17th International Conference on Machine Vision (ICMV 2024)

X-ray Anomaly Detection in Industrial Pipelines

Diamantis Rafail Papadam, Christos Papaioannidis, Alexandros Zamioudis, and Ioannis Pitas

Department of Informatics, Aristotle University of Thessaloniki, Greece

Funded by the European Union

Horizon Europe - SIMAR - 101070604

Introduction

- The SIMAR project aims at **automating** the **inspection** of **insulated pipes** in industrial facilities.
- Such automation allows for:
  - **Lowered risk** for human workers.
  - Inspection without the need of **insulation removal**.
- Pipes are inspected in two ways:
  - **Pulsed Eddy Current** (PEC) signals.
  - **X-ray** (Radiography).
- In our paper, we analyze **X-ray** images of **insulated pipes** to detect the presence of **corrosion**.

Funded by the European Union

Horizon Europe - SIMAR - 101070604

Dataset Description

- X-ray images are taken outside the insulation.
- The upper part (black), shows the **pipe** which is **not penetrated** by the X-ray.
- The lower part (grey), shows the **insulation** which is **penetrated** by the X-ray.

Methodology

- We tested several **state-of-the-art Anomaly Detection** algorithms to assess how well they can deal with our novel **X-ray task**.
- We simulated two types of noise that can occur in our setting:
  - **Poisson Noise**.
  - **Motion Blur Noise**. (horizontal)
- We evaluated a subset of the **Anomaly Detection** algorithms in terms of **robustness** to:
  - **3 Levels** of **Poisson Noise**.
  - **3 Levels** of **Motion Blur Noise**.
  - **1 Level** of **Combined Noise**.

Funded by the European Union

Horizon Europe - SIMAR - 101070604

Results

Algorithm	AUROC	F_1 Score	Accuracy	Precision	Recall
C-Flow	0.516	0.669	0.513	0.507	**0.988**
DFKDE	0.959	0.911	0.905	0.856	0.975
DFM	0.952	0.896	0.895	0.879	0.914
FastFlow	0.969	0.918	0.917	0.904	0.933
GANomaly	0.833	0.789	0.788	0.785	0.794
PaDiM	0.915	0.889	0.879	0.819	0.974
Patchcore	0.983	0.945	0.945	0.939	0.951
R-KDE	0.843	0.826	0.805	0.744	0.930
STFPM	0.962	0.909	0.905	0.875	0.945
U-Flow	**0.991**	**0.948**	**0.948**	**0.949**	0.947

Table 1: Algorithm Performance without Noise

Funded by the European Union

Horizon Europe - SIMAR - 101070604

Results

Algorithm	AUROC	F_1 Score	Accuracy
DFKDE	(0.957/0.869/0.818)	(0.916/0.813/0.765)	(0.911/0.786/0.734)
DFM	(0.949/0.798/0.795)	(0.879/0.752/0.731)	(0.881/0.709/0.698)
FastFlow	(0.848/0.622/0.695)	(0.791/0.712/0.718)	(0.749/0.623/0.636)
PaDiM	(0.911/0.825/0.768)	(0.883/0.808/0.749)	(0.877/0.784/0.724)
Patchcore	(**0.982**/**0.945**/**0.928**)	(**0.944**/**0.877**/**0.845**)	(**0.943**/**0.869**/**0.833**)
STFPM	(0.960/0.873/0.885)	(0.901/0.838/0.811)	(0.898/0.814/0.779)
U-Flow	(0.780/0.776/0.782)	(0.742/0.743/0.763)	(0.694/0.690/0.721)

Table 2: Algorithm Performance with Poisson Noise (low/medium/high)

Algorithm	AUROC	F_1 Score	Accuracy
DFKDE	(99.8%/90.6%/85.3%)	(**100.5**%/89.2%/84%)	(**100.7**%/86.9%/81.1%)
DFM	(99.7%/83.8%/83.5%)	(98.1%/83.9%/81.6%)	(98.4%/79.2%/78%)
FastFlow	(87.5%/64.2%/71.7%)	(86.2%/77.6%/78.2%)	(81.7%/67.9%/69.4%)
PaDiM	(99.6%/90.2%/83.9%)	(99.3%/90.9%/84.3%)	(99.8%/89.2%/82.4%)
Patchcore	(**99.9**%/**96.1**%/**94.4**%)	(99.9%/**92.8**%/**89.4**%)	(99.8%/**92**%/**88.1**%)
STFPM	(99.8%/90.7%/92%)	(99.1%/92.2%/89.2%)	(99.2%/89.9%/86.1%)
U-Flow	(78.7%/78.3%/78.9%)	(78.3%/78.4%/80.5%)	(73.2%/72.8%/76.1%)

Table 3: Algorithm Robustness to Poisson Noise (low/medium/high)

