Drone imaging for industrial infrastructure inspection

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Artificial Intelligence &
Information Analysis Lab

UAV Pipe Infrastructure Inspection

UAV Pipe Infrastructure Inspection

- **Overview**
- Pipe Region Segmentation
- Pipe Damage Detection
- 3D Pipe Damage Localization
- X-ray Pipe Damage Detection
- PEC Pipe Damage Detection

Overview

Main objective

- To develop an artificial intelligence system that will analyze all the captured data by SIMAR robotic systems to reduce the inspector workload and stress.

Overview

- **Insulated Pipe Region Segmentation**
  - Developed pipe segmentation algorithm: Pipe segmentation model.
  - Enriched the pipe segmentation dataset.
  - Extensive evaluation of the Pipe segmentation model.

- **Pipe Damage Detection/Classification**
  - Developed damage detection/classification algorithm: Lightweight DNN (Yolo, RT-DETR) detectors and changes detection algorithm.
  - Enriched damage detection/classification dataset.
  - Extensive evaluation of the developed algorithms.

Overview

- **3D Pipe Damage Localization**
  - Develop algorithms for creating 3D models of pipes (cylinders) using a) 3D point cloud, b) RGB video frames.
  - Projecting the 2D detected pipe damages on the 3D point cloud/map.
- **X-ray Pipe Damage Detection**
  - Developed algorithms for damage/corrosion detection on X-Ray images.
- **PEC Pipe Damage Detection**
  - Analyze/pre-process PEC data.
  - Test baseline methods for corrosion level detection.

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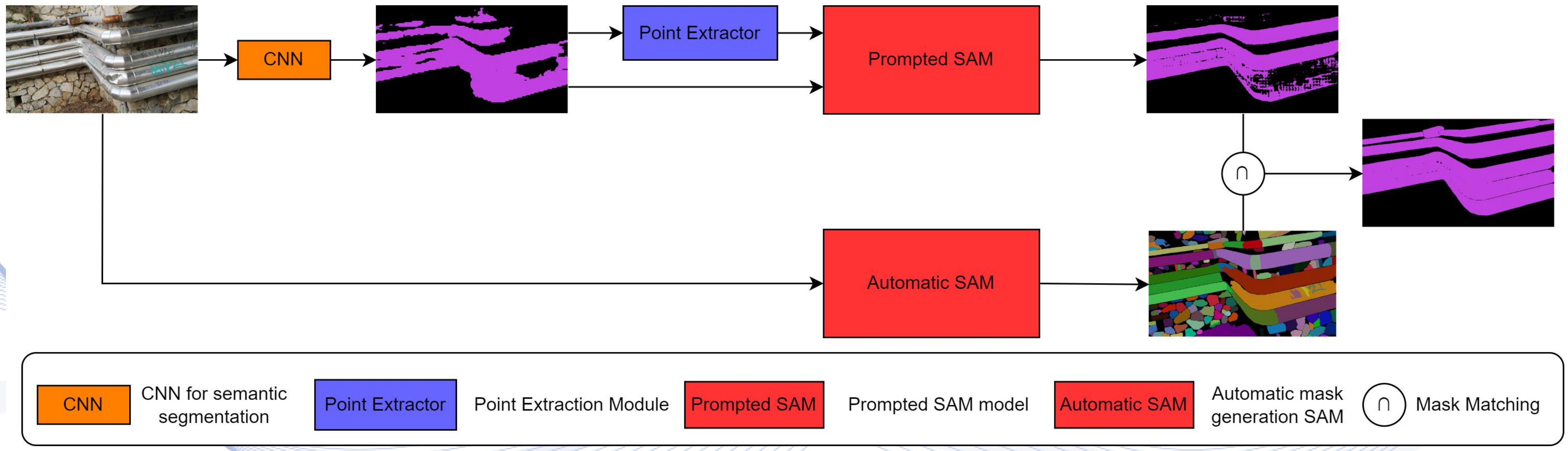
Pipe Region Segmentation

- Cooperation of a CNN segmentation model [PAP2021] 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.

Pipe Region Segmentation



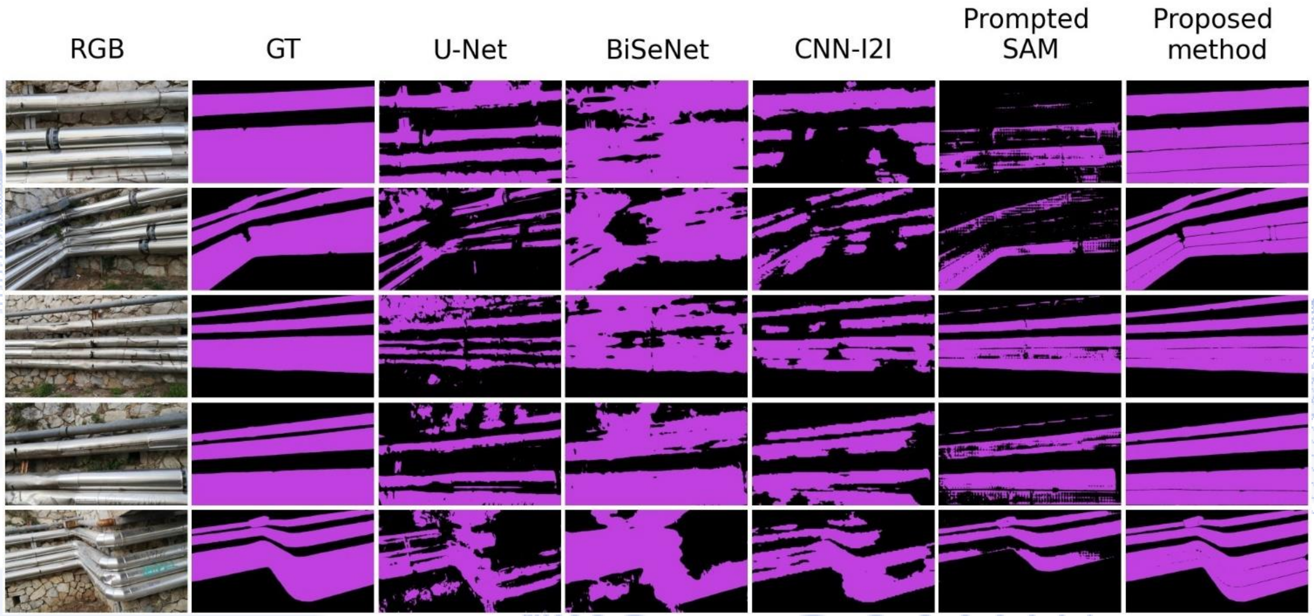
Pipe Region Segmentation

- 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 (AUTH site)

Pipe Region 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”, submitted as conference paper.

Pipe Damage Detection

Pipe image segmentation.

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Pipe Damage Detection

- **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 pipes.
    - Detects the images/patches that differ from learned distribution (and possibly contain damaged pipes).

Pipe Damage Detection

Pipe damage in a Greek factory.

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Pipe Damage Detection

Performance of damage detection/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 chan 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

Pipe Damage Detection

Overall pipe damage detection and visualization.

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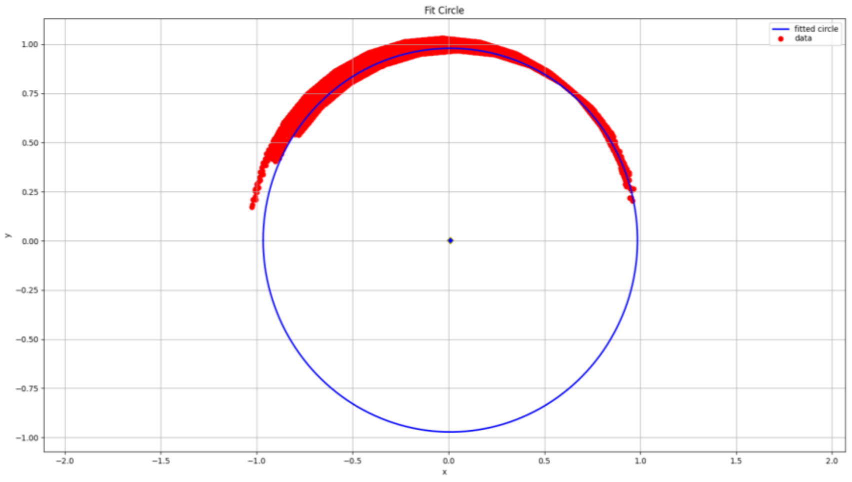
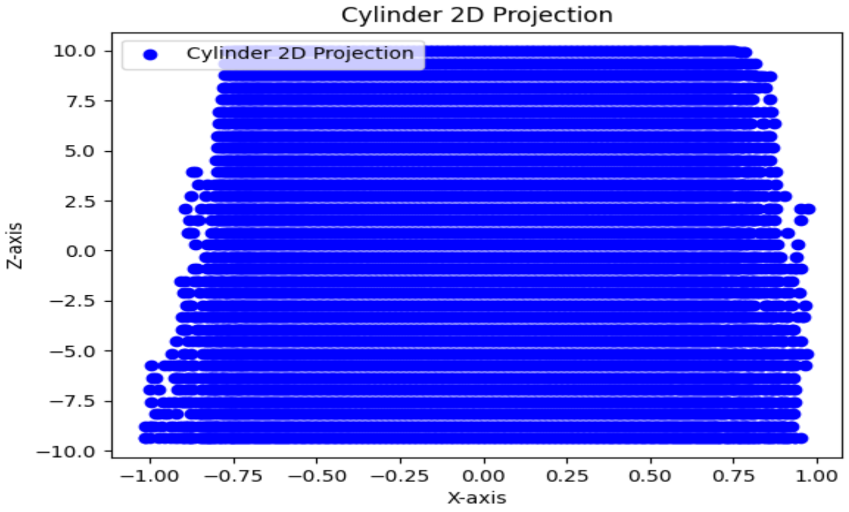
3D Pipe Damage Localization

