#1684

MULTI-DOMAIN UNPAIRED ULTRASOUND IMAGE ARTIFACT REMOVAL USING A SINGLE CONVOLUTIONAL NEURAL NETWORK

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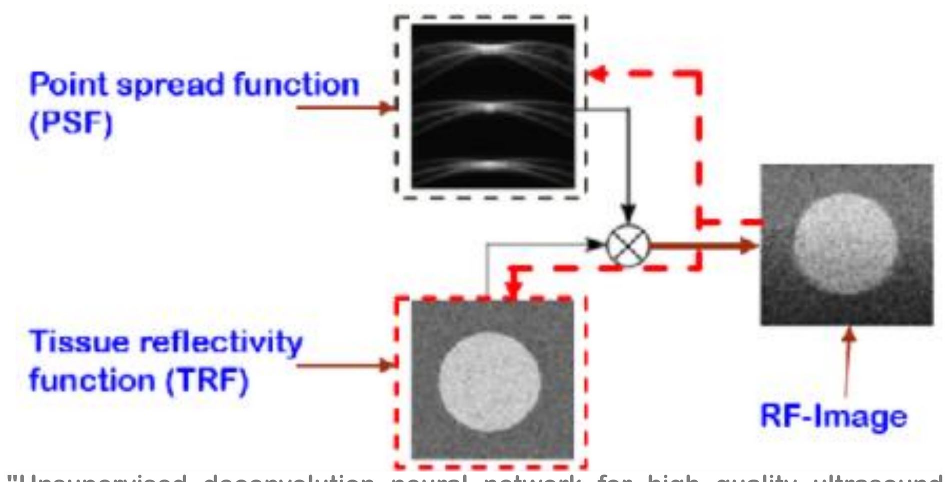
INTRODUCTION

Ultrasound image artifact

- Ultrasound imaging (US) suffers from distinct image artifacts from various sources.
- Many researchers have proposed various model-based iterative algorithms.
  → computationally expensive

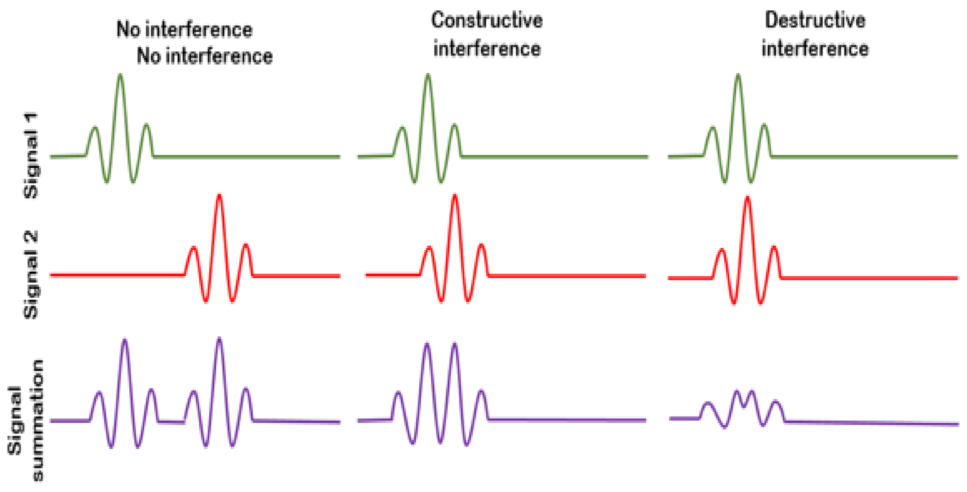
Various sources

- Blurring artifact
  → Limited by the bandwidth of the transducer



"Unsupervised deconvolution neural network for high quality ultrasound imaging." *International Ultrasonics Symposium (IUS)*. IEEE, 2020.

