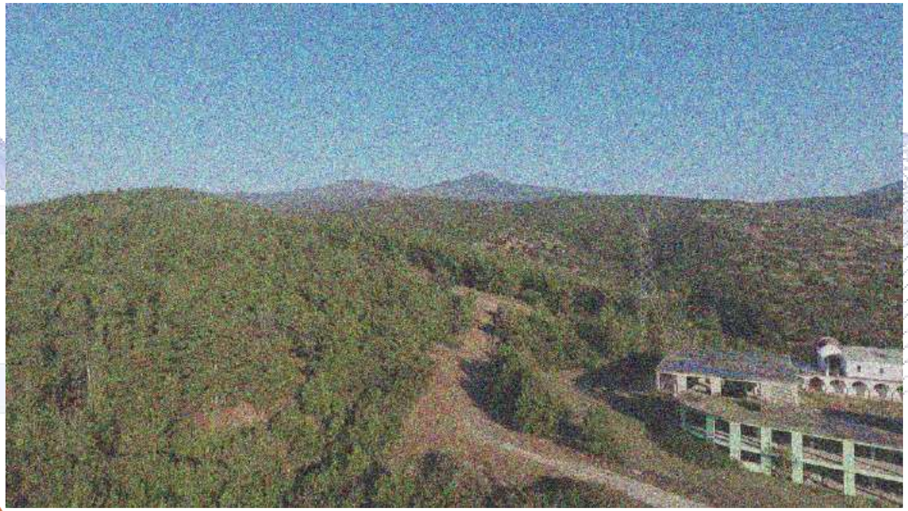


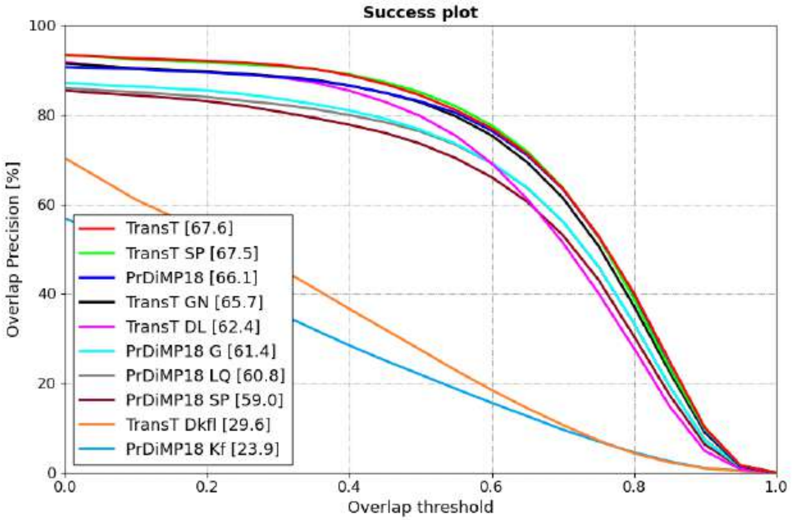
Robustness 2D Visual Object Tracking

- VOT-RT - A toolkit that allows evaluation against:
- Image acquisition: Gaussian, Salt and pepper, etc,
- Image transmission: Low Quality image, Key-frame loss.
- We evaluated many state-of-the-art tracking methods, and all suffer from performance loss in every case.



Robustness 2D Visual Object Tracking





Object detection and tracking

- Requirements similar to 2D visual detection/tracking:
- Method: Embedded DNNs.
- Hardware: GP-GPU equipped computing boards (e.g., Xavier).
- Software: Linux + Python.
- Training: Massive, annotated, domain-specific datasets.