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

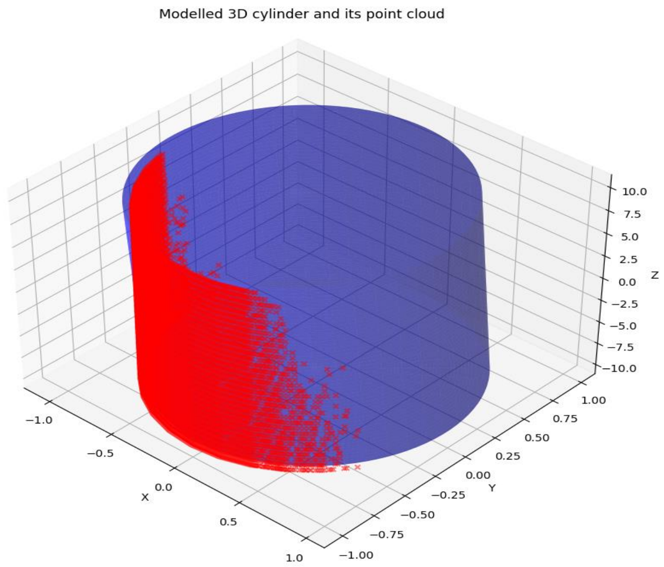
3D Pipe Damage Localization



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



PCA on the 3D point cloud

3D Pipe 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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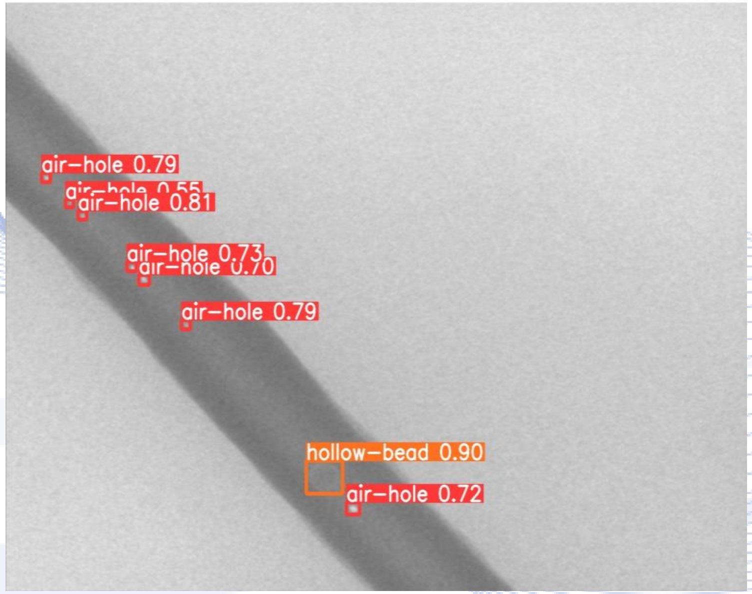
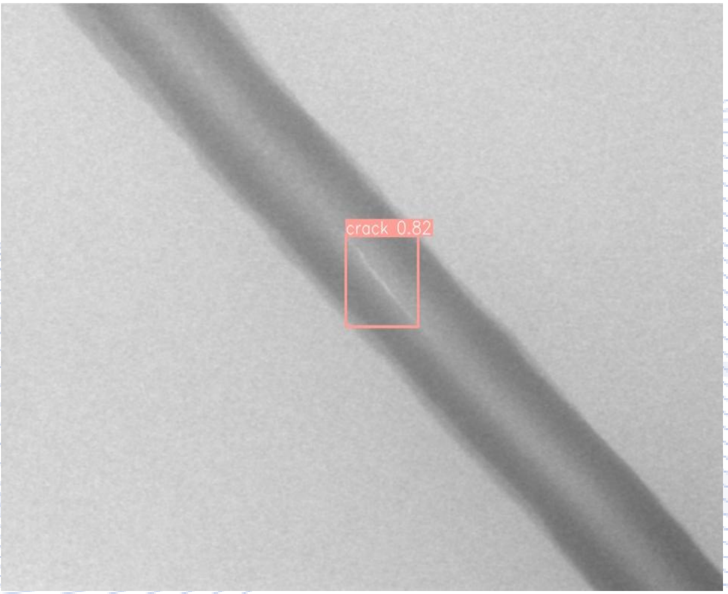
X-Ray Pipe Damage Detection

- Trained baseline models based on YOLO object detector [CHU2022].



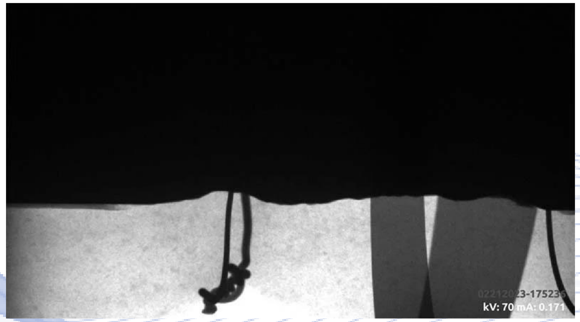


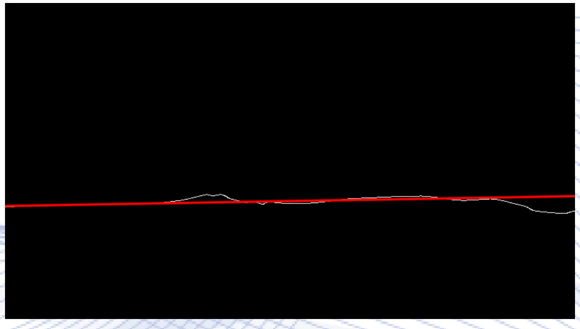
YOLOv8 Results	
Precision	0.97
Recall	0.96
mAP50	**0.98**
mAP50-95	0.71

X-Ray Pipe Damage Detection

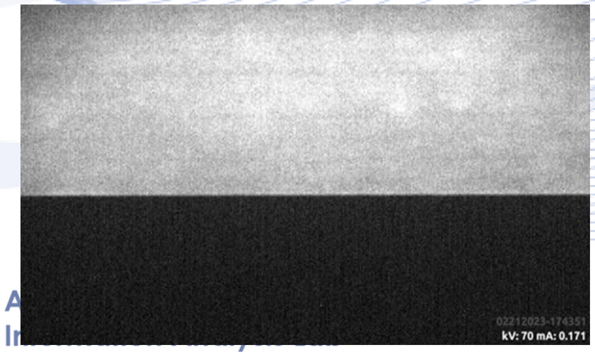
- Employ image processing techniques to detect the edge of the pipe.
- Detect corrosion by measuring the distance from the corresponding straight line that simulates a pipe without corrosion.