Funded by the European Union

Horizon Europe - SIMAR - 101070604

Results

Algorithm	AUROC	F_1 Score	Accuracy
DFKDE	(0.901/0.789/0.697)	(0.828/0.730/0.687)	(0.814/0.703/0.653)
DFM	(0.650/0.497/0.468)	(0.712/0.694/0.690)	(0.601/0.566/0.559)
FastFlow	(0.494/0.422/0.372)	(0.702/0.689/0.690)	(0.585/0.558/0.556)
PaDiM	(0.908/0.857/0.825)	(0.872/0.807/0.775)	(0.868/0.793/0.761)
Patchcore	(**0.980**/**0.952**/**0.903**)	(**0.942**/**0.908**/**0.835**)	(**0.942**/**0.909**/**0.837**)
STFPM	(0.943/0.916/0.890)	(0.887/0.847/0.832)	(0.882/0.849/0.827)
U-Flow	(0.842/0.764/0.657)	(0.803/0.713/0.694)	(0.815/0.708/0.563)

Table 4: Algorithm Performance with Motion Blur Noise (low/medium/high)

Algorithm	AUROC	F_1 Score	Accuracy
DFKDE	(94%/82.3%/72.7%)	(90.9%/80.1%/75.4%)	(89.9%/77.7%/72.2%)
DFM	(68.3%/52.2%/49.2%)	(79.5%/77.5%/77%)	(67.2%/63.2%/62.5%)
FastFlow	(51%/43.6%/38.4%)	(76.5%/75.1%/75.2%)	(63.8%/60.9%/60.6%)
PaDiM	(99.2%/93.7%/90.2%)	(98.1%/90.8%/87.2%)	(98.7%/90.2%/86.6%)
Patchcore	(**99.7%**/**96.8%**/91.9%)	(**99.7%**/**96.1%**/88.4%)	(**99.7%**/**96.2%**/88.6%)
STFPM	(98%/95.2%/**92.5%**)	(97.6%/93.2%/**91.5%**)	(97.5%/93.8%/**91.4%**)
U-Flow	(85%/77.1%/66.3%)	(84.7%/75.2%/73.2%)	(86%/74.7%/59.4%)

Table 5: Algorithm Robustness to Motion Blur Noise (low/medium/high)

Funded by the European Union

Horizon Europe - SIMAR - 101070604

Results

Algorithm	AUROC	F_1 Score	Accuracy	Precision	Recall
DFKDE	0.804	0.756	0.719	0.668	0.873
DFM	0.542	0.689	0.549	0.526	0.999
FastFlow	0.428	0.682	0.543	0.523	0.981
PaDiM	0.795	0.795	0.771	0.720	0.888
Patchcore	**0.900**	**0.847**	**0.843**	**0.823**	0.874
STFPM	0.745	0.751	0.691	0.628	0.933
U-Flow	0.695	0.686	0.546	0.524	0.992

Table 6: Algorithm Performance with medium-level Combined Noise

Algorithm	AUROC	F_1 Score	Accuracy
DFKDE	83.8%	83%	79.4%
DFM	56.9%	76.9%	61.3%
FastFlow	44.2%	74.3%	59.2%
PaDiM	86.9%	89.4%	87.7%
Patchcore	**91.6%**	**89.6%**	**89.2%**
STFPM	77.4%	82.6%	76.4%
U-Flow	70.1%	72.4%	57.6%

Table 7: Algorithm Robustness to medium-level Combined Noise

Funded by the European Union

ARISTOTLE UNIVERSITY OF THESSALONIKI

Horizon Europe - SIMAR - 101070604

Results

- Most **robust** algorithms to **Poisson noise**:
  - Patchcore (memory bank)
  - STFPM (teacher-student)
  - DFKDE (memory bank)
- Most **robust** algorithms to **motion blur noise**:
  - Patchcore (memory bank)
  - STFPM (teacher-student)
  - PaDiM (memory bank)
- Most **robust** algorithms to **combined noise**:
  - Patchcore (memory bank)
  - PaDiM (memory bank)
  - DFKDE (memory bank)

Conclusions

- Current state-of-the-art **Anomaly Detection** algorithms are capable of **effectively** dealing with our **novel X-ray task**.
- The most **robust-to-noise** algorithms are based on:
  - **Memory Banks**.
  - **Teacher-Student** architectures.

Funded by the European Union

Horizon Europe - SIMAR - 101070604

Q & A

Thank you very much for your attention!

Diamantis Rafail Papadam, Christos Papaioannidis, Alexandros Zamioudis, and Ioannis Pitas

Department of Informatics, Aristotle University of Thessaloniki, Greece

Contact: *pitas@csd.auth.gr*

Funded by the European Union

Horizon Europe - SIMAR - 101070604