ADVANCING INDUSTRIAL INSPECTION: A DATASET FOR AUTOMATED DAMAGE DETECTION IN INSULATED PIPES

Pantelis Mentesidis, Christos Papaioannidis, Ioannis Pitas

NUMBER 101070604 — SIMAR

Introduction

- Automated drone-based inspection with AI improves safety and efficiency in industries.

Fig. 1: Drone inspection on powerlines [1].

Fig. 2: Drone inspection on insulated pipes [2].

[1] *Aerial Core H2020 Project, https://aerial-core.eu/*

[2] *Piloting uses cases. PILOTING H2020 Project. (2023, December 19). https://piloting-project.eu/piloting-uses-cases/*

Introduction

- Early detection on pipe damages prevents leaks, ensuring operational effectiveness and environmental sustainability.

(a) RGB image.

(b) DNN results for pipe segmentation and damage detection.

Fig. 3: DNN inspection results on insulated pipes from Auth.

Introduction

- Complex structures and limited accessibility can introduce multiple challenges in industrial data collection.

- AI algorithm success depends on extensive, annotated data. However, collecting such data in industrial settings is far from trivial.

Introduction

- Introducing the Pipe Damage Image (PDI) dataset, designed for industrial pipe damage detection.
- PDI is a diverse data collection using mobile and UAV cameras for both indoor and outdoor pipe environments.
- PDI ensures redundant frame omission by utilizing pre-trained foundation models for frame filtering.
- Advanced DNN object detectors were tested on PDI to establish a damage detection benchmark.

Frame filtering and selection

- Video frames were processed and filtered to eliminate redundancy, enhancing dataset quality.

- CLIP was employed to compute similarity metrics between frames, aiding in correct data sampling.

- A similarity matrix constructed from image triplets was utilized as the frame filtering similarity metric.

PDI dataset composition

- 29 videos and 328 images, validated by annotators.
- 2,190 images with 4,672 bounding boxes for "hole" and "open insulation" damage types.
- Resolutions from 1920x1080 to 9504x6336 for diverse inputs.

(a) hole.

(b) open insulation.

Fig. 4: Labeled images of damaged pipes from Greek facilities.

Dataset splits

- First split: 1,912 training and 278 testing images, including data from all facilities for equitable model evaluation.

- Second split: 1,748 training and 408 testing images, separating data based on manufacturing facility locations, mirroring real-world deployment scenarios and enhancing model robustness through environmental diversity.

Experiments setup

- Utilized state-of-the-art DNN algorithms primarily from the YOLO family and an object detection Transformer.

- Experiments conducted on an NVIDIA GeForce RTX 2080 Ti for 100 epochs using image resolution of 1280x1280.

Results

- YOLOv6 emerged as the most effective model for industrial pipe damage detection, followed by YOLOv5 and RT-Detr.

- Performance notably declined in the second split, underscoring its increased challenge due to environmental diversity.

Model	mAP 0.50	mAP 0.50:95	mAR 0.50:95
Yolov5	0.432	0.216	0.405
Yolov8	0.371	0.168	0.317
Yolo-Nas	0.319	0.140	0.359
Yolov6	**0.519**	**0.251**	**0.444**
RT-Detr	0.398	0.210	0.398

Table 1: Baseline results on the first split.

Model	mAP 0.50	mAP 0.50:95	mAR 0.50:95
Yolov6	**0.302**	**0.127**	**0.237**
Yolov5	0.265	0.102	0.195
RT-Detr	0.227	0.092	0.273

Table 2: Baseline results on the more challenging, second split.

Results

Fig. 5: Inference of YOLOv6 on images from Greek facilities. (“open insulation” damage - pink box , “hole” damage - red box).

Conclusion

- Launched PDI dataset with 2,190 annotated RGB images for pipe damage detection. Two data splits were created for advanced DNN model training and testing, based on different scenarios.

- While the results of AI application in industrial environments are promising, multiple challenges of the pipe damage detection task, remain underexplored in literature.

- Our results encourage systematical data collection, for AI research to further improve industrial environment safety and efficiency.

Q & A

Thank you very much for your attention!

Prof. Ioannis Pitas,
Aristotle University of Thessaloniki,
pitas@csd.auth.gr