



Infrared Image Super-Resolution

via Heterogeneous Convolutional WGAN

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Self-Introduction



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University

**Guilin University of
Electronic Technology, China**

Research Topics

**Computer Vision
Image Processing
Generative Adversarial Networks**





1 Background

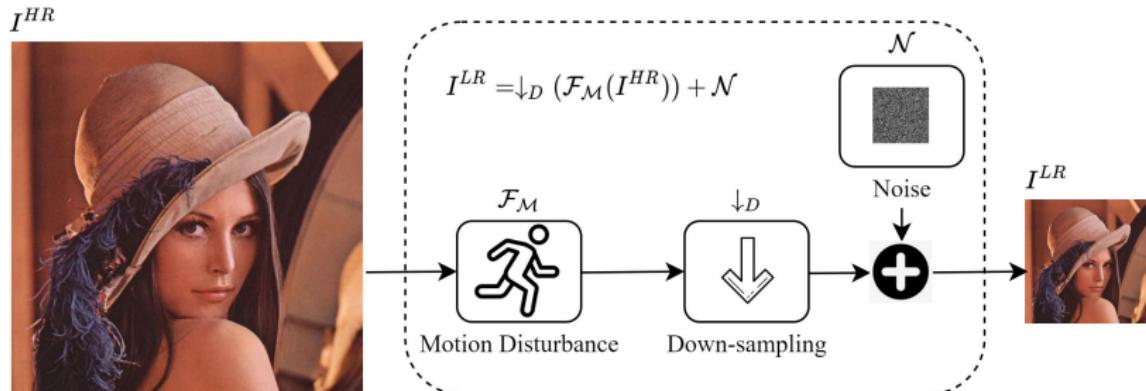
2 HetSRWGAN

3 Further Work

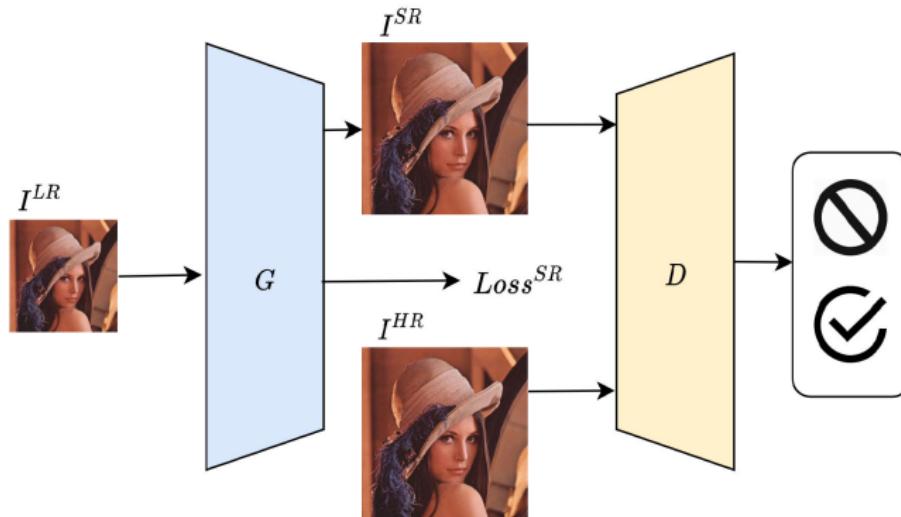
4 Reference



Single image super-resolution (SISR).



Generative adversarial networks(GANs)



$$\min_G \max_D V(D, G) = E_{x \sim p_{\text{data}}(x)} [\log D(x)] + E_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$



Generator Network

$G : P_G(x; \theta)$ Step.1 Sample $\{x^1, x^2, \dots, x^m\}$ from $P_{\text{data}}(x)$

