DOA-GAN: Dual-Order Attentive GAN for Image Copy-move Forgery Detection and Localization

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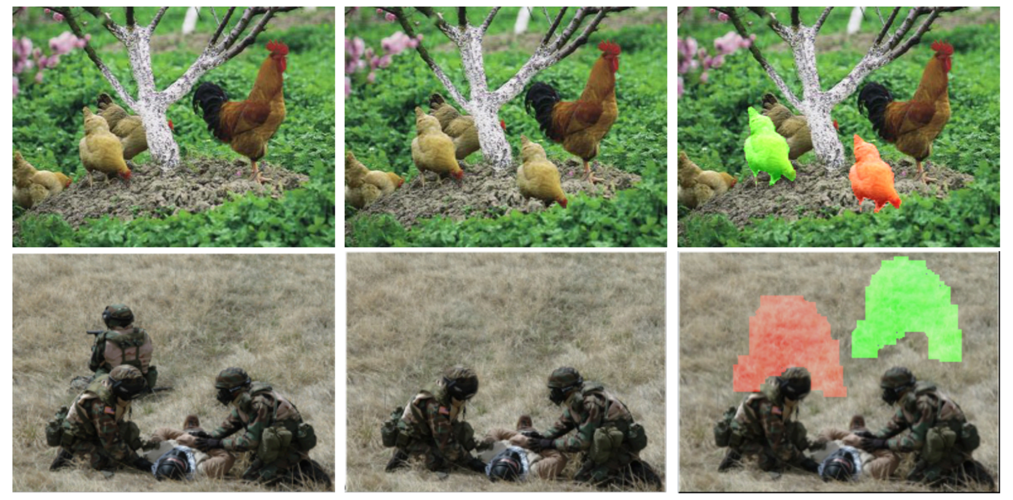
Problem & Background

- Copy-move image forgery could be used to add or hide some objects appearing a digital image, leading to a different interpretation.
- It could be misled if such a manipulated image was part of a criminal investigation → It is crucial to develop a robust image forensic tool for copy-move detection and localization.
- The results of existing approaches are still far from perfect. It is very challenging to distinguish copy-moves from incidental similarities, which occur frequently.



From left to right are original, forged, and GT images. Our goal is to automatically detect and localize the source (green) and the target (red) regions in forged images.

Contributions

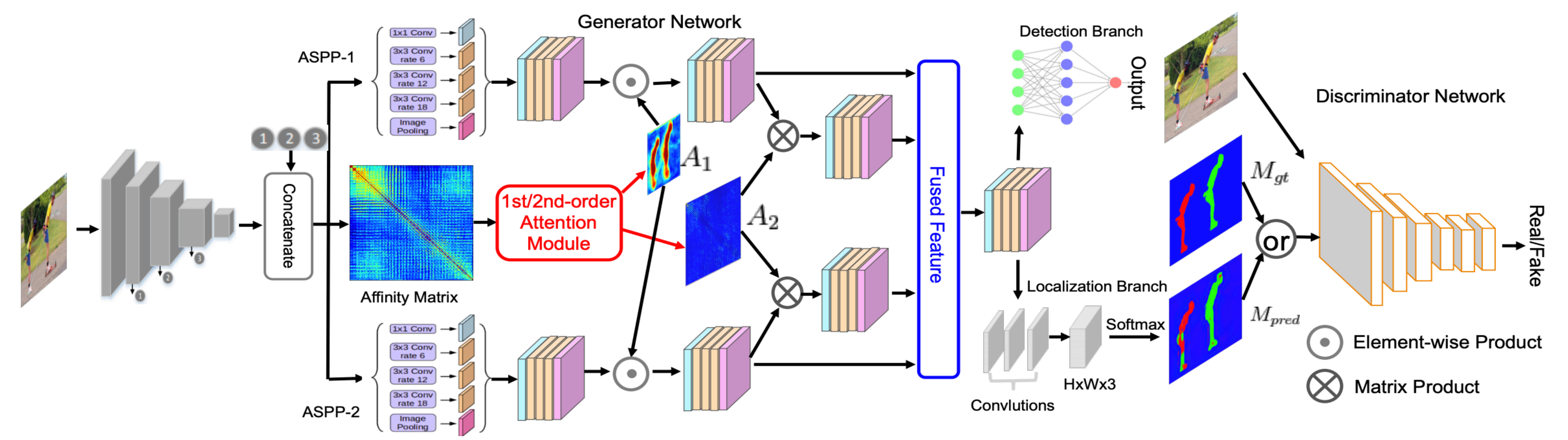
- We propose a dual-order attentive Generative Adversarial Network for image copy-move forgery detection and localization.
- Our 1st-order attention module is able to extract the copy-move location aware attention map and the 2nd-order attention module explores pixel-to-pixel inter-dependence.
- Extensive experiments strongly demonstrate that the proposed DOA-GAN clearly outperforms state-of-the-art.