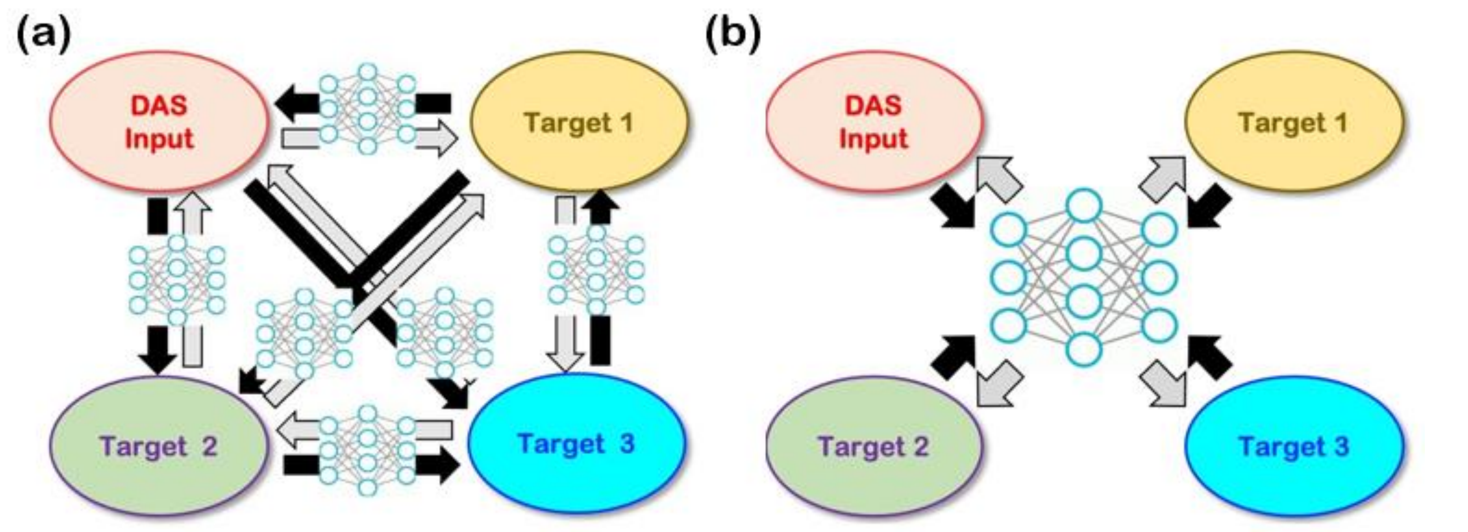
- Speckle pattern
  → Instructive & destructive signal interference



MOTIVATION

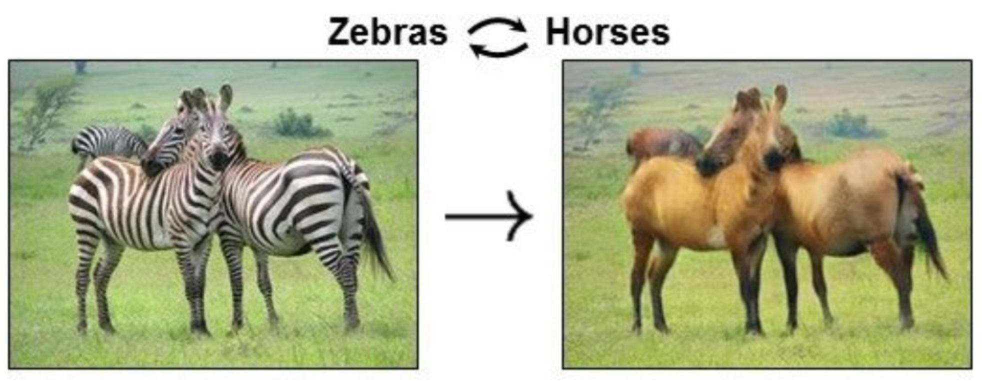
Deep learning model

- Various deep learning approaches have been proposed recently.
- Still have some technical hurdles for wide acceptance.
  → different types of artifacts which user prefers distinct choice of artifact suppression algorithms. (a)
- Recently, StarGAN proposed multi-domain image transfer models using a single generator. (b)