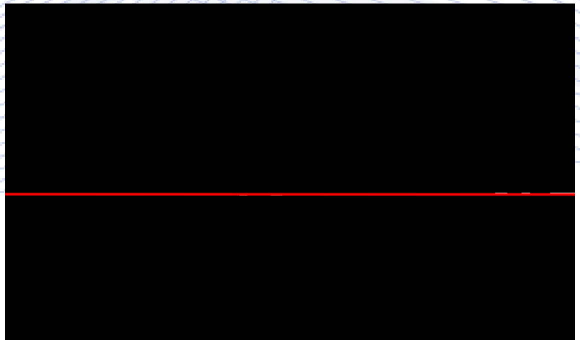
Images taken from [QSA]





Corrosion





No Corrosion

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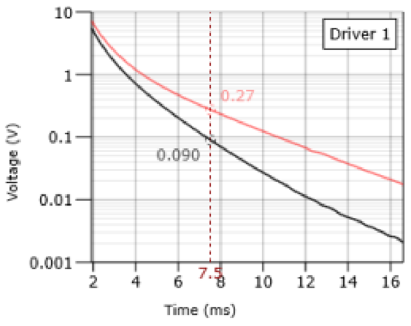
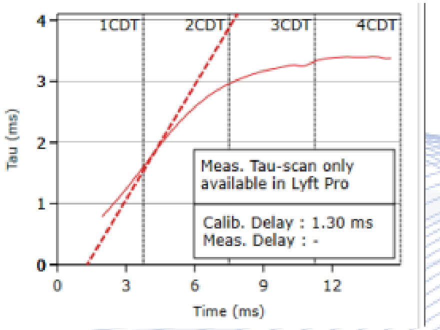
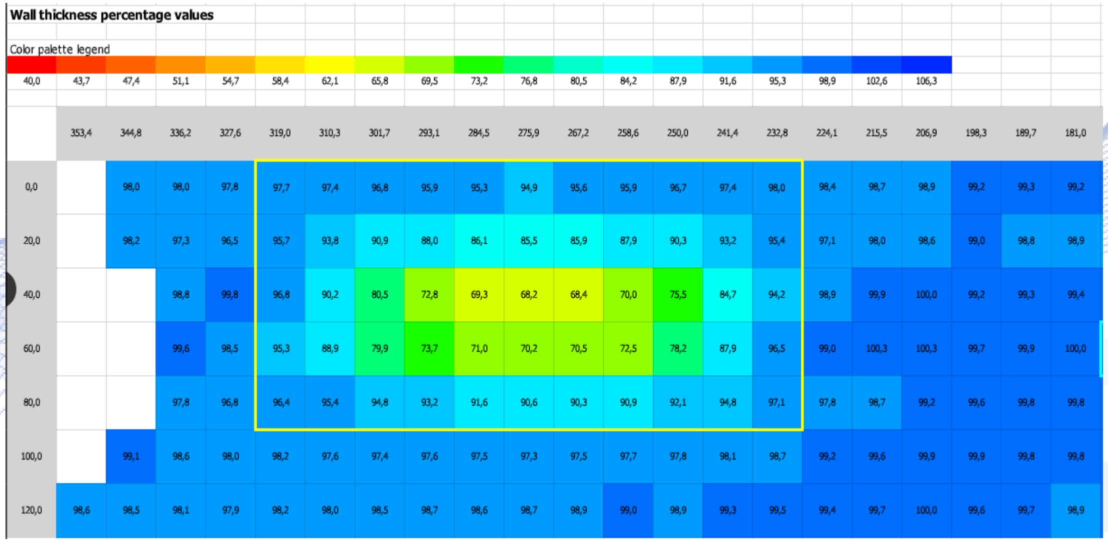
PEC Pipe Damage Detection

- A literature review is needed to identify deep learning methods and baselines for analyzing 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	98,9	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
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120,0	98,6	98,5	98,1	97,9	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.

UAV 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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Safe local manipulation interventions

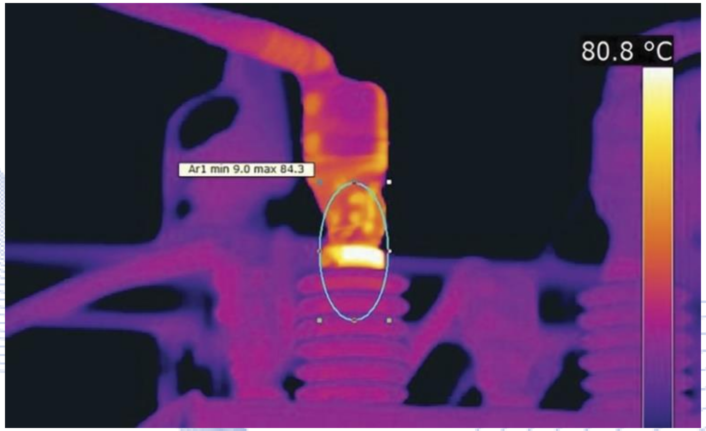
- Examples:
  - Installing anti-birds systems.
  - Cleaning isolator in power lines.

Co-working activities

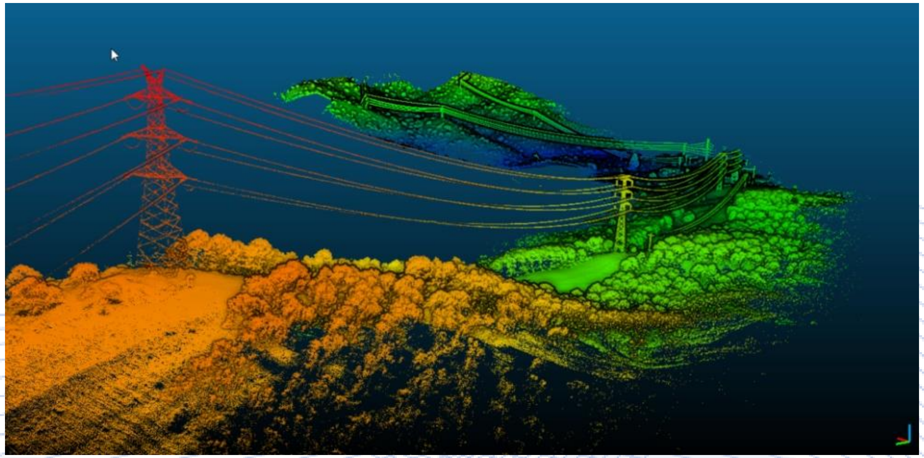
Infrastructure Inspection

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

Types of inspection



Thermography

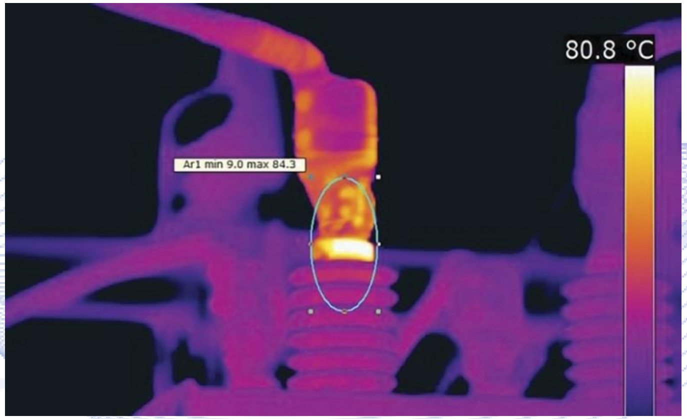


3D mapping (LIDAR)

Camera & video

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.