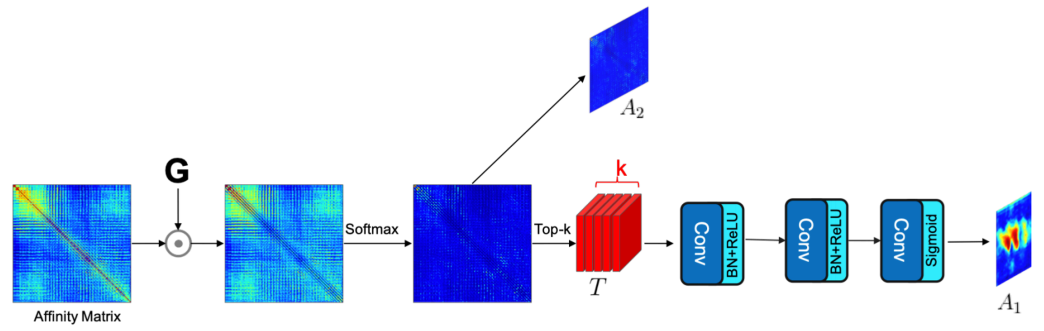
Datasets and Metrics

Datasets: USC-ISI, CASIA, and CoMoFD; Metrics: recall, precision, F1 for both pixel-wise localization and image-level detection.

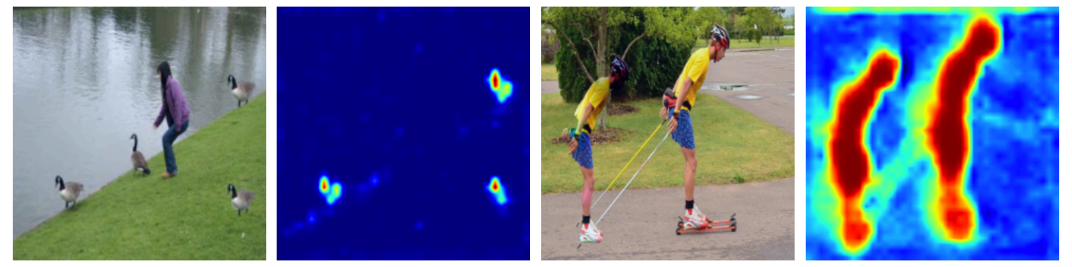
This work was closely supervised by Chengjiang Long when Ashraful Islam was a summer intern at Kitware, Inc.

Proposed Approach





1st/2nd-order Attention Module



$$\mathcal{L} = \mathcal{L}_{\mathrm{adv}} + \alpha\mathcal{L}_{\mathrm{ce}} + \beta\mathcal{L}_{\mathrm{det}}.$$

$$\mathcal{L}_{\mathrm{adv}}(G,D) = E_{(I,M)}[\log(D(I,M)) + \log(1 - D(I,G(I)))]$$

$$\mathcal{L}_{\mathrm{ce}} = \frac{1}{H \times W \times 3} \sum_{k=1}^{3}\sum_{i=1}^{H}\sum_{j=1}^{W} M(i,j,k)\log\widehat{M}(i,j,k)$$

$$\mathcal{L}_{\mathrm{det}} = y_{\mathrm{im}}\log(\hat{y}_{\mathrm{im}}) + (1-y_{\mathrm{im}})\log(1-\hat{y}_{\mathrm{im}})$$