Step.2

$$L = \prod_{i=1}^m P_G(x^i; \theta)$$

$$z_{\sim p_G} \in I^{SR}$$

Step.3

$$x_{\sim p_{\text{data}}} \in I^{LR}$$

$$\theta^* = \arg \max_{\theta} \prod_{i=1}^m P_G(x^i; \theta) = \arg \max_{\theta} \log \prod_{i=1}^m P_G(x^i; \theta)$$

$$= \arg \max_{\theta} \sum_{i=1}^m \log P_G(x^i; \theta)$$

$$\approx \arg \max_{\theta} E_{x \sim P_{\text{data}}} [\log P_G(x; \theta)]$$

$$= \arg \max_{\theta} \int_x P_{\text{data}}(x) \log P_G(x; \theta) dx - \int_x P_{\text{data}}(x) \log P_{\text{data}}(x) dx$$

$$= \arg \min_{\theta} KL(P_{\text{data}} \| P_G)$$



$$Loss^{SR}$$



Discriminator Network

$$V(G, D) = E_{x \sim P_{\text{data}}} [\log D(x)] + E_{x \sim P_G} [\log(1 - D(x))]$$

$$x_{\sim p_G} \in I^{SR}$$



$$V = E_{x \sim P_{\text{data}}} [\log D(x)] + E_{x \sim P_G} [\log(1 - D(x))]$$

$$= \int_x P_{\text{data}}(x) \log D(x) dx + \int_x P_G(x) \log(1 - D(x)) dx$$

$$x_{\sim p_{\text{data}}} \in I^{HR}$$



$$\therefore D^*(x) = \frac{P_{\text{data}}(x)}{P_{\text{data}}(x) + P_G(x)}$$

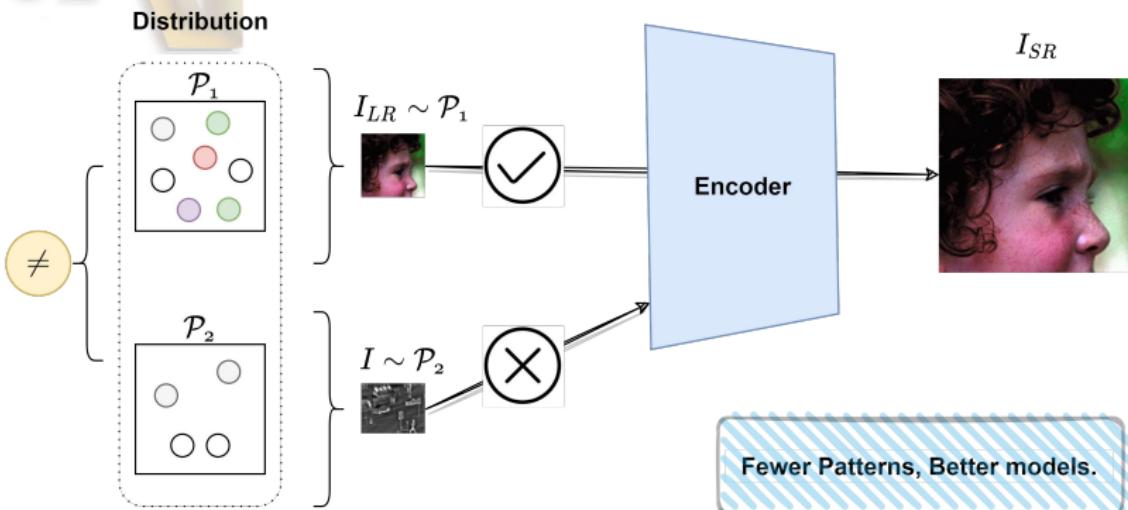
$$= -2 \log 2 + \text{KL} \left(P_{\text{data}} \parallel \frac{P_{\text{data}} + P_G}{2} \right) + \text{KL} \left(P_G \parallel \frac{P_{\text{data}} + P_G}{2} \right)$$

$$= -2 \log 2 + 2 \text{JS}(P_{\text{data}} \parallel P_G)$$

$$\text{Ref: } JS(p \parallel q) = \frac{1}{2} KL \left(p \parallel \frac{p+q}{2} \right) + \frac{1}{2} KL \left(q \parallel \frac{p+q}{2} \right)$$



Method is needed.



Datasets



Training

1,000 infrared images.

Test

TWO test datasets available for evaluation.