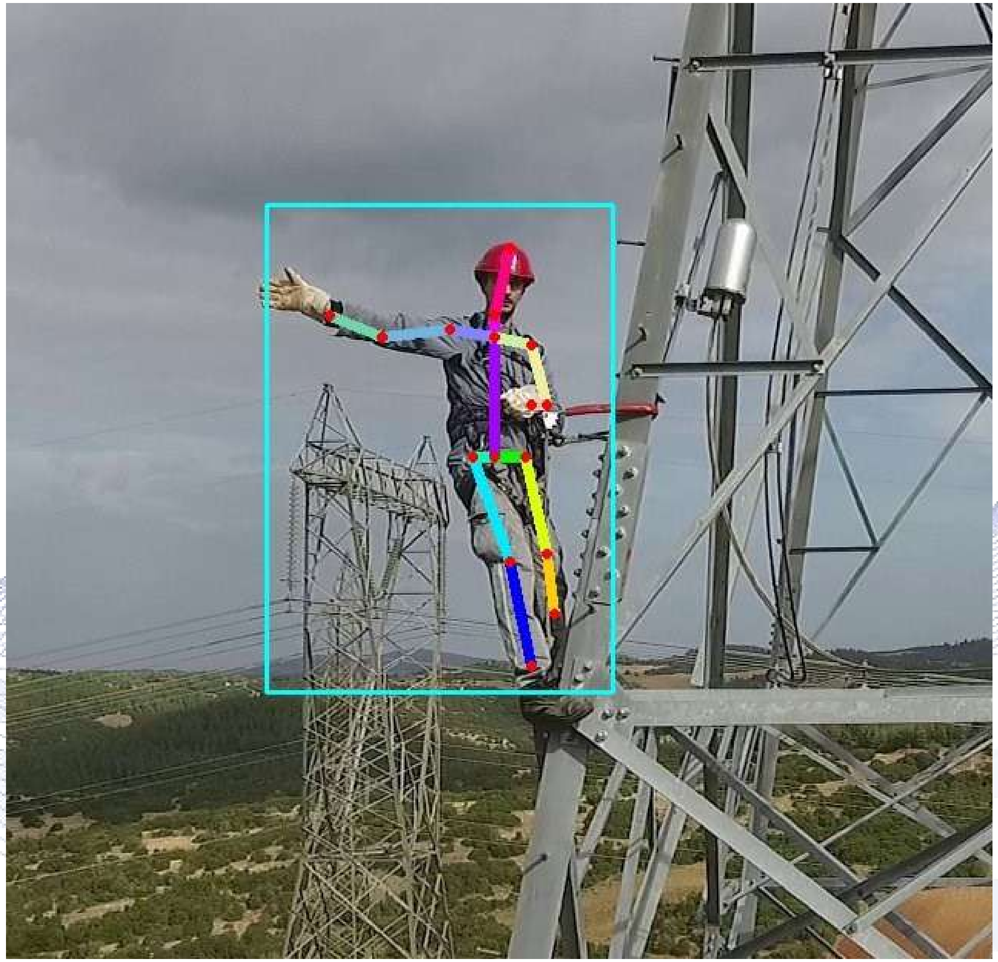
Human posture estimation

a) Original image; b) Body joints heatmap; c) Human posture estimation.

Human-drone interaction

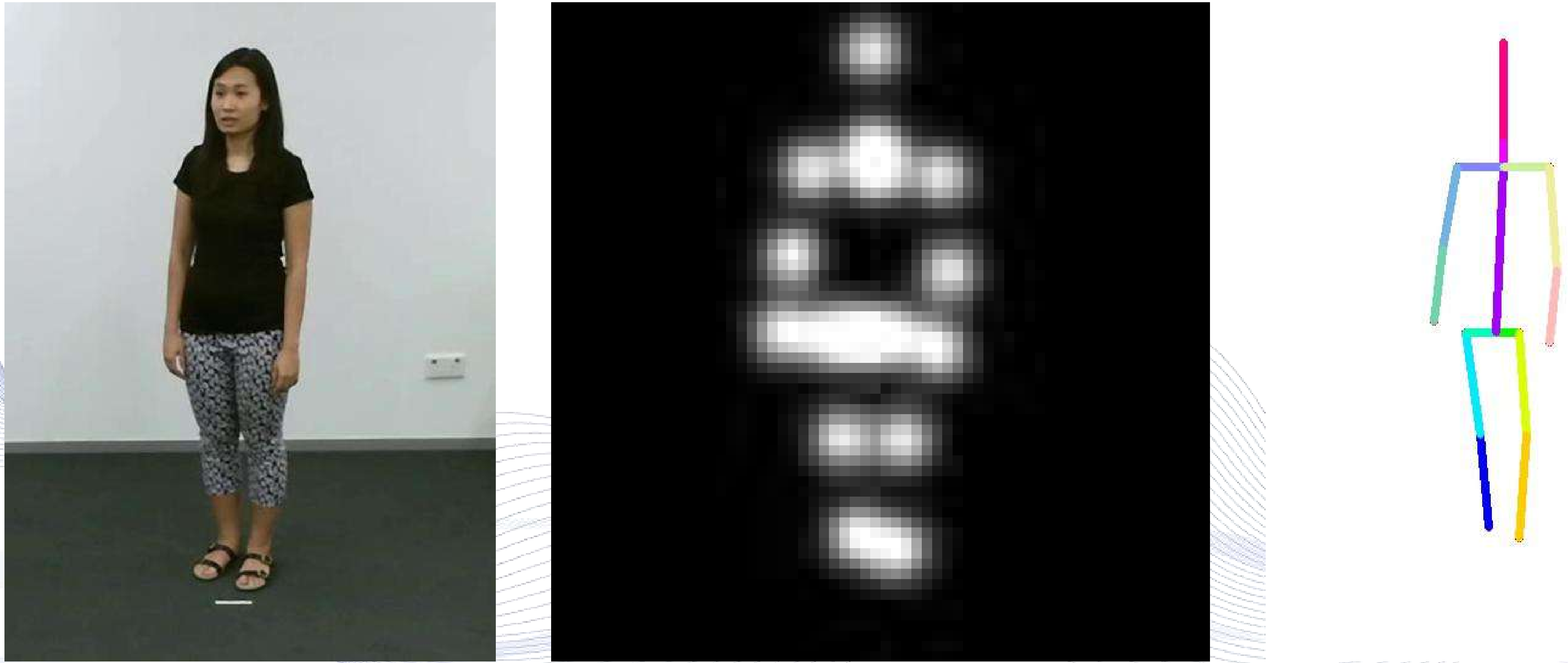
- Goals: The UAV/Aerial Co-Worker:
  - Can verify that the technician follows pre-set safety rules at all times.
  - May perceive the technician's current activity (e.g., climbing a pole) in order to get into suitable position for assisting him.
  - Is able to interact visually with the technician by interpreting pre-defined communication hand gestures.
  - AUTH may also potentially employ semantic image/instance segmentation for assisting in the above tasks and for augmenting algorithm performance.

Human posture estimation



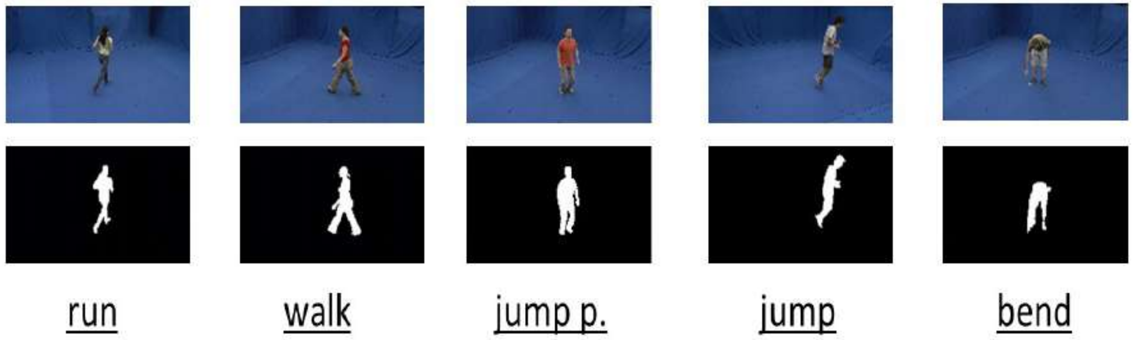
Human posture estimation.