USC-ISI

Methods	Precision (Localization)			Recall (Localization)			F1 (Localization)			Detection		
	P	S	T	P	S	T	P	S	T	Precision	Recall	F1
BusterNet [46]	93.71	55.85	53.84	99.01	38.26	48.73	96.15	40.84	48.33	89.26	80.14	84.45
ManTra-Net [47]	93.50	8.66	48.53	**99.22**	2.28	28.43	96.08	2.97	30.58	68.72	85.82	76.32
U-Net [38]	91.66	32.67	47.16	97.16	19.06	40.90	94.88	23.09	44.15	82.61	66.13	73.46
NA-GAN	95.87	35.30	59.32	96.91	41.64	52.32	95.40	33.25	55.94	80.19	85.64	82.82
FOA-GAN	95.06	52.82	71.17	97.24	43.32	62.06	96.04	43.43	65.90	94.13	94.54	94.33
SOA-GAN	95.53	50.94	70.20	98.17	40.86	66.58	**97.80**	42.50	67.19	95.50	92.30	93.87
DOA-GAN w/o ASPP-1	96.71	61.04	70.94	98.84	43.13	66.69	97.67	45.04	67.23	95.11	93.13	94.10
DOA-GAN w/o ASPP-2	96.08	60.70	65.20	99.43	39.18	68.76	97.62	44.13	65.41	92.97	91.75	92.35
DOA-GAN w/o $\mathcal{L}_{\mathrm{adv}}$	95.80	72.30	83.60	96.27	60.32	79.10	96.01	63.25	80.45	95.45	93.09	94.25
DOA-GAN w/o $\mathcal{L}_{\mathrm{det}}$	**97.35**	75.58	83.96	97.98	**64.19**	80.31	97.51	65.21	81.08	90.31	94.78	92.49
DOA-GAN	96.99	**76.30**	**85.60**	98.87	63.57	**80.45**	97.69	**66.58**	**81.72**	**96.83**	**96.14**	**96.48**

Quantitative Results

	Methods	Year	Precision	Recall	F1
Det	Block-ZM	2010	68.97	53.69	60.38
	DCT-Match	2012	63.74	46.31	53.46
	Adaptive-Seg	2015	93.07	25.59	40.14
	DenseFiled	2015	**99.51**	30.61	46.82
	BusterNet	2018	48.34	75.12	58.82
	DOA-GAN	2019	63.39	**77.00**	**69.53**
Loc	Block-ZM	2010	10.09	3.01	3.30
	DCT-Match	2012	8.80	1.90	2.40
	Adaptive-Seg	2015	23.17	5.14	7.42
	DenseField	2015	20.55	20.91	20.36
	BusterNet	2018	42.15	30.54	33.72
	DOA-GAN	2019	**54.70**	**39.67**	**41.44**

CASIA

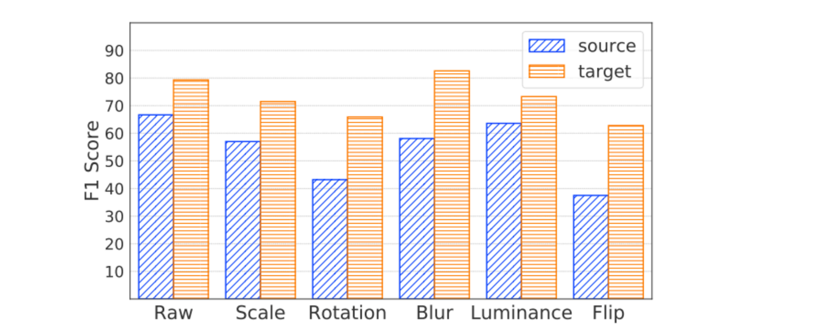
	Methods	Year	Precision	Recall	F1
Det	Block-ZM	2010	51.72	20.87	29.74
	DCT-Match	2012	50.48	29.77	37.46
	Adaptive-Seg	2015	65.66	43.37	52.24
	DenseField	2015	**80.34**	20.10	32.15
	BusterNet	2018	53.20	57.41	55.22
	DOA-GAN	2019	60.38	**65.98**	**63.05**
Loc	Block-ZM	2010	2.90	2.50	1.73
	DCT-Match	2012	3.53	3.41	2.03
	Adaptive-Seg	2015	23.02	13.27	13.46
	DenseField	2015	22.23	23.63	22.60
	BusterNet	2018	**51.25**	28.20	35.34
	DOA-GAN	2019	48.42	**37.84**	**36.92**

CoMoFoD

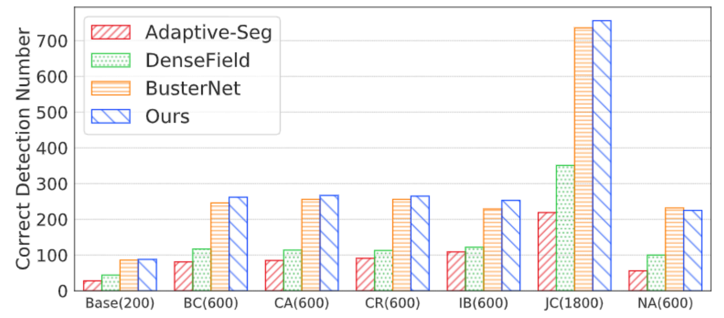
Qualitative Results

From left to right are the input image; results of Adaptive-Seg DenseField, BusterNet , and our DOA-GAN; and the GT mask. (top: CASIA; bottom: CoMoFoD)