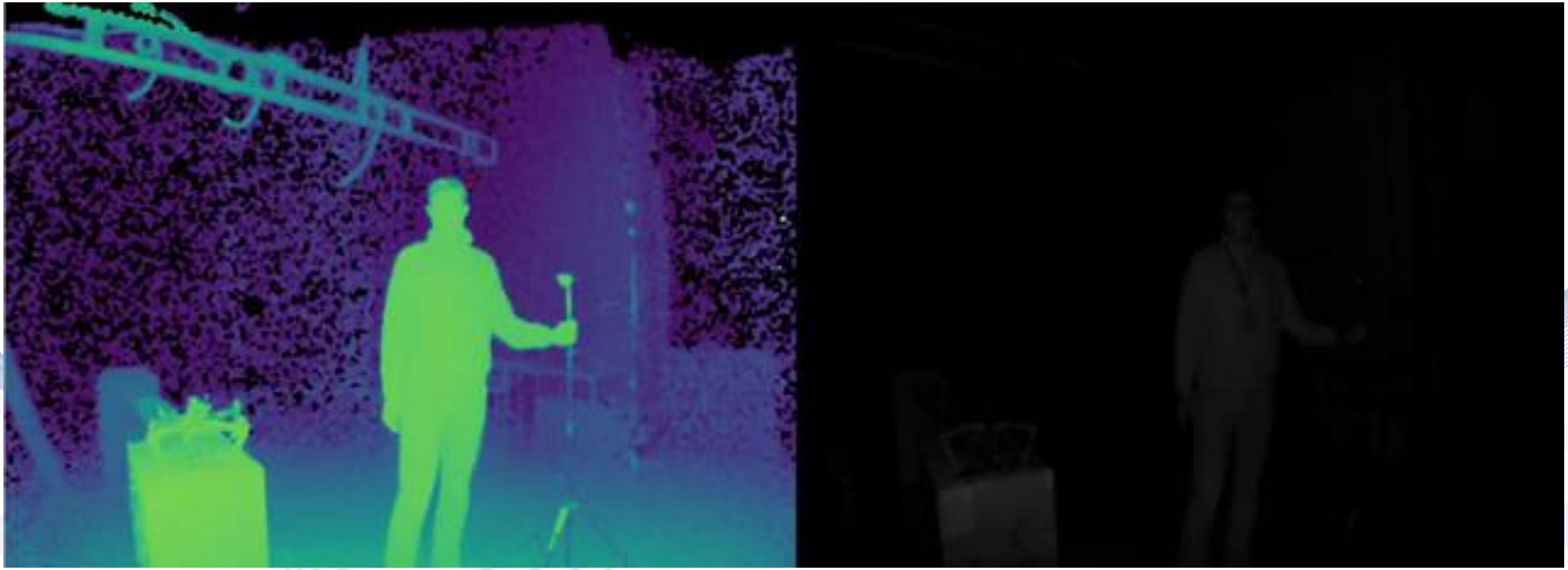


3D LIDAR

- 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

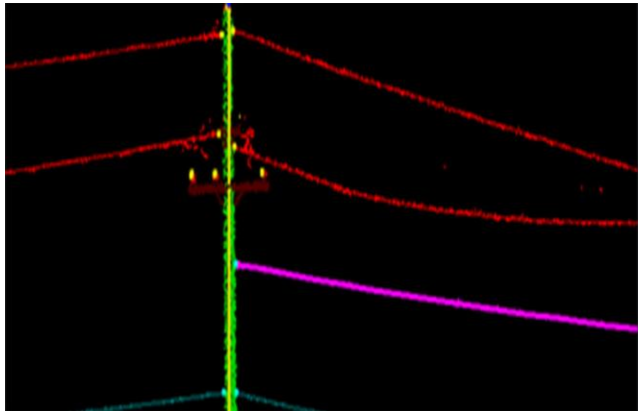
Latency & Motion blur.

Dynamic Range.

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:

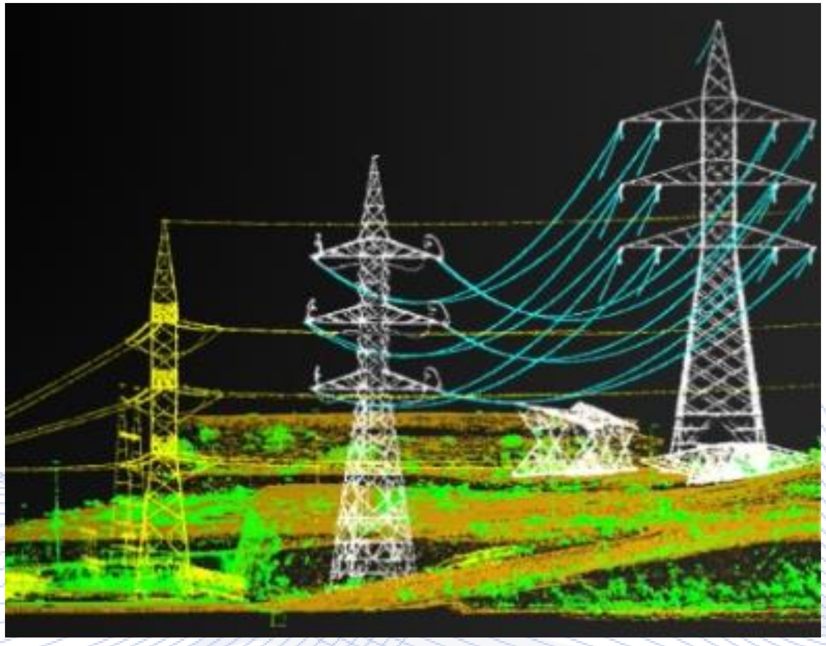
$$\mathbf{y} = \mathbf{C}(\mathbf{A}\mathbf{x} \otimes \mathbf{B}\mathbf{h}).$$

- 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



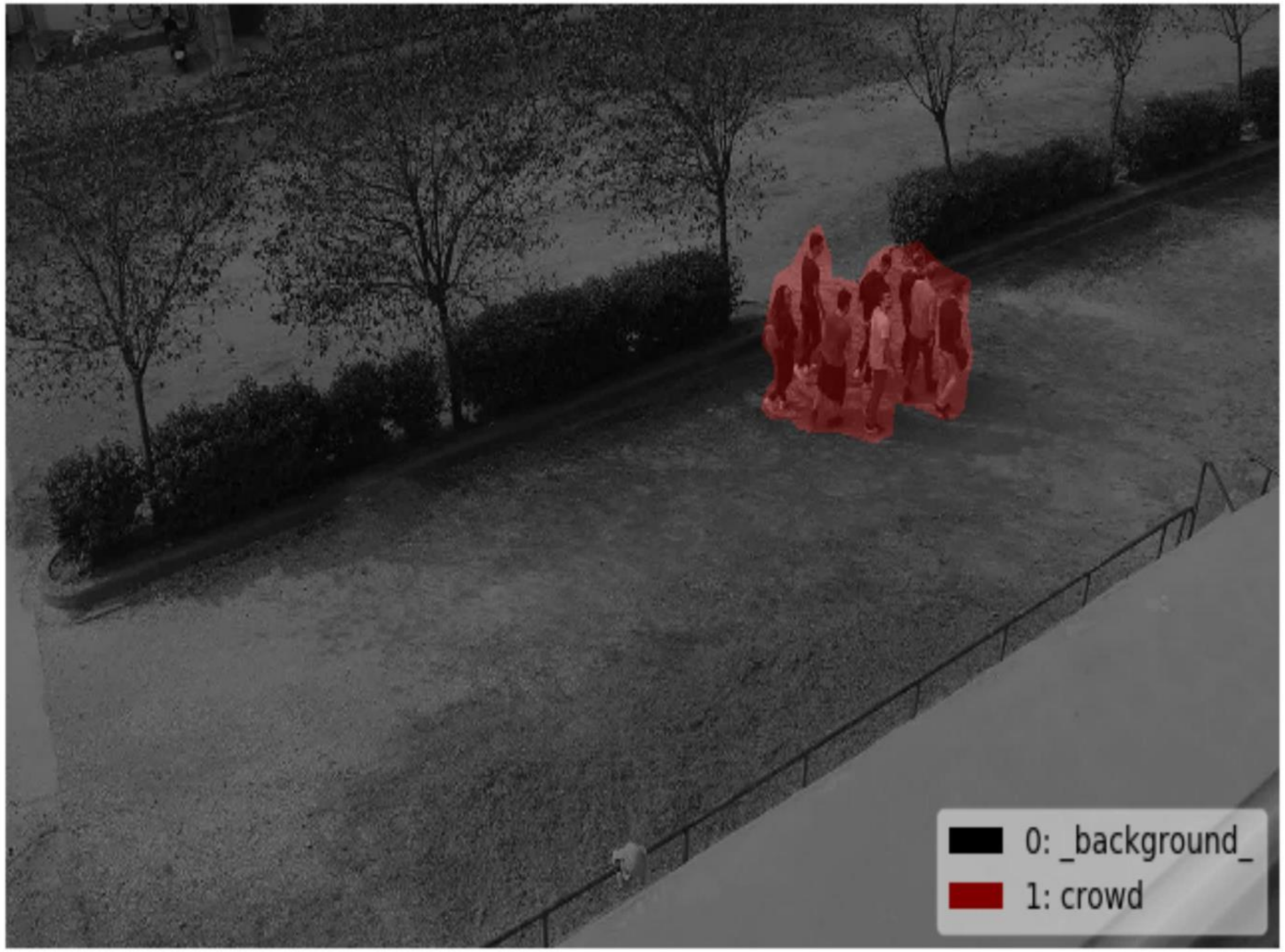
Geometric modeling of the 3D world.