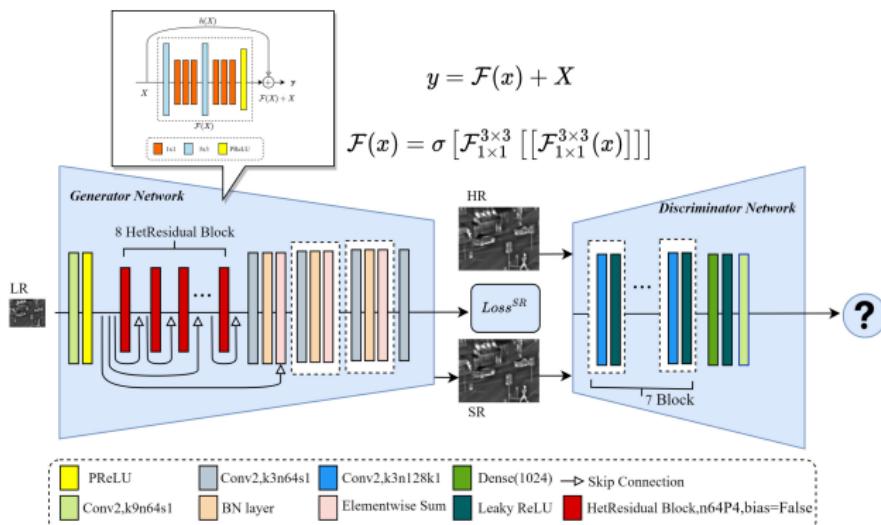
Link

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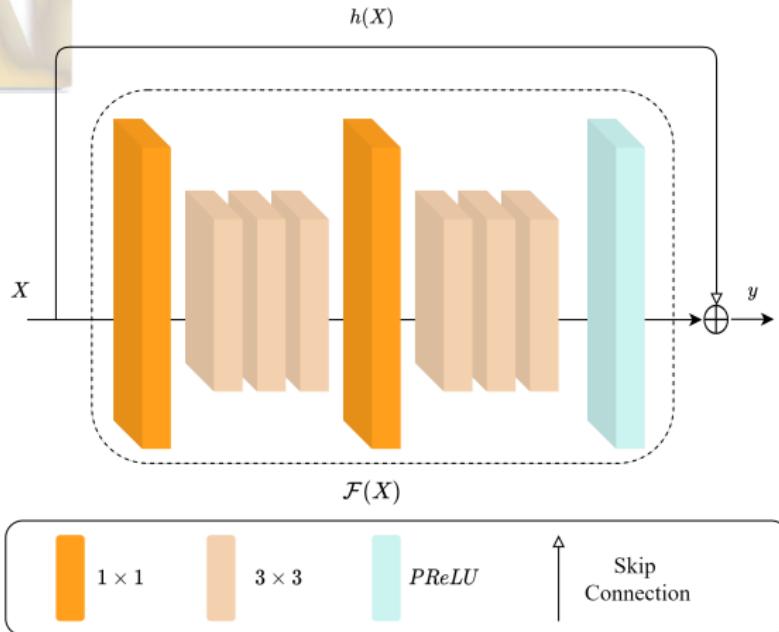