Human posture estimation

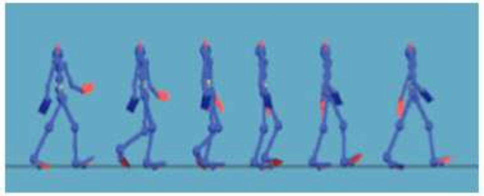


a) Original image; b) Body joints heatmap; c) Human posture estimation.

Human action recognition

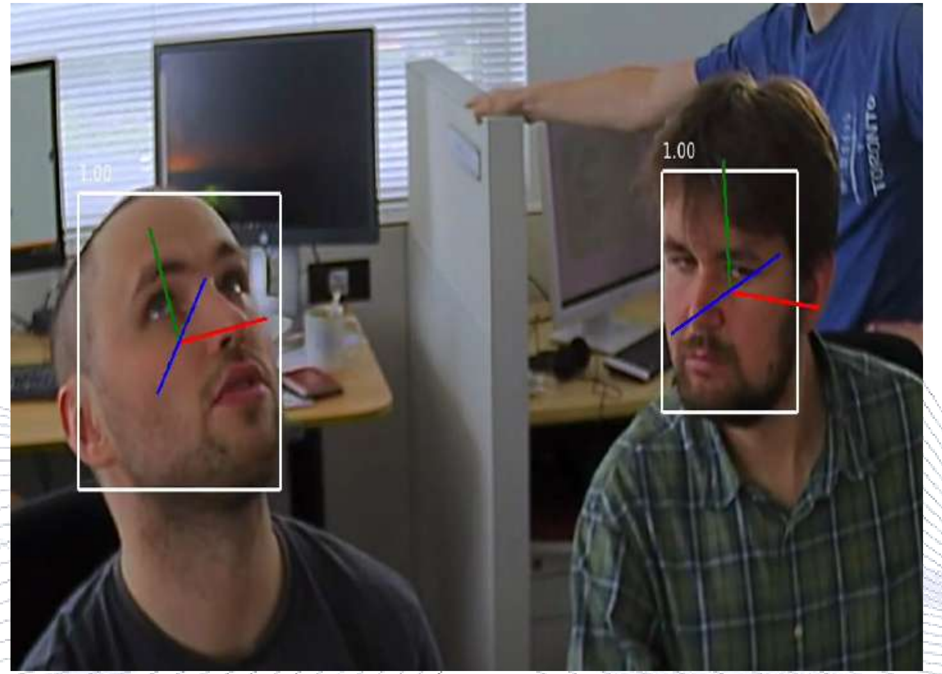


walk



walk

Human pose estimation



Facial pose estimation.

Gesture recognition

Language of visual gestures for drone control:

- Extend one arm to the side
- Cross arms (form X with forearms)
- Raise one arm upwards
- Palms together (namaste gesture)
- Victory sign
- Ok sign (thumbs up)

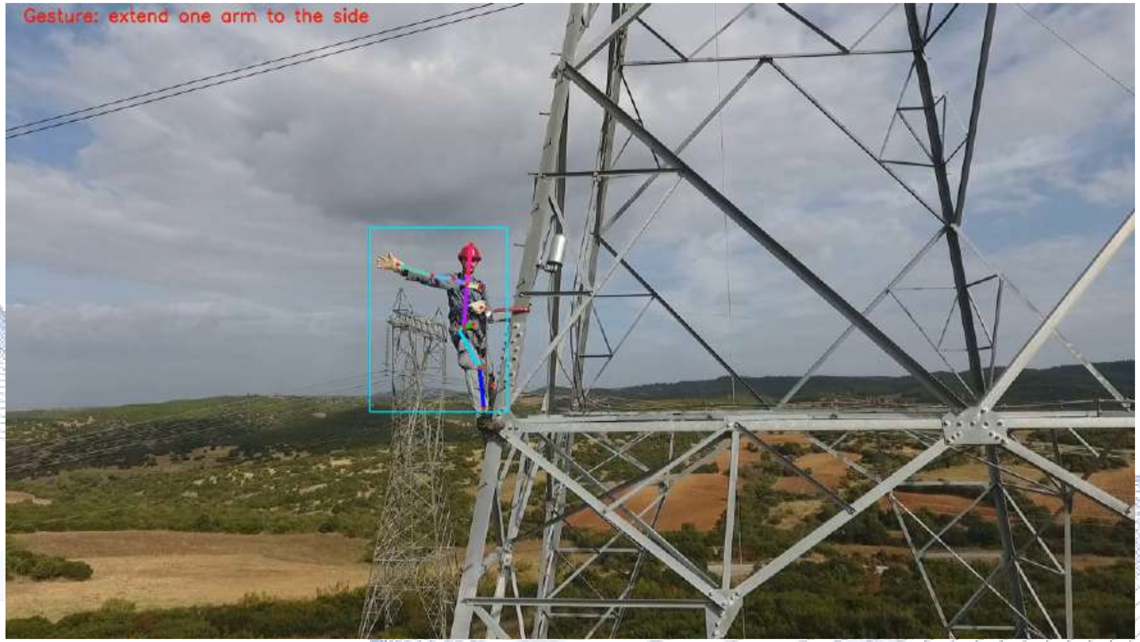
Gesture recognition

- A gesture dataset was created for training, using three data sources:
  - UAV gestures dataset (thumbs up, cross arms, victory, palms together) [PER2018].
  - NTU dataset (thumbs up, cross arms, raise one arm upwards) [SHA2019].
  - Video acquisition performed by AUTH.
- A novel gesture recognition method was developed, relying ***on CNNs and LSTM networks***, yielding a maximum test set ***classification accuracy of 89.22%***.