Semantic 3D World Mapping

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

Semantic 3D World Mapping

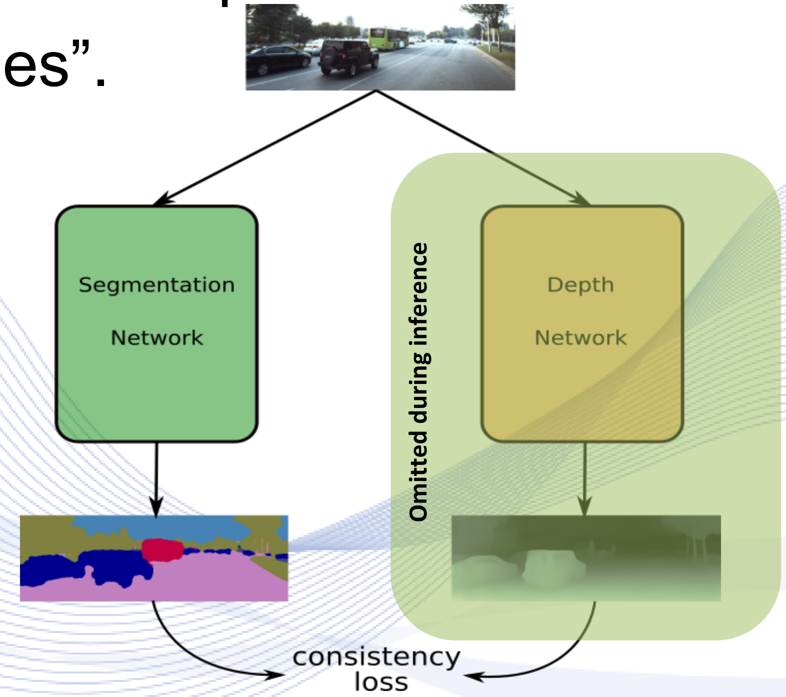
- ***Semantic image segmentation:***
  - Crowd detection and localization.



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”.

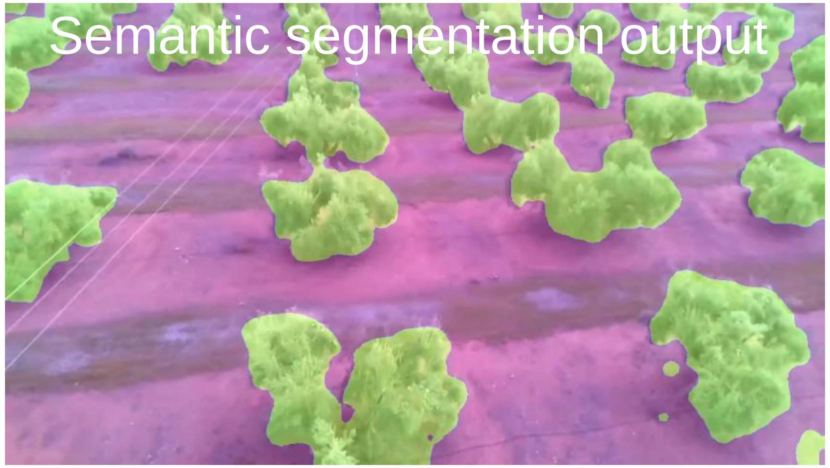
Method	Mean IoU	Inference (ms)
Yu et al.	39.557%	**6.2**
Klingner et al.	34.318%	6.4
Novosel et al.	37.683%	8.3
Chen et al. (pretrained)	39.610%	**6.2**
Chen et al. (multitask)	38.153%	9
Ours	**40.597%**	**6.2**

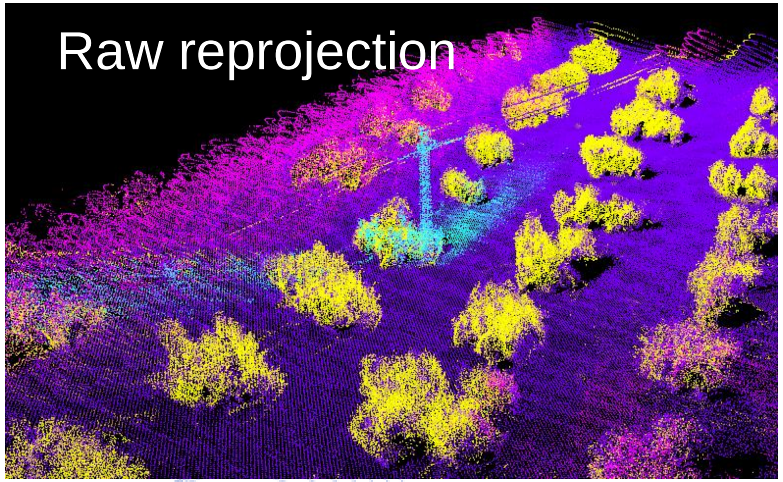


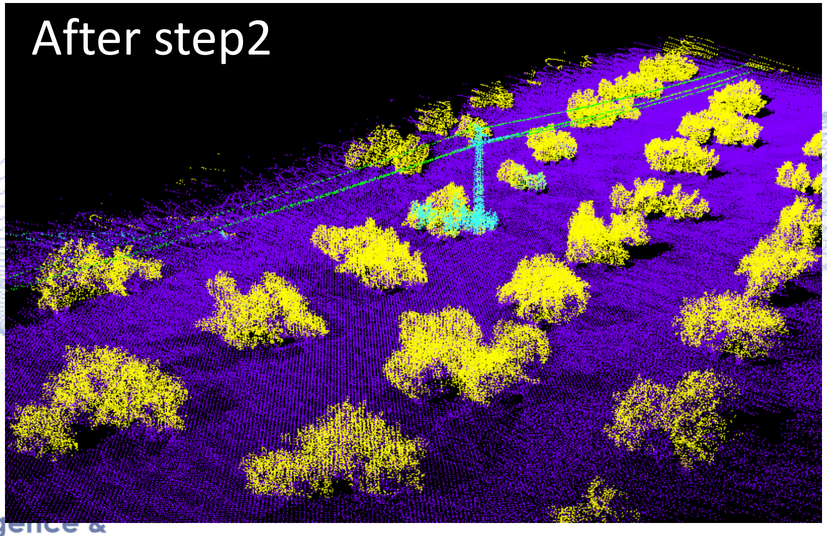
Semantic Image Segmentation Guided by Scene Geometry [PAPAD2021].