HetSRWGAN

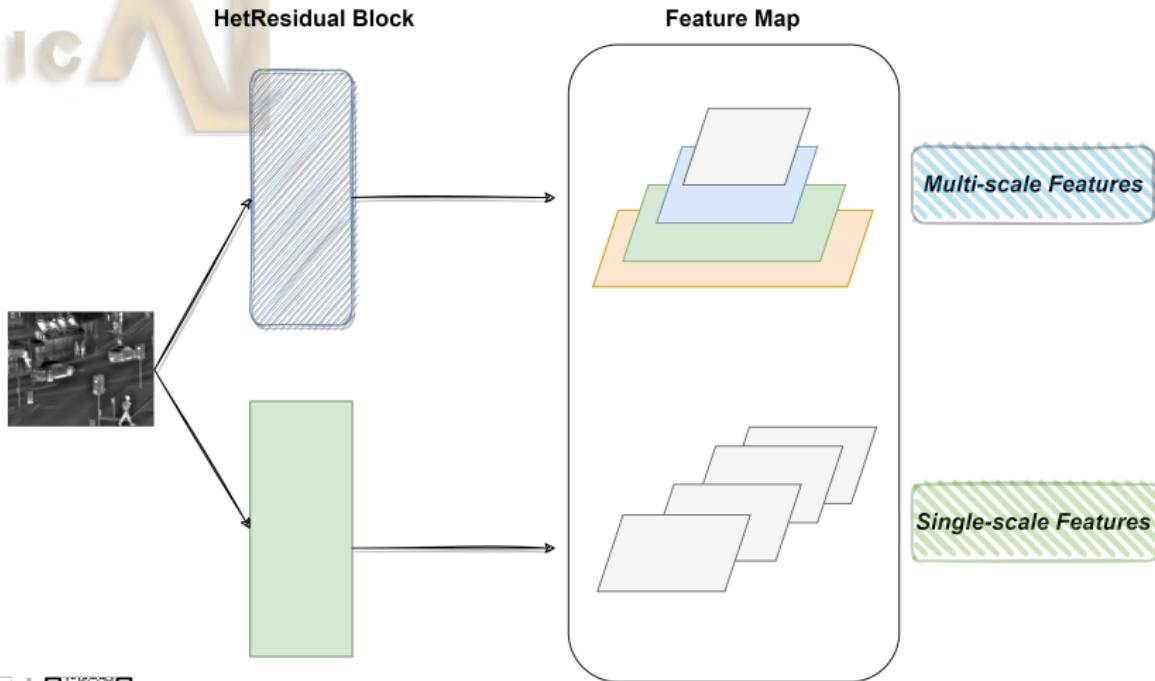
- The HetSRWGAN is a lightweight GAN architecture that applies a plug-and-play Heterogeneous Kernel-Based Residual Block.



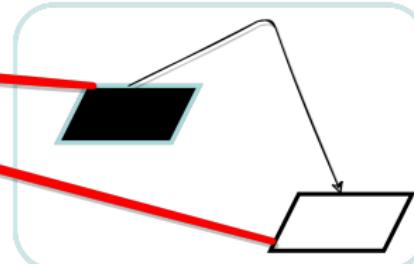
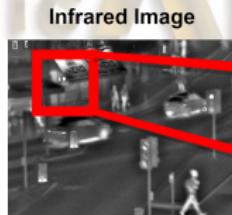
Heterogeneous Kernel-Based Residual Block



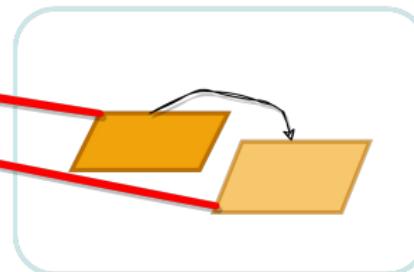
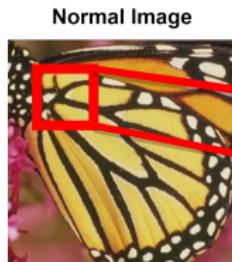
Feature Map



Gradient Function



The gradient variation between pixels are significant !



The gradient between pixel does not shift clearly...



Let's try using the gradient as a loss function !



Gradient Cosine Similarity Loss Function

- We chose the gradient of the image as the feature that measures the similarity between the two images.

Algorithm 1 Gradient Cosine Similarity Loss Function**Input:** I^{SR} , I^{HR} **Output:** Gradient Cosine Similarity

1: Infrared images can be processed into RGB images.

2: **while** not convergent **do**3: $I^{HR} \rightarrow (\mathbf{I}_{G_r}^{HR}, \mathbf{I}_{G_g}^{HR}, \mathbf{I}_{G_b}^{HR})$ 4: $I^{SR} \rightarrow (\mathbf{I}_{G_r}^{SR}, \mathbf{I}_{G_g}^{SR}, \mathbf{I}_{G_b}^{SR})$ 5: $\mathbf{X}' = [\mathbf{I}_{G_r}^{HR}, \mathbf{I}_{G_g}^{HR}, \mathbf{I}_{G_b}^{HR}]_{1 \times m}$ 6: $\mathbf{Y}' = [\mathbf{I}_{G_r}^{SR}, \mathbf{I}_{G_g}^{SR}, \mathbf{I}_{G_b}^{SR}]_{1 \times m}$ 7: $F_{\cos}(\mathbf{X}', \mathbf{Y}') = \frac{\mathbf{X}'^T \cdot \mathbf{Y}'}{\|\mathbf{X}'\| \cdot \|\mathbf{Y}'\|}$ 8: **return** $F_{\cos}(\mathbf{X}', \mathbf{Y}')$ **Step.1**

$$I^{SR} \longrightarrow (\mathbf{I}_{G_r}^{SR}, \mathbf{I}_{G_g}^{SR}, \mathbf{I}_{G_b}^{SR})$$

$$I^{HR} \longrightarrow (\mathbf{I}_{G_r}^{HR}, \mathbf{I}_{G_g}^{HR}, \mathbf{I}_{G_b}^{HR})$$