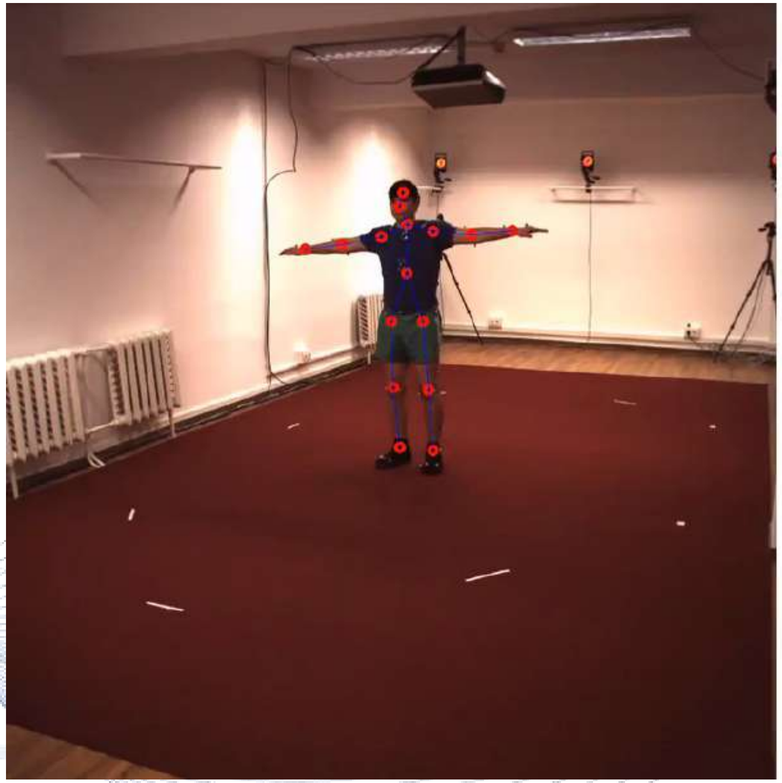
Human posture estimation

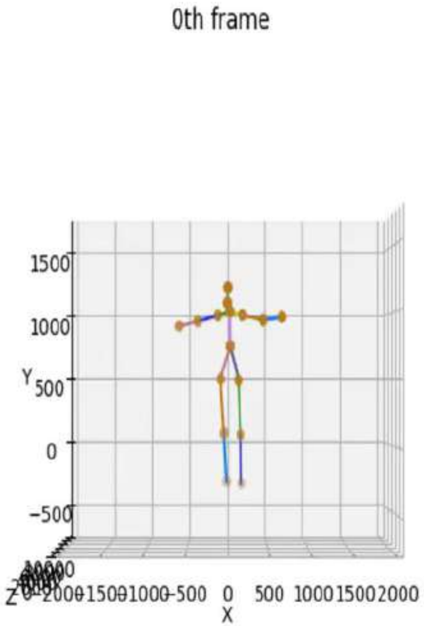
- AUTH developed a novel 2D human posture/body joint/skeleton estimation method based on deep CNNs using an image segmentation approach, utilizing a multi-task segmentation + I2I (GAN) network architecture.
- It receives an image of a localized person as input and predicts a dense heatmap for each body joint in a predefined joints set (skeleton).
- The final 2D pixel coordinates of each joint are obtained by post-processing the body joint heatmaps.