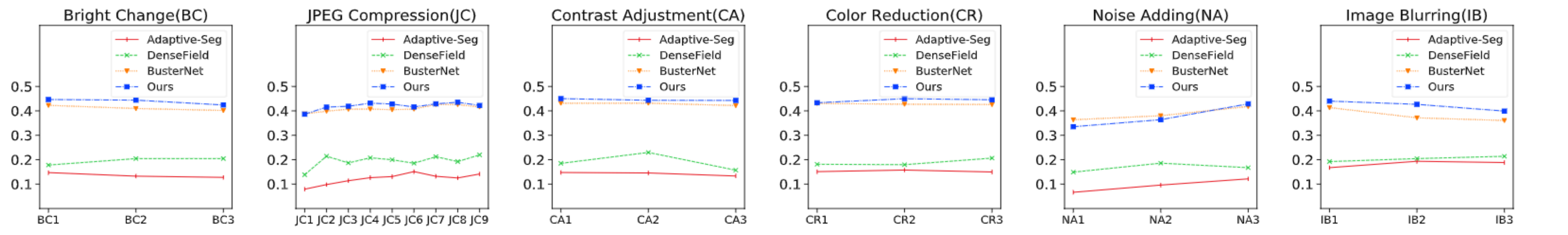
Robustness Analysis



Invariance Analysis on our self-collected dataset generated from MS-COCO.



Number of correctly detected images on CoMoFoD under attacks.



F1 scores on CoMoFoD under attacks.

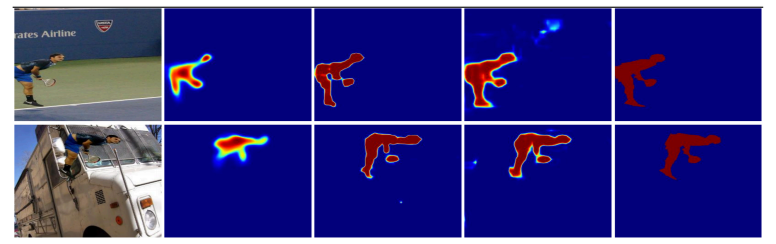
Failure Cases

Failure cases: (1) when the copy region is just extracted from the uniform background and pasted on the same background, (2) when the scale has been changed significantly.

Extension to Other Manipulation Types

Method	Source			Target		
	IoU	F1	MCC	IoU	F1	MCC
DMVN [45]	37.2	48.4	32.3	42.0	53.5	36.7
DMAC [23]	76.5	81.2	76.7	85.6	90.0	85.2
DOA-GAN	**86.4**	**91.0**	**86.2**	**92.4**	**95.4**	**91.8**

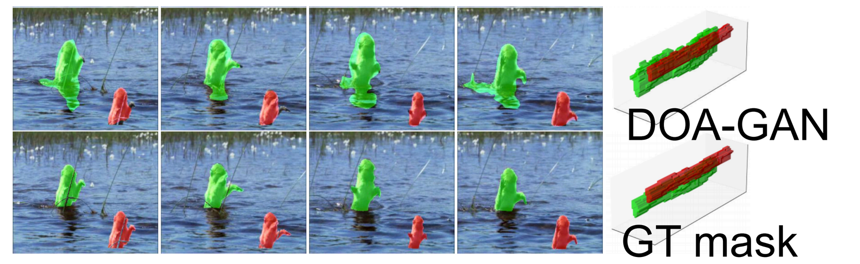
Image splicing on MS-COCO



Input images, results of DMVN, DMAC, DOA-GAN, and GT mask.

Method	F1 Score			IoU		
	S	T	A	S	T	A
PatchMatch [11]	-	-	11.7	-	-	9.8
DMVN [45]	27.2	33.8	37.2	20.5	25.76	27.3
DMAC [23]	39.5	39.0	45.2	31.1	30.5	35.3
DOA-GAN	**62.9**	**62.3**	**65.0**	**50.7**	**49.6**	**53.3**

Video copy-move on self-collected dataset.



Acknowledgement

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