FREDNET: A Frequency and Decomposed-Spatial Network for Industrial Defect Signal Detection

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TAKEAWAYS

78.3% NEU-DET mAP@0.5 +4.8 over RT-DETR-R18

69.5% GC-10 mAP@0.5 +3.5 over RT-DETR-R18

18.99M Parameters lightweight DETR detector

60.3G FLOPS efficient defect recognition

FreDNet combines frequency-domain dynamic convolution with decomposed spatial interaction to accurately and efficiently detect small, diverse, and noisy industrial defects in real time.

MOTIVATION

- Industrial defect signals are small, diverse, noisy, and difficult to distinguish from complex backgrounds.
- CNN detectors are efficient but limited in global structural modeling.
- Transformer detectors improve global reasoning but still suffer from information loss and multi-scale semantic gaps.

KEY CHALLENGES

- Diverse Spectral Defect Patterns
- Information Loss in Spatial Feature Interactions
- Semantic Gaps in Multi-scale Feature Fusion

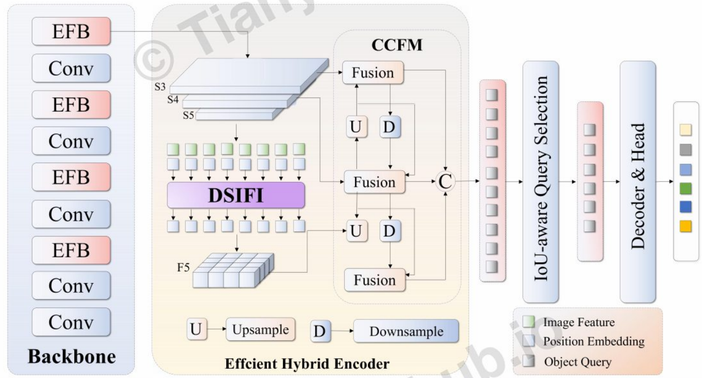
CONTRIBUTIONS

- **FreDNet:** a signal-processing-oriented detection transformer for industrial defect signal detection.
- Efficient Frequency Block (**EFB**): frequency-domain dynamic convolution for adaptive spectral defect modeling.
- Decomposed Spatial Intra-scale Feature Interaction **(DSIFI)**: preserving feature relationships and enhancing spatial continuity.

ABLATION STUDY

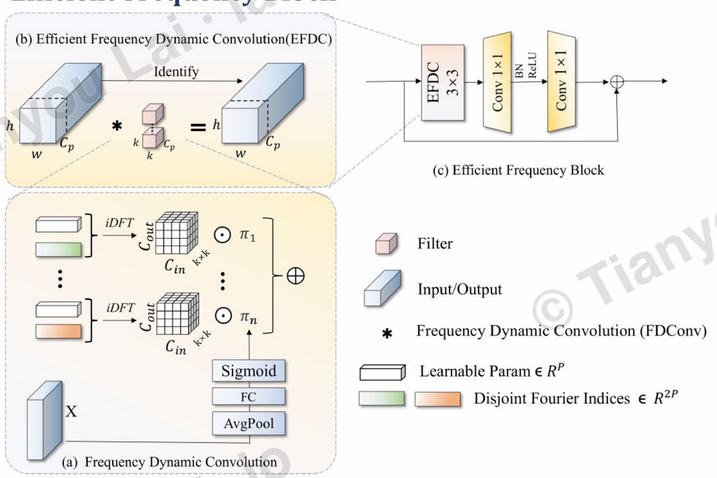
Model	NEU-DET			GC-10		
	P	R	mAP@0.5	P	R	mAP@0.5
FreDNet	**79.8**	**69.9**	**78.3**	**72.2**	**65.8**	**69.5**
w/o EFB	76.9	69.5	77.1	70.5	66.9	68.6
w/o DSIFI	74.2	68.7	75.4	69.3	65.1	67.5
w/o EFB & DSIFI	71.8	67.0	73.5	68.4	64.8	66.0

METHOD OVERVIEW



◆FreDNet integrates EFB and DSIFI into an RT-DETR-based end-to-end detection framework.

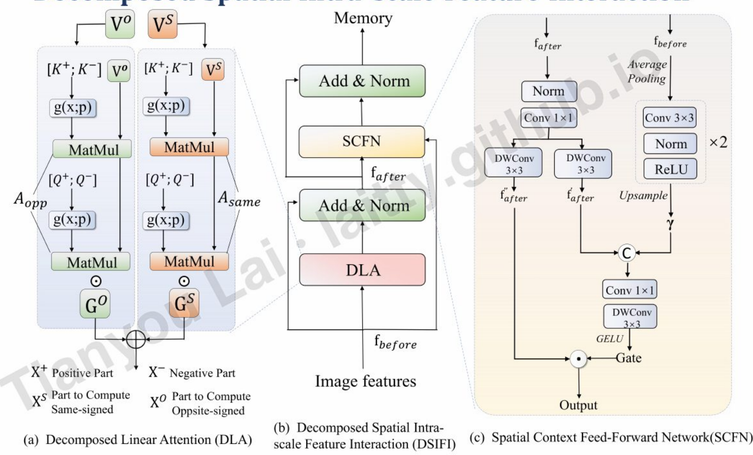
Efficient Frequency Block



$$Y_{EFDC} = \mathrm{Concat}\left[\sum_{i=1}^{n} \pi_i \cdot \left(W^i * X_{1:C_p}\right), X_{C_p+1:C_{in}}\right]$$

- W^i : frequency-generated dynamic kernels.
- π_i : content-adaptive spectral weighting.
- $X_{1:c_p}$: high-importance channels processed by FDConv.
- $X_{c_p+1:c_{in}}$: remaining channels preserved by identity mapping.

Decomposed Spatial Intra-scale Feature Interaction



(a) Decomposed Linear Attention (DLA) (b) Decomposed Spatial Intra-scale Feature Interaction (DSIFI) (c) Spatial Context Feed-Forward Network(SCFN)

Decomposed Linear Attention

$$\langle Q, K\rangle = \langle Q^+, K^+\rangle + \langle Q^-, K^-\rangle - \langle Q^+, K^-\rangle - \langle Q^-, K^+\rangle$$

- Same-signed terms capture positive-positive and negative-negative feature correlations.
- Opposite-signed terms recover cross-sign information lost in conventional linear attention.

MAIN RESULTS

Dataset	Model	P	R	mAP@0.5	mAP@0.5:0.95
NEU-DET	RT-DETR-R18	0.718	0.670	0.735	0.429
	YOLOv8m	0.775	0.708	0.763	0.425
	FreDNet	**0.798**	0.699	**0.783**	**0.451**
Dataset	**Model**	**P**	**R**	**mAP@0.5**	**mAP@0.5:0.95**
GC-10	RT-DETR-R18	0.684	0.648	0.660	0.328
	YOLOv8m	0.718	0.634	0.675	0.344
	FreDNet	**0.722**	**0.658**	**0.695**	**0.354**

CONCLUSION

- FreDNet combines frequency-domain dynamic convolution and decomposed spatial interaction for industrial defect signal detection.
- EFB enhances frequency-aware defect representation, while DSIFI preserves richer spatial feature relationships.
- Experiments on NEU-DET and GC-10 demonstrate improved accuracy, efficiency, and generalization.

* Further improvements have been achieved, with an extended journal version under preparation.

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