Human posture – gesture recognition

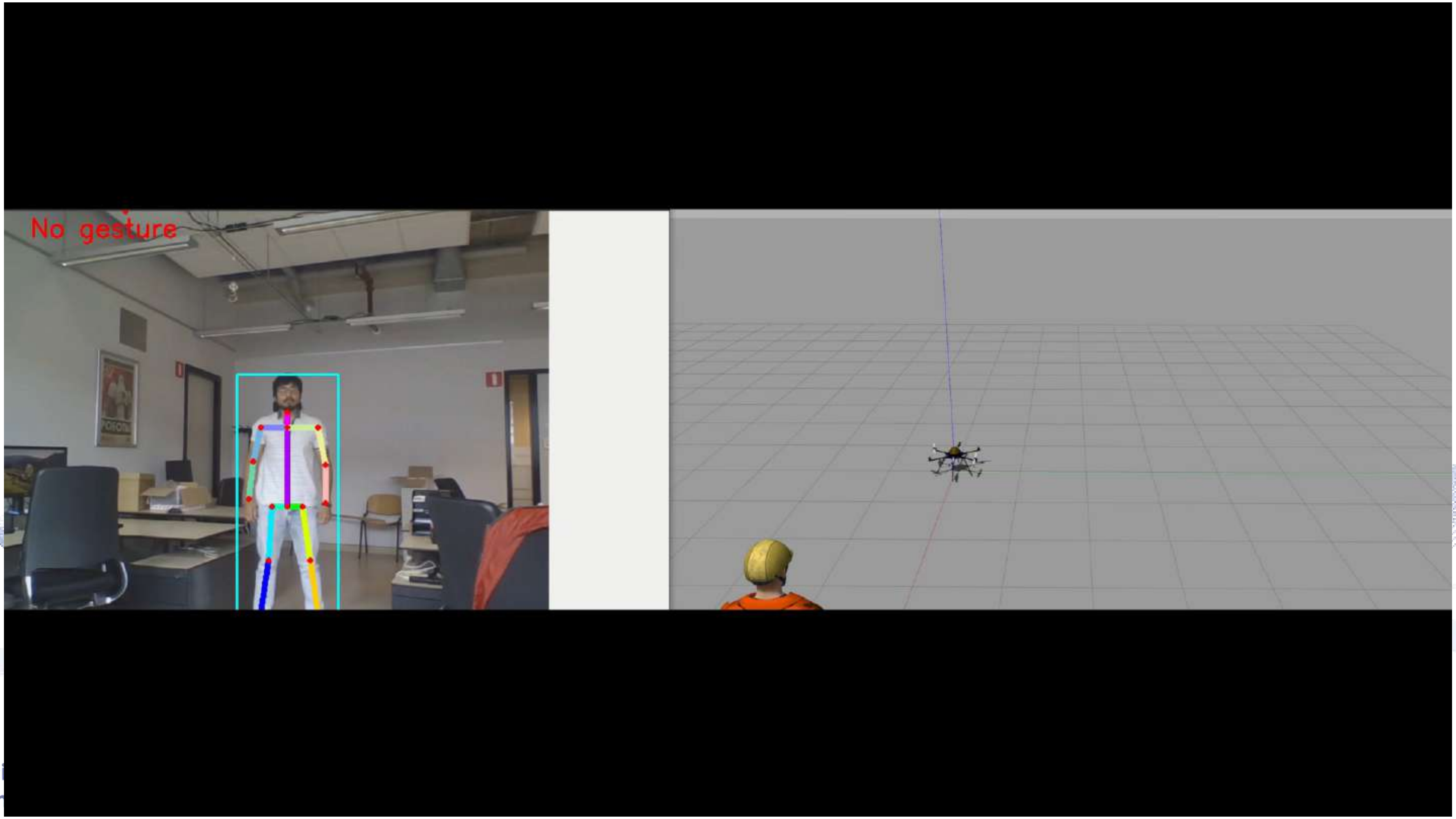


Human posture – gesture recognition





Gesture-based control



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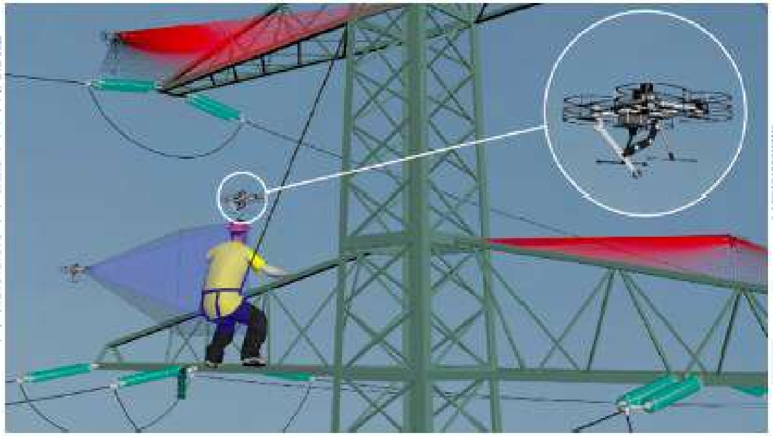
Coordination of a Heterogeneous Team of ACWs

- 3 main ACW activities:
- Safety-ACW - equipped with a surveillance camera (blue).
- Inspection-ACW – inspection sensor (red).
- Physical-ACW - equipped with a manipulator to provide tools required by workers



Infrastructure Inspection

- Overview
- Sensors
- Visual analysis
- **Drone operations**

Autonomous landing/perching

- Develop an autonomous landing and perching scheme (i.e., planning and control) that allows different flying platforms to land in confined spaces and perch on complex surfaces, such as, e.g., tower structures or electrical power lines.
- The system will be able to evaluate different landing positions for their feasibility and plan landing paths in real time that guide the aerial robots safely to the desired landing or perching spot while avoiding any obstacles.

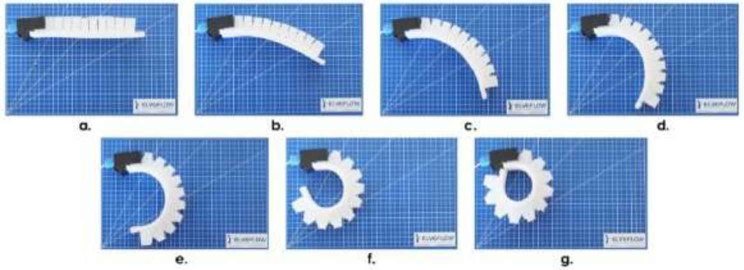
Autonomous landing

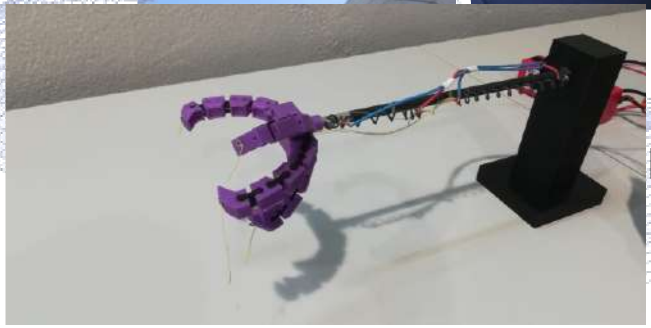
Autonomous perching

- Sensor fusion to exploit synergies:
- Perching steps:
- Preparation
  - Multi-sensor detection & tracking of perching candidates
    - LIDAR
- Fast approach to perching zone
  - Multi-sensor Visual Servoing:
    - event cameras
- Short distance approach & perching
- Multi-sensor Visual Servoing.

