Exploring Resolution and Degradation Clues as Self-supervised Signal for Low Quality Object Detection

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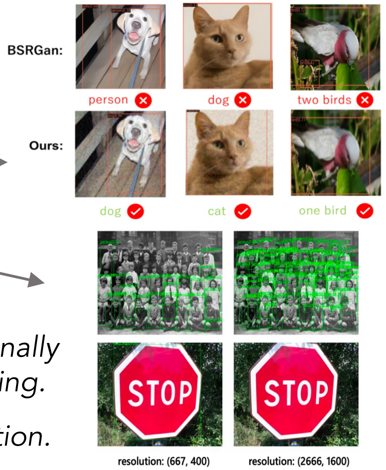
Motivation & Contribution:

Degradation Conditions:

1. *Noise, Blur, Low-Resolution Always Affect Vision Tasks.*
2. *Restoration methods may not such effectiveness.*
3. *Scale GAP in Object Detection Task.*

Our Contributions:

1. *Take the degradation types as self-supervised signals.*
2. *Combine super-resolution and object detection, we additionally design a ARRD decoder on detectors for self-supervised learning.*
3. *AERIS get SOTA performance, even with lower input resolution.*



Experiment Results (Best Results on both single and multi degradation):

Test Set	Pre-process	Training Strategy	CenterNet (ResNet-18) AP	AP_s	AP_m	AP_l	CenterNet (Swin-T) AP	AP_s	AP_m	AP_l
COCO	-	Detection	30.1	10.6	33.2	47.2	36.9	17.9	41.8	52.9
COCO-d	-	Detection	14.5	1.2	10.4	38.6	19.9	2.7	16.9	46.2
	bicubic (×2)		16.2	4.1	15.3	31.1	18.6	4.0	17.8	39.7
	bicubic (×4)		8.0	4.6	10.5	10.1	10.6	**5.7**	12.8	16.7
	SRGAN [31] (×2)		14.8	2.6	14.3	27.9	16.6	3.0	16.5	33.4
	DBPN [20] (×2)		15.0	3.5	14.3	27.4	16.7	3.4	16.1	32.0
	Real-SR [4] (×2)		14.2	2.6	12.4	29.5	17.3	3.6	17.0	34.1
	BSRGAN [60] (×2)		16.8	4.2	15.8	36.9	20.2	4.8	18.1	40.5
	BM3D		10.4	0.8	6.8	27.9	10.9	0.7	8.8	35.1
	Restormer [59]		11.4	1.2	7.2	34.8	11.9	1.4	8.9	33.4
	-	Deg t	17.6	2.3	15.4	41.9	20.9	3.1	20.3	47.6
		Deg t + N	17.9	2.5	15.9	42.5	21.0	3.0	20.4	48.2
		D_r + Detection	17.7	**4.8**	15.8	41.0	21.4	5.6	19.6	46.3
		AERIS	**18.4**	2.7	**16.4**	**42.5**	**21.6**	3.2	**20.4**	**49.0**

Multi-degradation condition, blue background means higher resolution.

(a) Noise.

Method \ σ	(5, 50)	15	25	50
-	22.8	26.8	23.8	15.4
IRCNN [62]	22.6	26.8	24.2	16.8
Swin-IR [33]	24.2	28.0	25.6	19.3
Restormer [59]	23.8	27.6	25.1	18.9
Deg t + N	24.3	27.6	25.0	18.3
D_r + Detection	24.8	28.5	25.5	19.4
AERIS	**25.1**	**28.7**	**26.5**	**20.2**

(b) Blur.

Method \ k	Mix			
-	26.7	25.8	23.9	23.1
EPLL [66]	27.8	26.8	25.4	25.2
IRCNN [62]	26.7	26.9	24.1	22.8
Deg t + N	28.8	27.5	27.6	27.8
D_r + Detection	28.5	27.7	27.5	27.3
AERIS	**29.3**	**28.6**	**28.0**	**28.2**

(c) Down-sampling (Ratio: **2**).