BACKGROUND

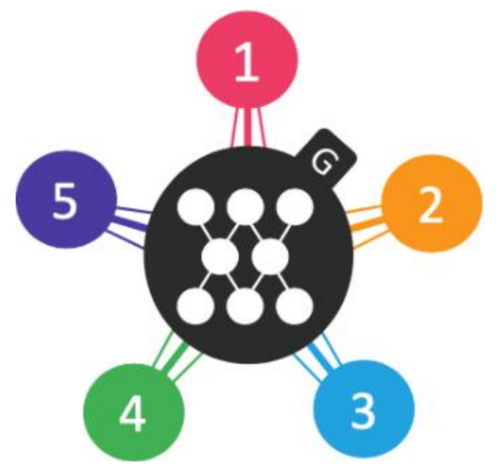
Single-domain image-to-image translation (CycleGAN)



"Unpaired image-to-image translation using cycle-consistent adversarial networks." CVPR, 2017.

- Representative unpaired image-to-image translation method using cycle-consistency loss.

Multi-domain image-to-image translation (StarGAN)

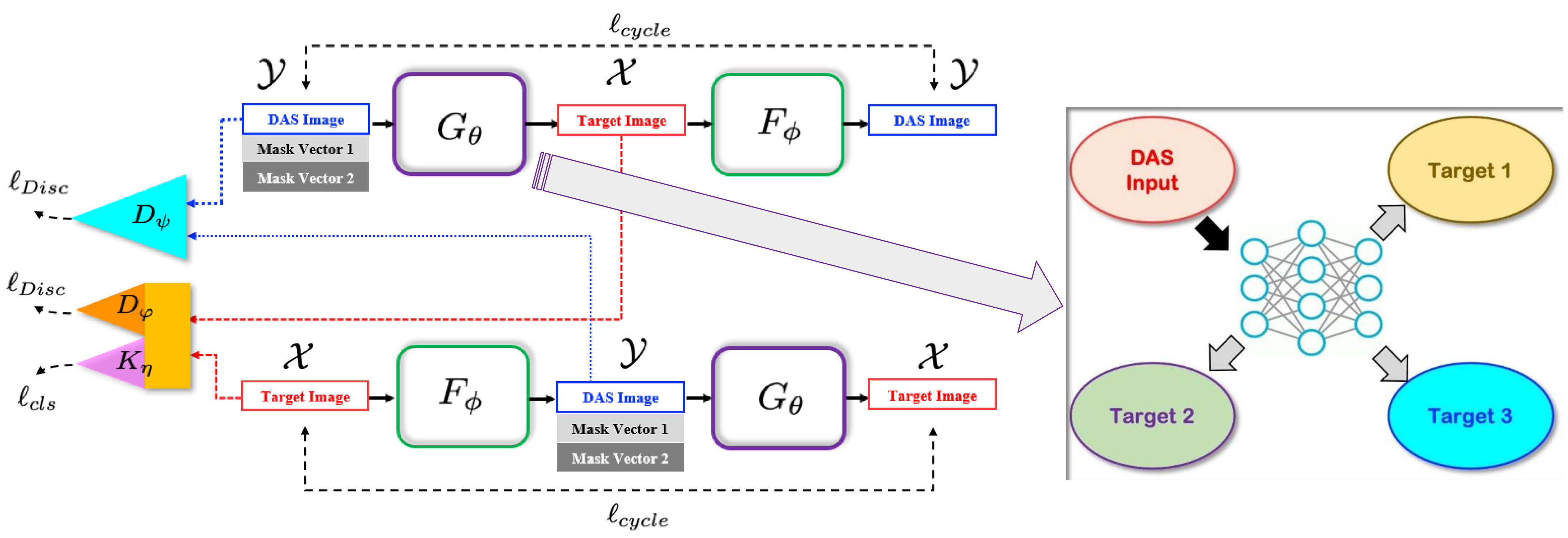


"Stargan: Unified generative adversarial networks for multi-domain image-to-image translation." CVPR, 2018.

- Representative multi-domain image-to-image translation method using single generator.

→ DAS images are obtained from the scanner, it is not necessary to re-generate from other domain image.