End-effectors for holding/grabbing

- Bio-inspired actuators for compliant co-working and close range inspection.



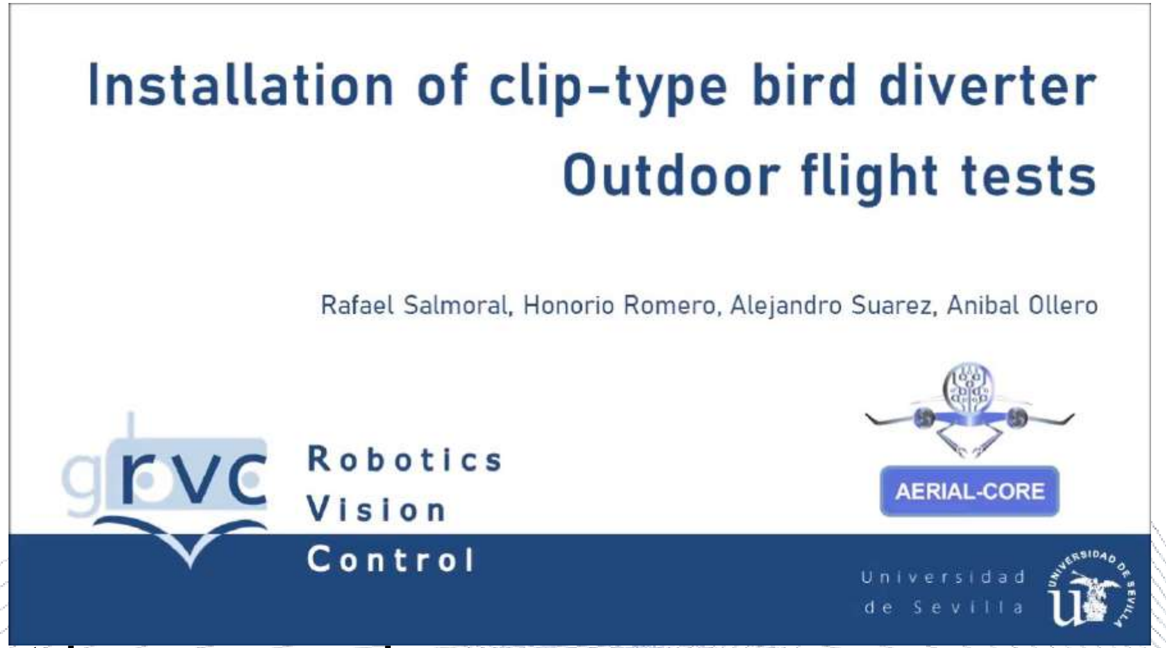


Manipulation while holding/perching

Manipulation while holding/perching

Voltage check with custom end-effector.