Method \ metric	AP	AP_s	AP_m	AP_l
-	20.2	1.5	16.1	49.8
SRGAN [31] (×2)	24.0	6.2	25.4	39.8
DBPN [20] (×2)	25.1	7.3	27.1	41.9
Swin-IR [33] (×2)	25.4	7.6	27.0	42.4
D_r + Detection	26.0	8.4	26.2	46.5
AERIS	25.4	4.6	25.8	**49.6**
AERIS (×2)	**26.8**	**8.6**	**28.8**	45.2

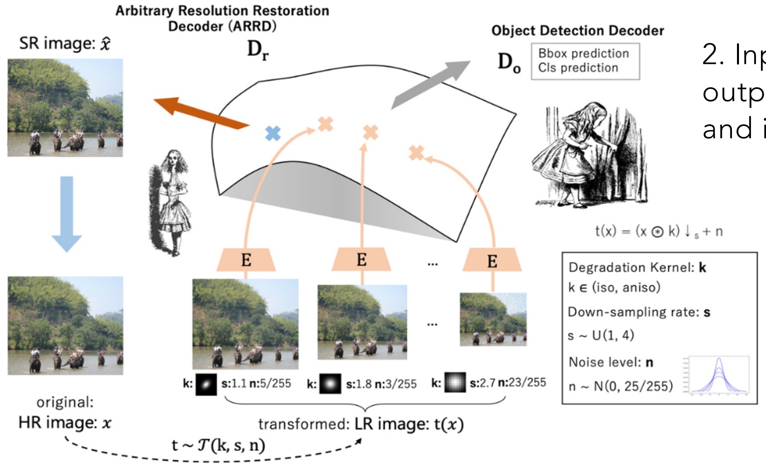
(d) Down-sampling (Ratio: **4**).

Method \ metric	AP	AP_s	AP_m	AP_l
-	8.2	0.0	3.2	33.1
DBPN [20] (×2)	14.8	1.0	9.9	39.7
DBPN [20] (×4)	12.2	1.7	11.7	23.4
Swin-IR [33] (×2)	15.2	1.1	10.1	39.9
Swin-IR [33] (×4)	12.8	1.8	12.2	23.4
D_r + Detection	15.1	1.8	12.7	40.1
AERIS	13.0	0.8	10.2	**42.6**
AERIS (×2)	**15.8**	**2.0**	**13.2**	40.9

Single-degradation condition, noise/ blur/ low-resolution.

Demo Show:
(a). Original Image
(b) Low-Resolution Degraded Image
(c)/(d)/(e): Restoration Methods
(f) Our AERIS
[background is outputs of ARRD]

Proposed Method (AERIS, Auto-Encoding Resolution In Self-supervision):



2. Input the t(x) to encoder E, and output both for $\boxed{\text{object detection}}$ and image restoration:

self-supervised learning	supervised learning
decoder: Dd	decoder: Do

Arbitrary Resolution Restoration Decoder (ARRD)

1. x ----> t(x): Base on the image degradation function $t(x) = (x \circledast k) \downarrow_s + n$,

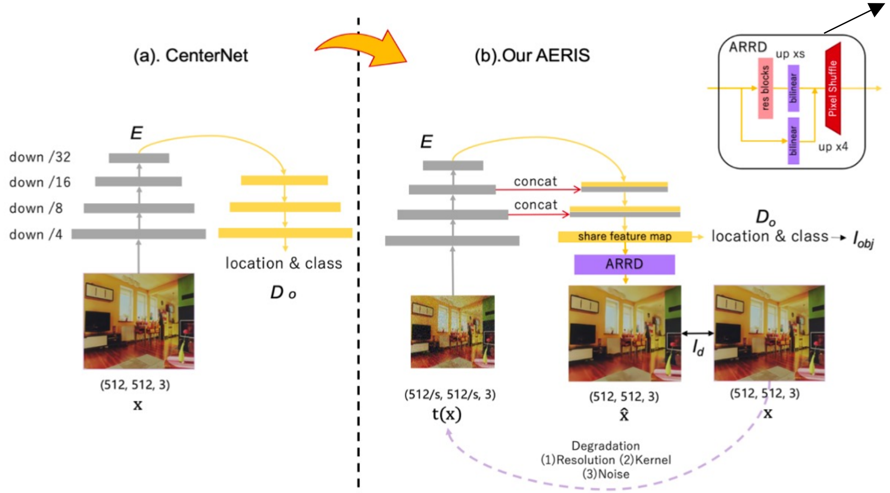
Blur Kernel k :
isotropic Gaussian kernels k_{iso}
anisotropic Gaussian kernels k_{aniso}

Noise n :
Zero-mean additive white Gaussian noise
$n \sim N(0, \sigma)$ $\sigma \sim U(0, 25/255)$ (*e.g.* 13.2/255).

Resolution s :
Random from 1~4
Type: Bicubic/ Bilinear/ Nearest

Implement on the detector (CenterNet for example):

ARRD: residual bilinear with pixel-shuffle



Restoration loss:

$$l_d = |\hat{x} - x|_1 = |D_r(E(t(x))) - x|_1.$$

Total loss: object detection loss

$$l_{total} = l_{obj} + \lambda \cdot l_d,$$