Step.2

$$\mathbf{X}' = [\mathbf{I}_{G_r}^{HR}, \mathbf{I}_{G_g}^{HR}, \mathbf{I}_{G_b}^{HR}]_{1 \times m}$$

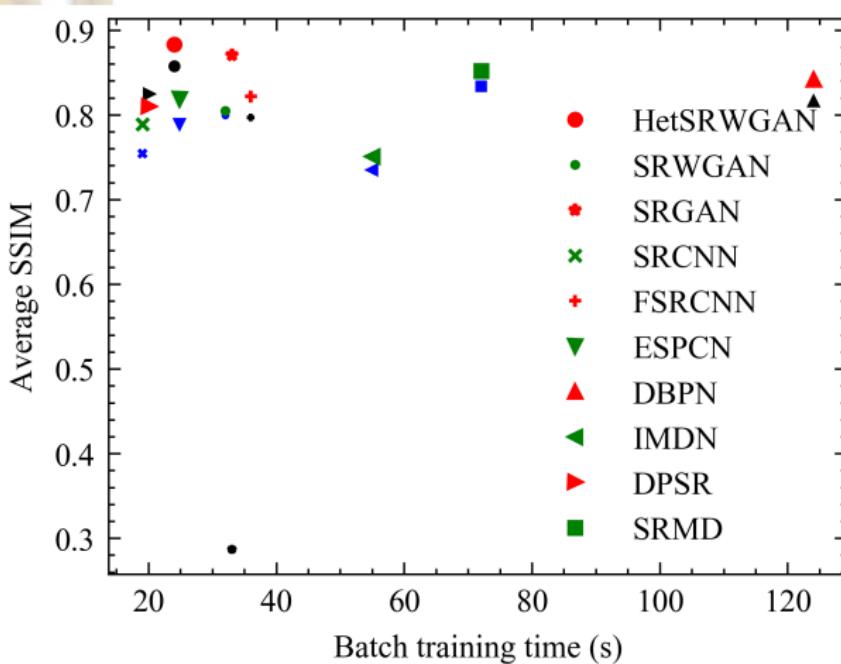
$$\mathbf{Y}' = [\mathbf{I}_{G_r}^{SR}, \mathbf{I}_{G_g}^{SR}, \mathbf{I}_{G_b}^{SR}]_{1 \times m}$$

Step.3

$$F_{\cos}(\mathbf{X}', \mathbf{Y}') = \frac{\mathbf{X}'^T \cdot \mathbf{Y}'^T}{\|\mathbf{X}'\| \cdot \|\mathbf{Y}'\|}$$



Experimental Results (HetSRWGAN)



Qualitative Results (HetSRWGAN)