MULTI-DOMAIN US IMAGE ARTIFACT REMOVAL USING SINGLE CNN



Loss function

$$\min_{\theta,\phi,\eta}\max_{\varphi,\psi} L_{mlt} = \lambda_{cyc}L_{cyc}(\theta,\phi) + L_{disc}(\theta,\phi;\varphi,\psi) + \lambda_{GP}L_{GP}(\varphi,\psi) + \lambda_{cls}L_{cls}(\theta,\eta)$$

Cyclic loss

$$L_{cyc} = E_{x\sim P_x}[x - G_\theta(F_\phi(x))] + E_{y\sim P_y}[y - F_\phi(G_\theta(y))]$$

Discriminator loss

$$L_{disc} = E_{x\sim P_x}[D_\varphi(x)] - E_{y\sim P_y}[D_\varphi(G_\theta(y))] + E_{y\sim P_y}[D_\psi(y)] - E_{x\sim P_x}[D_\psi(F_\phi(x))]$$

Gradient-Penalty loss

$$L_{GP} = -E_{x\sim P_x}[(\|\nabla_{\tilde{x}}D_\varphi(\tilde{x})\|_2 - 1)^2] - E_{y\sim P_y}[(\|\nabla_{\tilde{y}}D_\psi(\tilde{y})\|_2 - 1)^2]$$

Classification loss

$$L_{cls} = -E_{x\sim P_x}[p(x)\log K_\eta(x)] - E_{y\sim P_y}[p(G_\theta(y))\log K_\eta(G_\theta(y))]$$

RESULTS

Multi-Domain US image artifact removal

Dataset

- *In vivo* and tissue mimicking phantoms.
- Four parts of the carotid and thyroid areas of 10 volunteers.
  (8 (train) + 2 (test))
- Unpaired training with target dataset generated from conventional iterative method.
- Datasets are focused B-mode using linear probe with operating frequency of 8.5 MHz

Target Generation

- Deconvolution

"Increasing axial resolution of ultrasonic imaging with a joint sparse representation model." TUFFC, 2016.

- Speckle removal

"A non-local low-rank framework for ultrasound speckle reduction." *CVPR*, 2017.

Deconvolution performance evaluation

	In vivo					Phantom				
	PSNR	SSIM	CNR	GCNR	CR	PSNR	SSIM	CNR	GCNR	CR
a	17.15	0.68	0.82	0.52	7.97	15.27	0.74	1.25	0.60	11.41
b	X	X	0.74	0.53	9.15	X	X	1.13	0.56	12.24
c	24.35	0.79	0.79	0.55	9.13	21.48	0.82	1.26	0.60	14.01
d	23.97	0.80	0.75	0.53	8.61	21.54	0.81	1.14	0.56	13.84
e	20.07	0.72	0.77	0.50	7.53	19.07	0.76	1.15	0.57	9.59
f	23.86	0.79	0.76	0.53	8.98	22.13	0.84	1.19	0.58	13.03