Manipulation while flying, holding and perching

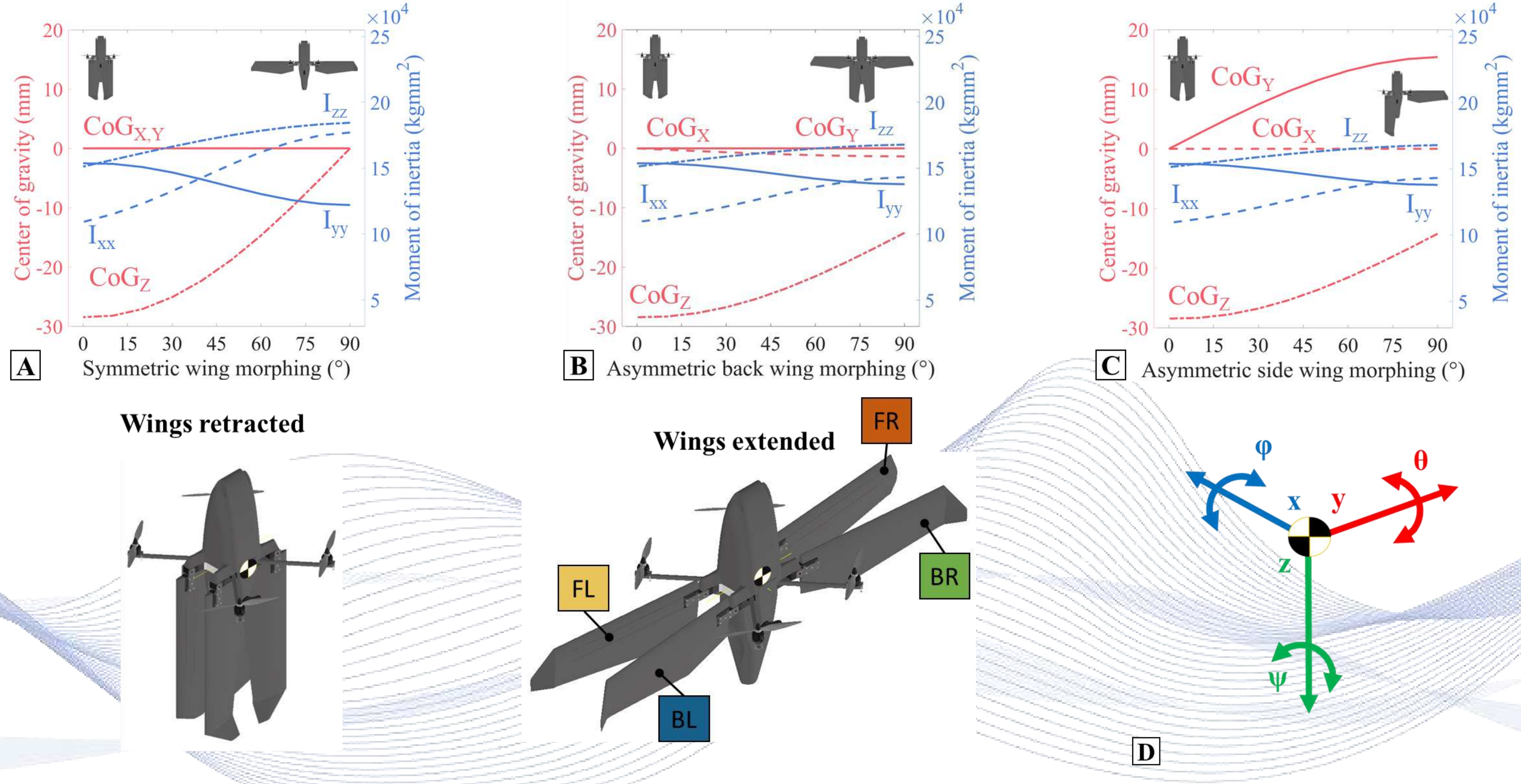


Main challenges outdoor scenario:

- Physical interaction on flight during installation.
- Motion constraints during the installation phase.
- Positioning accuracy, dependent on GPS visibility.

Morphing

Morphing



C. Vourtsis, D. Floreano, N. S. Müller, W. J. Stewart, and V. C. Rochel, “Method for wind harvesting and wind rejection in flying drones,” 2022, PCT patent pending

Morphing

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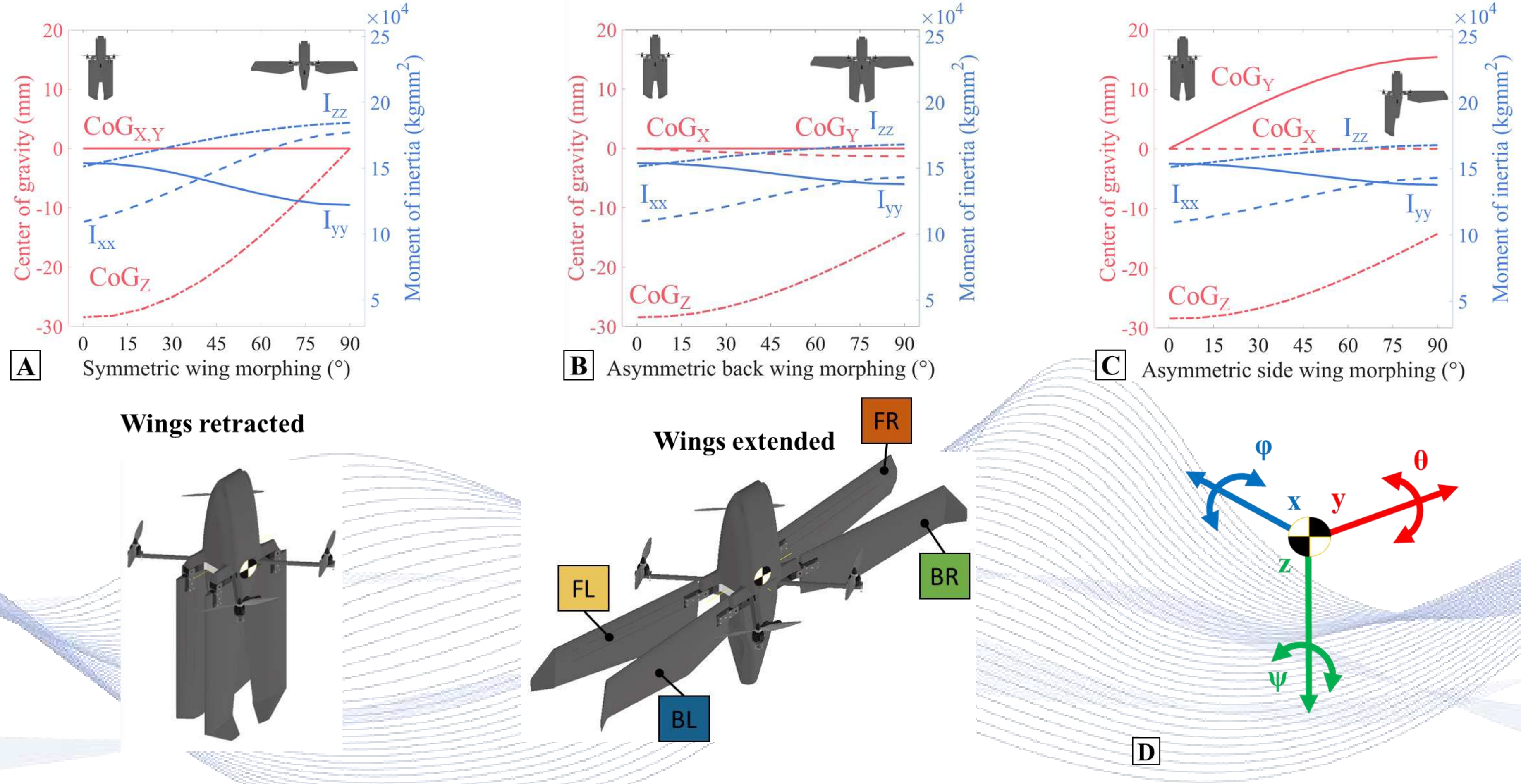
Morphing

Morphing



C. Vourtsis, D. Floreano, N. S. Müller, W. J. Stewart, and V. C. Rochel, “Method for wind harvesting and wind rejection in flying drones,” 2022, PCT patent pending