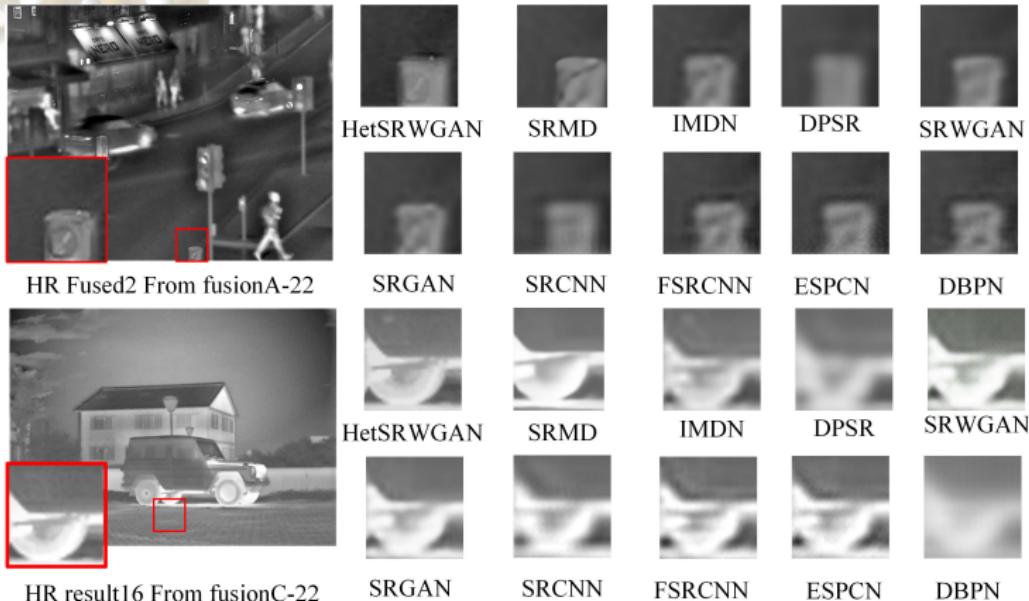
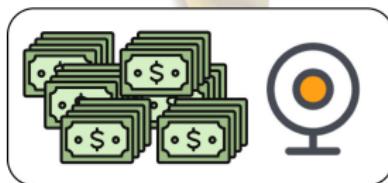