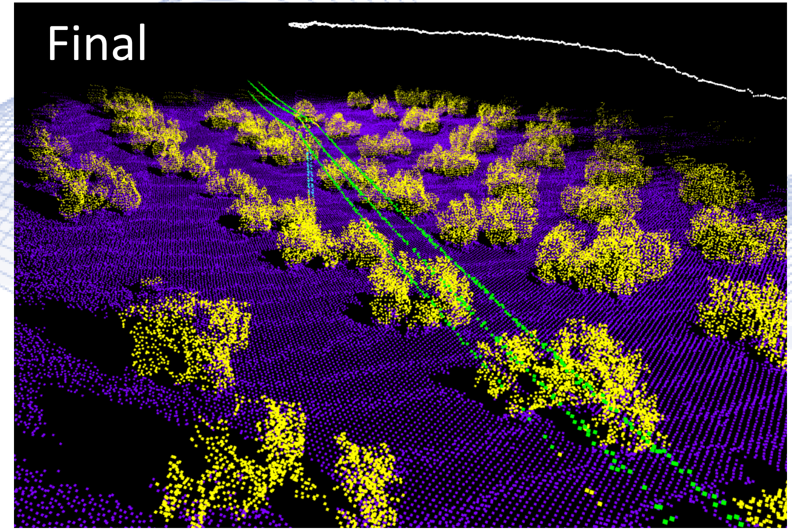
Semantic Segmentation

Semantic 3D World Mapping

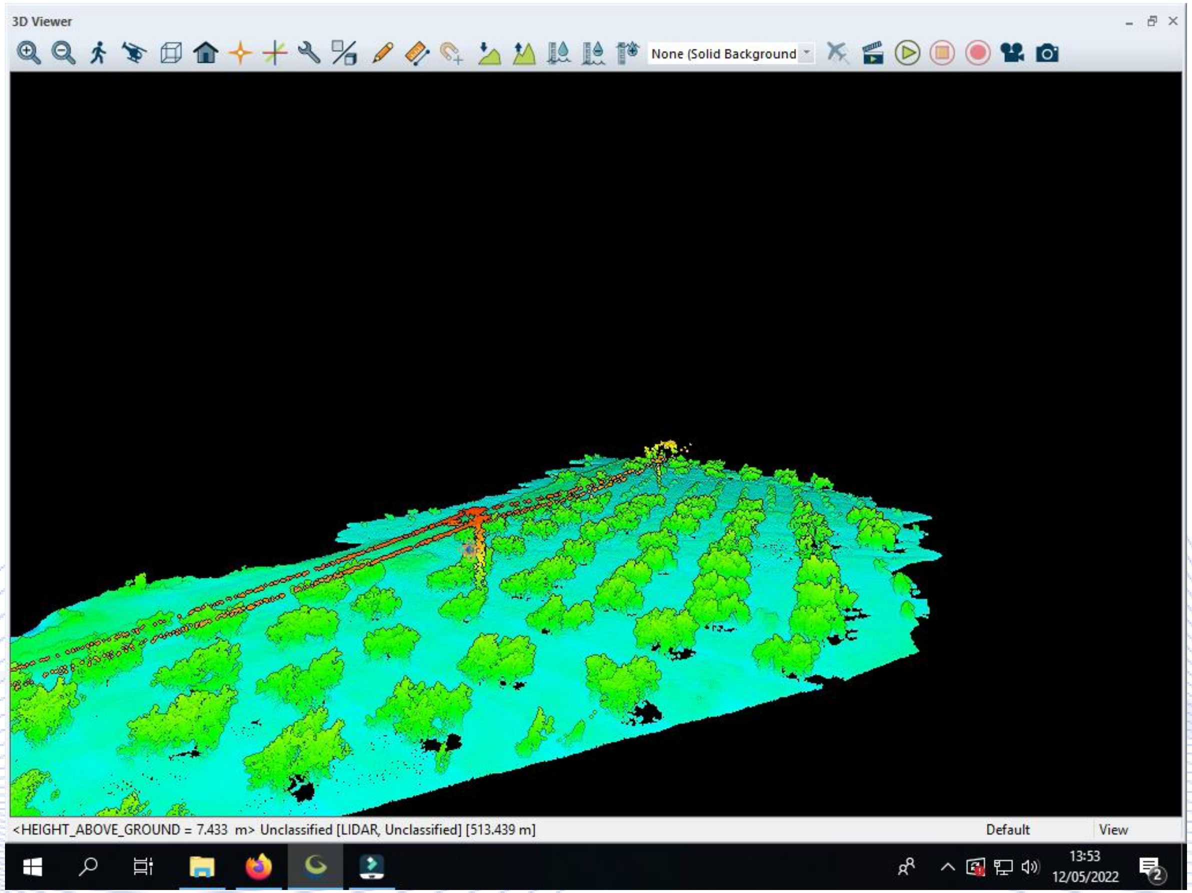




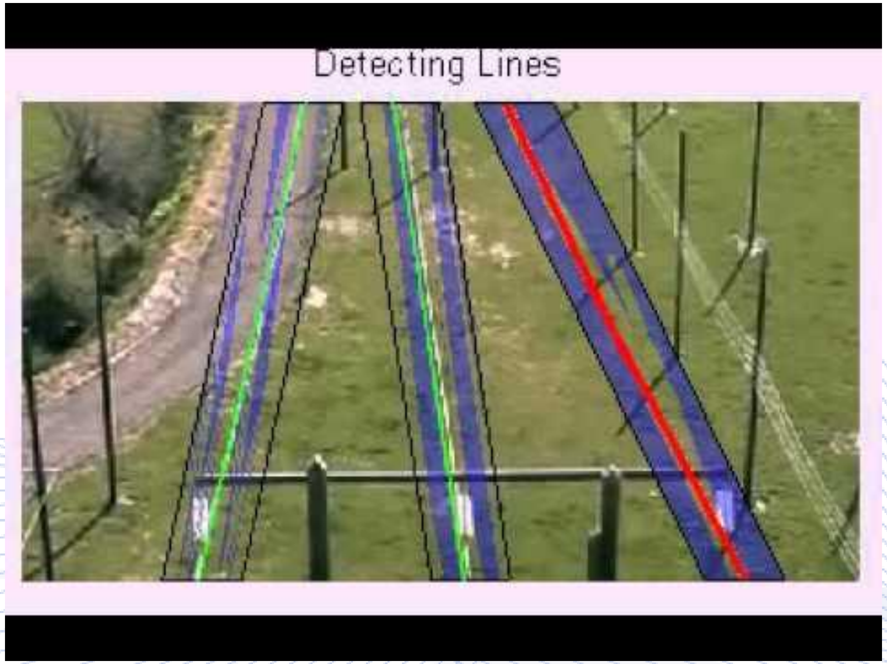




Semantic 3D World Mapping



Object detection and tracking



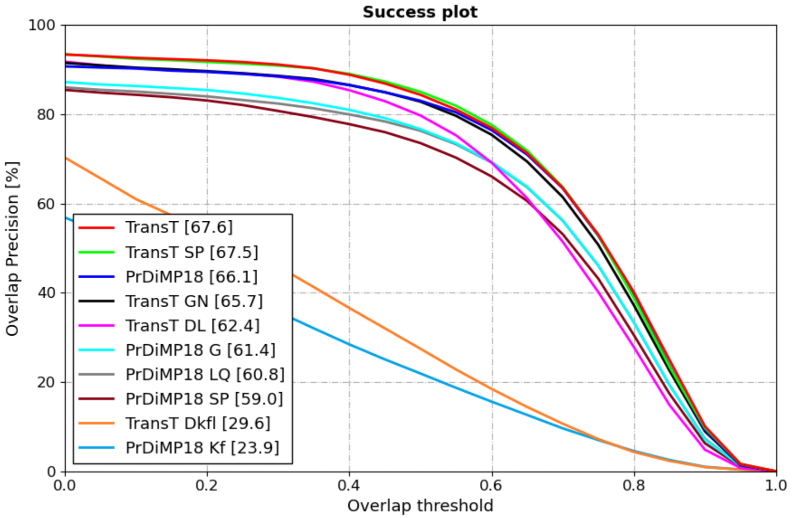
Deep learning for power line detection and tracking.

Object detection and tracking

- 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**

Robustness 2D Visual Object Tracking



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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.