Morphing

Simulations

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Bibliography

- [NIK2000] N. Nikolaidis and I. Pitas, 3D Image Processing Algorithms, J. Wiley, 2000.
- [PIT2000] I. Pitas, “Digital Image Processing Algorithms and Applications”, J. Wiley, 2000.
- [PIT2013] I. Pitas, “Digital Video and Television ” , Createspace/Amazon, 2013.
- [BRO2014] Bro, Rasmus, and Age K. Smilde. "Principal component analysis." Analytical methods 6.9 (2014): 2812-2831.
- [LIU2016] Liu, Wei, et al. "SSD: Single Shot Multibox Detector." European Conference on Computer Vision. 2016.
- [PIT2017] I. Pitas, “Digital video processing and analysis ” , China Machine Press, 2017 (in Chinese).
- [PER2018] Perera, Asanka G., Yee Wei Law, and Javaan Chahl. "UAV-GESTURE: A dataset for UAV control and gesture recognition." *Proceedings of the European Conference on Computer Vision (ECCV)*. 2018.
- [NOM2019] P. Nousi, I. Mademlis, I. Karakostas, A.Tefas and I.Pitas, "Embedded UAV Real-time Visual Object Detection and Tracking" in Proceedings of the IEEE International Conference on Real-time Computing and Robotics 2019 (RCAR2019), Irkutsk, Russia, 2019.
- [KAR2019] I. Karakostas, V. Mygdalis, A.Tefas and I.Pitas, "On Detecting and Handling Target Occlusions in Correlation-filter-based 2D Tracking" in Proceedings of the 27th European Signal Processing Conference (EUSIPCO), A Coruna, Spain, September 2-6, 2019

Bibliography

- [SHA2019] A. Shahroudy, J. Liu, T. Ng and G. Wang, "NTU RGB+D: A Large Scale Dataset for 3D Human Activity Analysis," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016, pp. 1010-1019.
- [PAP2019] C. Papaioannidis and I.Pitas, "3D Object Pose Estimation using Multi-Objective Quaternion Learning", IEEE Transactions on Circuits and Systems for Video Technology, 2019.
- [NOU2019a] P. Nousi, A.Tefas and I.Pitas, "Deep Convolutional Feature Histograms for Visual Object Tracking" in Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Brighton, UK, 2019.
- [NOU2019b] P. Nousi, D. Triantafyllidou, A.Tefas and I.Pitas, "Joint Lightweight Object Tracking and Detection for Unmanned Vehicles" in Proceedings of the IEEE International Conference on Image Processing (ICIP), Taipei, Taiwan, September 22-25, 2019.
- [KAR2020] I. Karakostas, I. Mademlis, N.Nikolaidis and I.Pitas, "Shot Type Constraints in UAV Cinematography for Autonomous Target Tracking", Elsevier Information Sciences, vol. 506, pp. 273-294, 2020.
- [NIC2020] C. Nicolas, et al. "End-to-End Object Detection with Transformers." arXiv preprint arXiv:2005.12872 (2020).

Bibliography

- [BOC2020] A. Bochkovskiy, CY Wang and HY M. Liao. “YOLOv4: Optimal Speed and Accuracy of Object Detection”. arXiv, 2020.
- [PIT2021] I. Pitas, “Computer vision”, Createspace/Amazon, in press.
- [PIT2021] I. Pitas, “Optimal multidimensional cyclic convolution algorithms for deep learning and computer vision applications”, in Proceedings of the International Conference on Autonomous Systems (ICAS), 2021.
- [PAP2021a] C. Papaioannidis, I. Mademlis and I. Pitas, “Autonomous UAV Safety by Visual Human Crowd Detection Using Multi-Task Deep Neural Networks”, ICRA, 2021.
- [PAP2021b] Papadopoulos, Sotirios, I. Mademlis and I. Pitas, “Semantic Image Segmentation Guided by Scene Geometry”, in Proceedings of the International Conference on Autonomous Systems (ICAS), *2021*.
- [KAR2021] I. Karakostas, V. Mygdalis, and I. Pitas,“Adversarial optimization scheme for online tracking model adaptation in autonomous systems”, ICIP (special session on Autonomous Vehicle Vision), 2021.
- [YAN2021] Dingming Yang, Yanrong Cui, Zeyu Yu & Hongqiang Yuan, "Deep learning based steel pipe weld defect detection." *Applied Artificial Intelligence* 35.15 (2021): 1237-1249.

Bibliography

- [DIET2021] A.Dietsche, G.Cioffi, J.Hidalgo-Carrió, D. Scaramuzza Autonomous Persistent Power line Tracking using Events, IROS 2021
- [PAT2022] Karsten Roth, Latha Pemula, Joaquin Zepeda, Bernhard Scholkopf, Thomas Brox, Peter Gehler, "Towards total recall in industrial anomaly detection", *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition,* 2022.
- [CHU2022] Li, Chuyi, et al. "YOLOv6: A single-stage object detection framework for industrial applications." arXiv preprint arXiv:2209.02976 (2022).
- [AKY 2022] Akyon, Fatih Cagatay, Sinan Onur Altinuc, and Alptekin Temizel. "Slicing aided hyper inference and fine-tuning for small object detection." 2022 IEEE International Conference on Image Processing (ICIP). IEEE, 2022.
- [WEN2023] Lv, Wenyu, et al. "Detrs beat yolos on real-time object detection." arXiv preprint arXiv:2304.08069 (2023).
- [PSA] D. Psarras, C. Papaioannidis, V. Mygdalis, and I. Pitas, "A Unified DNN-Based System for Industrial Pipeline Segmentation", submitted as conference paper.
- [QSA] QSA GLOBAL. OpenVision HD Demo. url=https://www.qsa-global.com/openvision-hd

Q & A

Thank you very much for your attention!

More material in
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