Image Data Dilemma

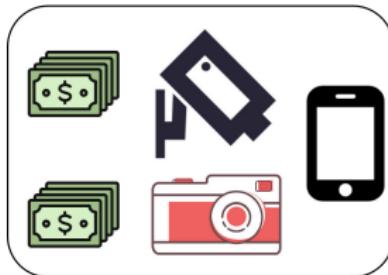
Specialized Equipment



Difficult to Use



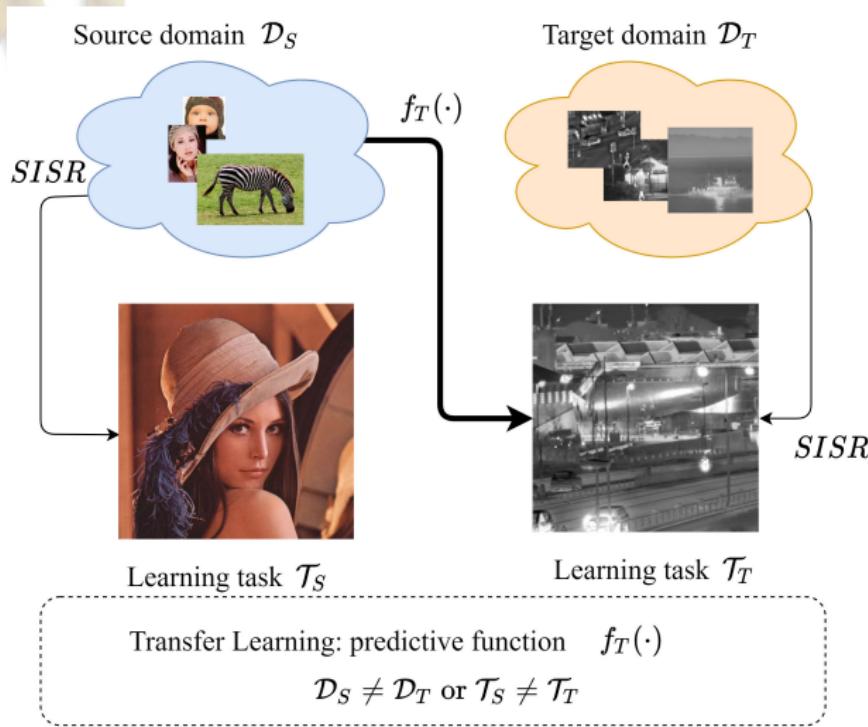
Common Equipment



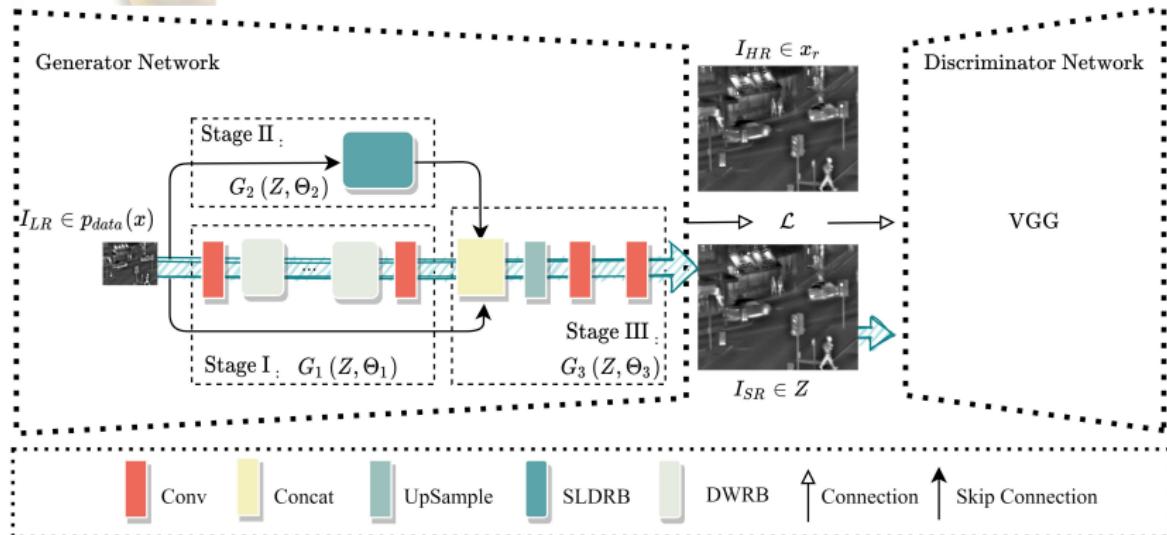
Easy to Use



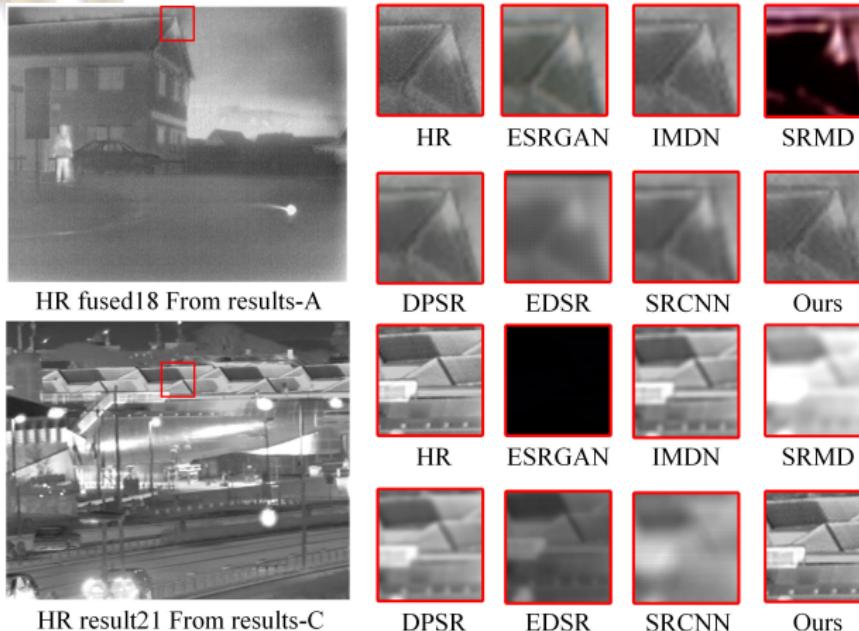
Transfer Learning



PSRGAN Architecture



Qualitative Results (PSRGAN)



Reference



- Huang Y., Jiang Z., Wang Q., Jiang Q., Pang G. (2021) Infrared Image Super-Resolution via Heterogeneous Convolutional WGAN. In PRICAI 2021: Trends in Artificial Intelligence. PRICAI 2021. Lecture Notes in Computer Science, vol 13032. Springer, Cham.
- Y. Huang, Z. Jiang, R. Lan, S. Zhang and K. Pi, "Infrared Image Super-Resolution via Transfer Learning and PSRGAN," in IEEE Signal Processing Letters, vol. 28, pp. 982-986, 2021.





Thank you for watching!

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