Simulations

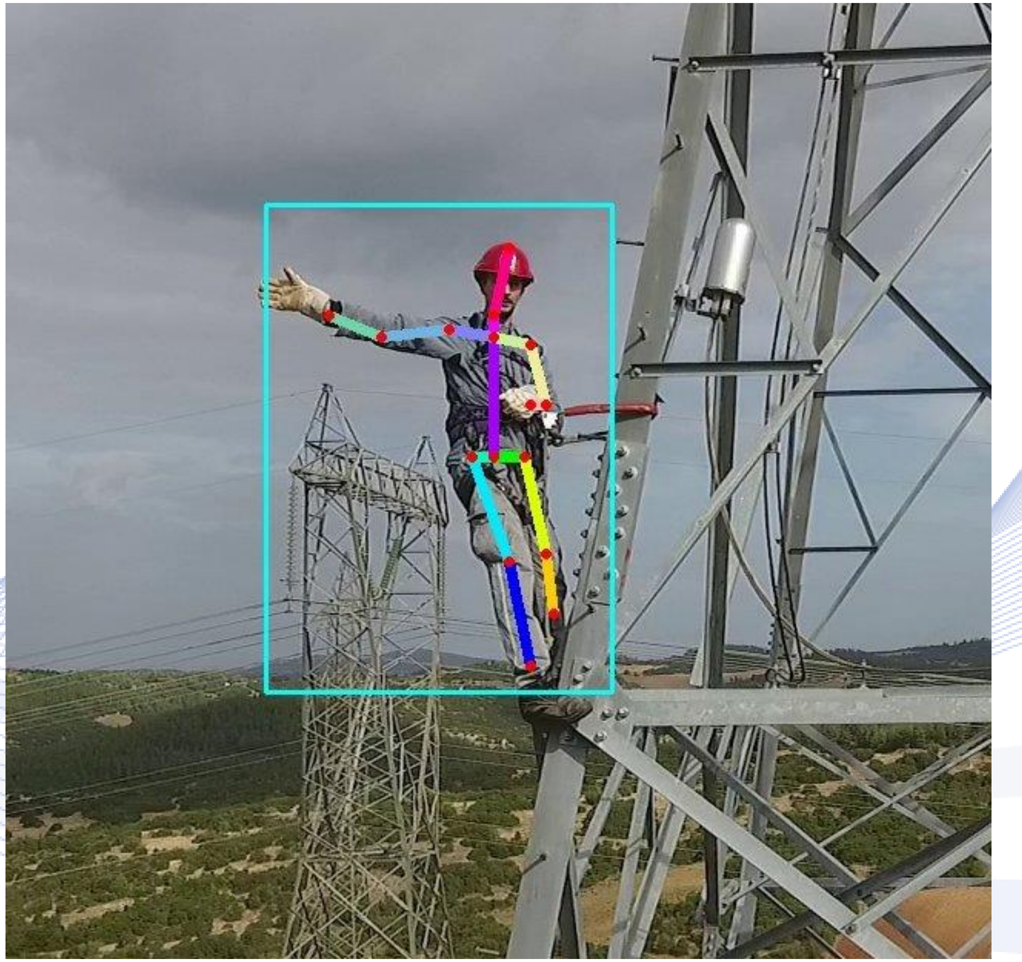
Human posture estimation

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

Human-drone interaction

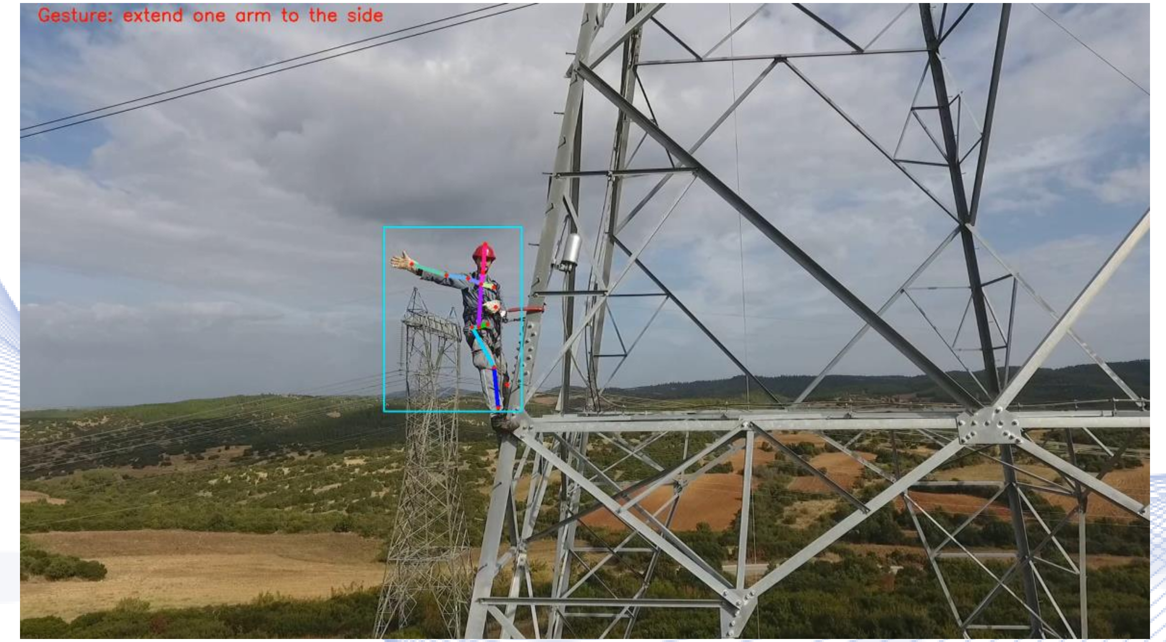
- Goals: The UAV/Aerial Co-Worker:
  - Can verify that the technician follows pre-set safety rules at all times.
  - May perceive the technician’s current activity (e.g., climbing a pole) in order to get into suitable position for assisting him.
  - Is able to interact visually with the technician by 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

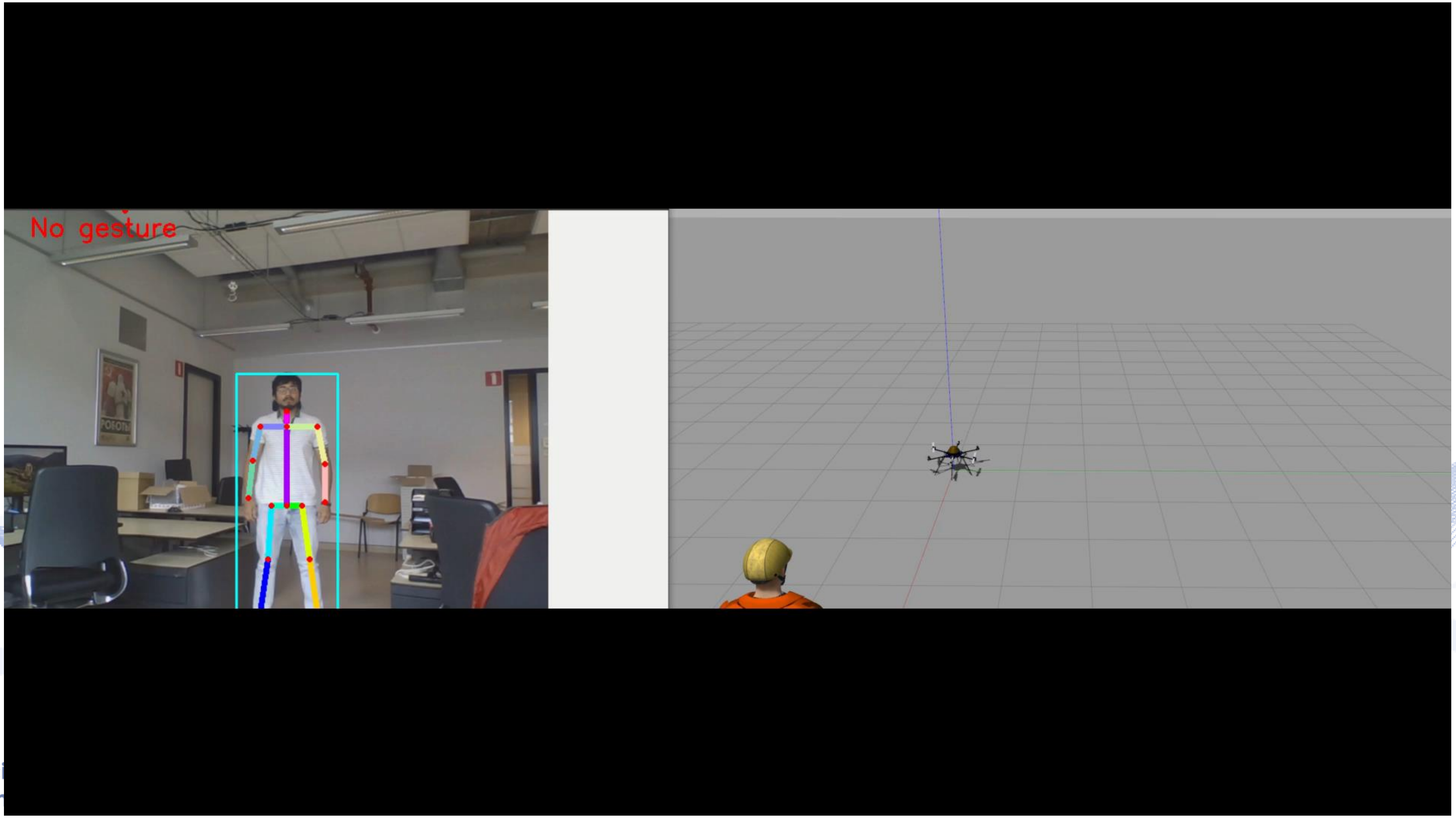


Human posture estimation.

Human posture – gesture recognition



Gesture-based control



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**

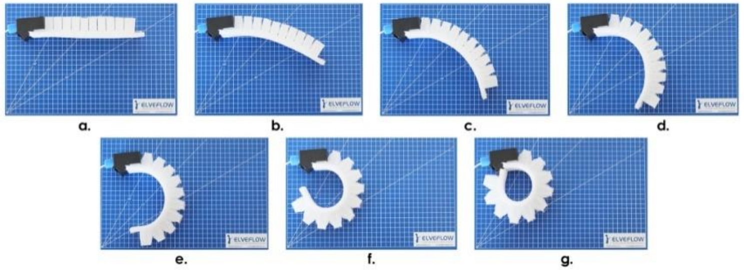
Artificial Intelligence & Information Analysis Lab

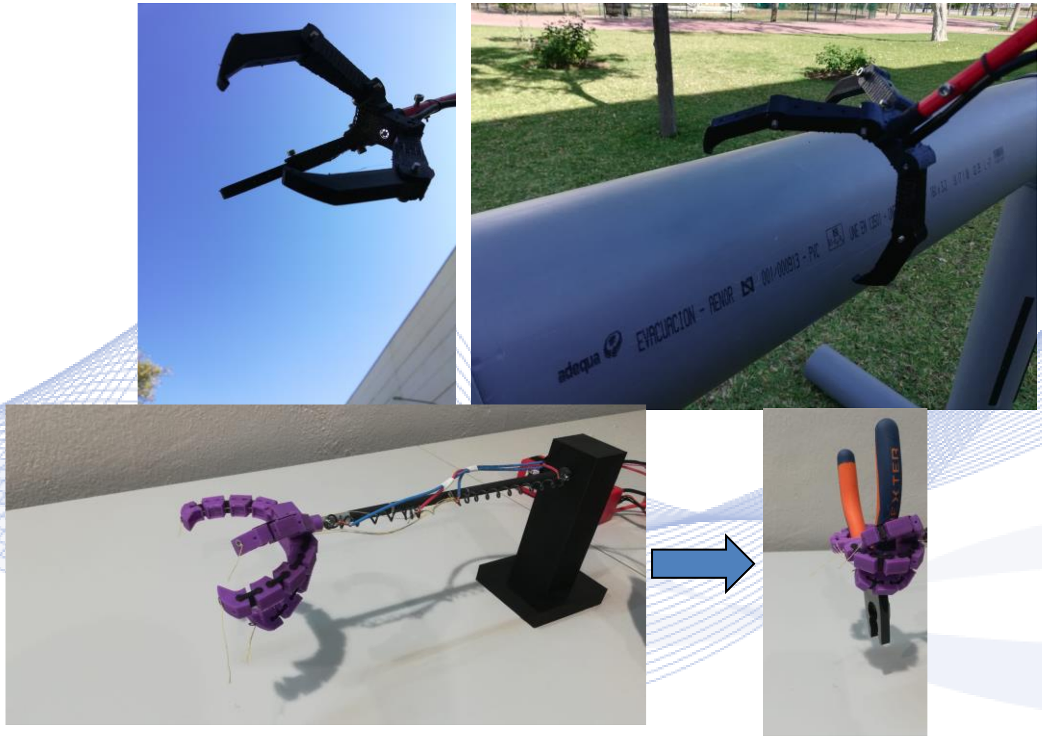
Autonomous perching

- 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.