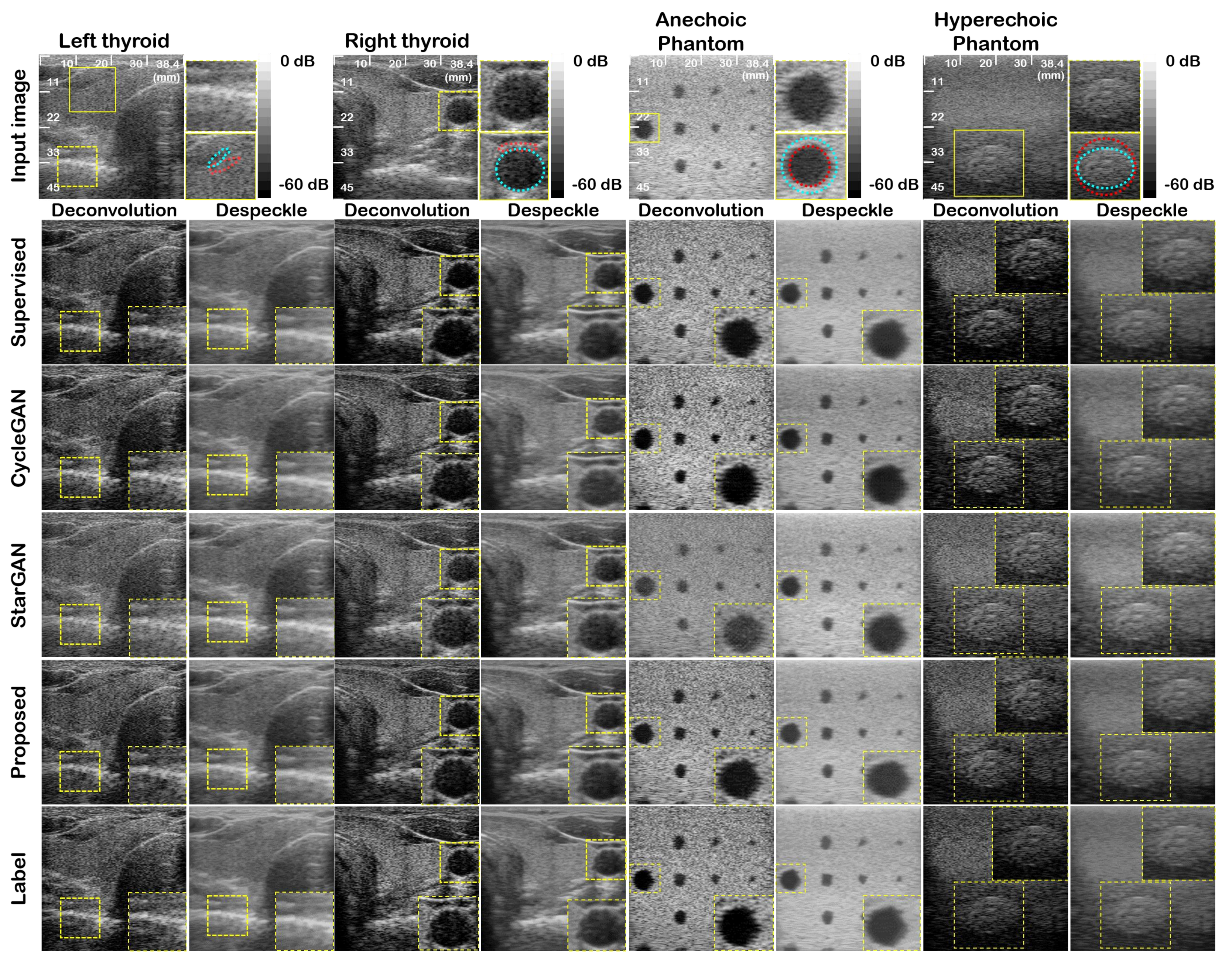
Despeckle performance evaluation

	In vivo					Phantom				
	PSNR	SSIM	CNR	GCNR	CR	PSNR	SSIM	CNR	GCNR	CR
a	26.99	0.65	0.82	0.52	7.97	26.68	0.66	1.25	0.60	11.41
b	X	X	1.02	0.62	7.52	X	X	1.46	0.65	10.79
c	35.58	0.93	1.04	0.62	7.29	29.68	0.90	1.49	0.67	11.98
d	29.62	0.89	1.05	0.61	7.38	19.96	0.84	1.39	0.64	11.97
e	31.73	0.89	0.99	0.59	7.57	28.74	0.87	1.38	0.65	11.34
f	31.78	0.91	1.02	0.61	7.86	30.02	0.89	1.49	0.67	12.52

(a : Input, b : Label, c : Supervised, d : CycleGAN, e : StarGAN, f : Proposed)

PSNR : Peak Signal to Noise Ratio / SSIM : Structural Similarity

CNR : Contrast Noise Ratio / GCNR : Generalized Contrast Noise Ratio / CR : Contrast Ratio



CONCLUSION

- We proposed multi-domain ultrasound (US) image artifact removal method using single convolutional neural network.
- A single network can provide blurring removed or speckle suppressed image.

ACKNOWLEDGEMENT

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