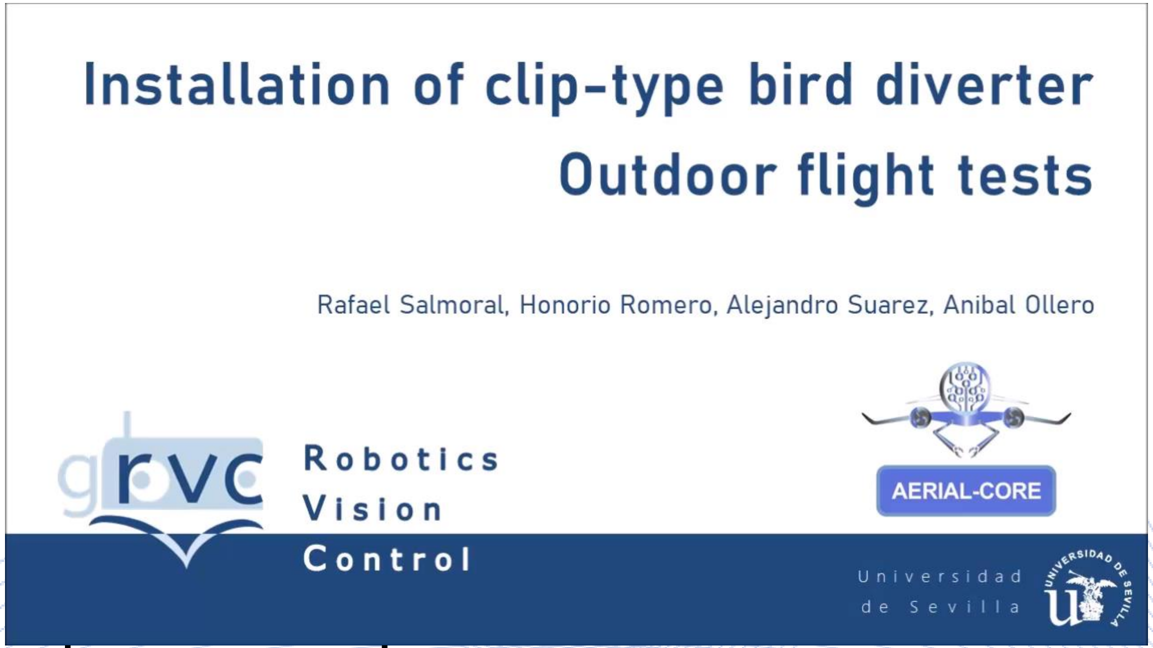


Manipulation while holding/perching

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.

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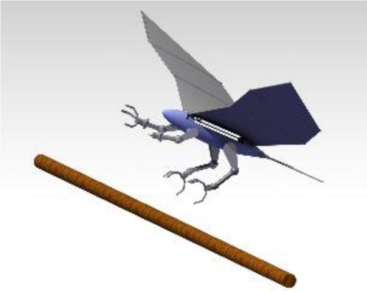
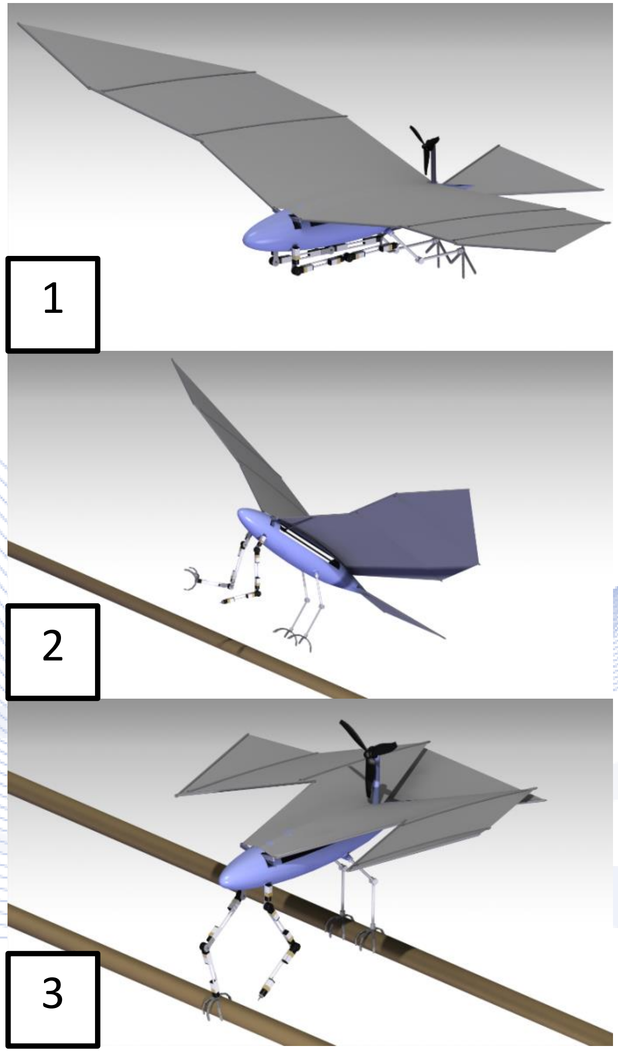
Morphing

- ***Flapped wing*** to fixed wing.
- Fixed to rotary.
- ***Ornithopters*** can potentially achieve better efficiency, maneuverability and safety.





Morphing

Morphing

Bibliography

[PIT2021] I. Pitas, “Computer vision”, Createspace/Amazon, in press.

[PIT2017] I. Pitas, “Digital video processing and analysis ” , China Machine Press, 2017 (in Chinese).

[PIT2013] I. Pitas, “Digital Video and Television ” , Createspace/Amazon, 2013.

[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.

Bibliography

[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

[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

[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

[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

[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

Bibliography

[NOT2019b] 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.

[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.

[PAPAD2021] 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*.

[PAP2021] C. Papaioannidis, I. Mademlis and I. Pitas, "Autonomous UAV Safety by Visual Human Crowd Detection Using Multi-Task Deep Neural Networks", ICRA, 2021.

[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

[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.

Bibliography

[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

[BOC2020] A. Bochkovskiy, CY Wang and HY M. Liao. “YOLOv4: Optimal Speed and Accuracy of Object Detection”. arXiv, 2020.

[DIET2021] A.Dietsche, G.Cioffi, J.Hidalgo-Carrió, D. Scaramuzza Autonomous Persistent Power line Tracking using Events, IROS 2021

[LIU2016] Liu, Wei, et al. "SSD: Single Shot Multibox Detector." European Conference on Computer Vision. 2016.

[NIC2020] C. Nicolas, et al. "End-to-End Object Detection with Transformers." arXiv preprint arXiv:2005.12872 (2020).

[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.

Bibliography

[PSA] D. Psarras, C. Papaioannidis, V. Mygdalis, and I. Pitas, “A Unified DNN-Based System for Industrial Pipeline Segmentation”, submitted as conference paper.

[CHU2022] Li, Chuyi, et al. "YOLOv6: A single-stage object detection framework for industrial applications." arXiv preprint arXiv:2209.02976 (2022).

[WEN2023] Lv, Wenyu, et al. "Detrs beat yolos on real-time object detection." arXiv preprint arXiv:2304.08069 (2023).

[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.

[QSA] QSA GLOBAL. OpenVision HD Demo. url=https://www.qsa-global.com/openvision-hd

[BRO2014] Bro, Rasmus, and Age K. Smilde. "Principal component analysis." Analytical methods 6.9 (2014): 2812-2831.

[PIT2017] I. Pitas, “Digital video processing and analysis ” , China Machine Press, 2017 (in Chinese).

Bibliography

[PIT2013] I. Pitas, “Digital Video and Television ”, Createspace/Amazon, 2013.
[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.

Q & A

Thank you very much for your attention!

More material in
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