

# A Two-Stage Approach for Single Thermal Image Restoration

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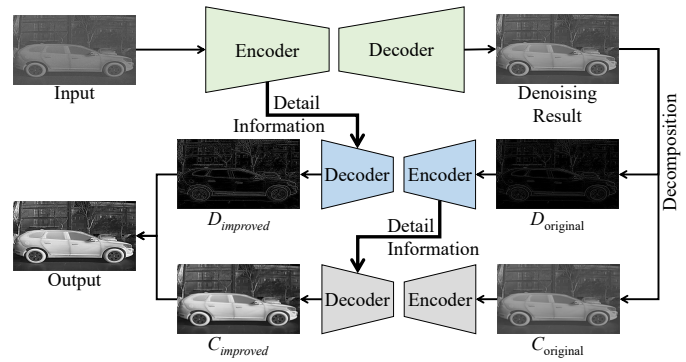
Thermal images, extensively utilized in various communication applications, are concurrently impacted by noise, contrast, and details. However, existing image restoration methods, designed for RGB domain, exhibit suboptimal effects when applied to thermal domain due to a lack of consideration for the interaction between noise and contrast, consequently resulting in detail losses. In this letter, we propose a two-stage deep network based on this interaction for thermal image enhancement. Our network decouples the image restoration task into a denoising stage and a contrast improvement stage for simultaneous denoising and contrast improvement. Detail information is extracted, preserved, and fused in the process of the entire network to avoid the detail losses. Extensive experiments show that our proposed method outperforms other state-of-the-art approaches in terms of PSNR, SSIM, and visual effect.

**Introduction:** Thermal images, which play a crucial role in thermal communication systems [1–4], military communication networks [5–8], remote sensing [9], and pattern recognition [10], often encounter significant degradation issues, including noise [11, 12], low contrast [13, 14], and missing details [15, 16]. These challenges significantly impact the visual quality and downstream tasks [17, 18]. Therefore, enhancing thermal images holds great significance for their effective application.

Over the past few decades, image restoration has predominantly relied on transform-based approaches [3, 19] and model-based methods [20–22]. Despite their historical significance, these methods have encountered limited adoption due to their inherent inflexibility. More recently, inspired by the remarkable success of deep learning, researchers have increasingly shifted their focus towards learning-based techniques [23–27]. However, learning-based methods were initially designed for the visible RGB domain, restricting their effectiveness to addressing specific issues like noise, low contrast, or diminished details. When applied to thermal images facing challenges of both noise contamination and reduced contrast, these approaches struggle to simultaneously suppress noise and enhance contrast.

In pursuit of these objectives, we present a two-stage methodology for enhancing thermal images, with a focus on concurrent denoising, contrast improvement, and detail preservation. Our network divides the thermal image restoration task into two stages: the denoising stage and the contrast improvement stage. Each stage employs an Encoder-Decoder architecture. The initial denoising stage is executed to mitigate the impact of noise on overall contrast. Subsequently, the contrast improvement stage takes the denoised output as input, producing the final result. The second stage adopts a decoupling and aggregation strategy, preventing noise amplification and concurrently enhancing both contrast and details. To minimize detail loss throughout these stages, the encoder's extracted details information from the denoising stage is fused into the decoder of the contrast improvement stage. For effective network training and validation, we curated a dedicated dataset specifically for thermal image restoration. The key contributions of this letter can be summarized as follows:

- We present a unified network based on the interrelationship between noise and contrast within thermal images for simultaneous denoising and contrast improvement.
- We develop a novel dataset specifically tailored for thermal image restoration, representing a significant contribution to the field of thermal image restoration.
- Experiments validate the effectiveness of our approach in noise suppression, contrast improvement. Quantitative and qualitative estimation attest to the robust performance of our method.



**Fig 1** Flowchart of our network.

**Related Work:** Over the past few decades, numerous image denoising methods have been introduced, with our particular emphasis on learning-based techniques closely aligned with our work [28–30]. In recent years, significant strides have been made in the advancement of supervised learning methods for image denoising. These techniques involve training denoisers on sets of clear/noisy image pairs. Zhang et al. [23] introduced DnCNN, a model that integrates convolutional neural networks with residual learning for blind denoising. Zhang et al. [25] propose IRCNN, which is a fast and effective denoiser integrated into a model-based optimization method for image denoising. Zhang et al. [26] present FFDNet for fast and flexible image denoising based on supervised learning. Zhang et al. [31] have also made significant contributions in the field of few-shot learning methods. Meanwhile, Liu et al. [32] have introduced a novel lightweight network designed specifically for deep learning applications. Additionally, in their groundbreaking work, Zhang et al. [33] present an innovative approach for adaptive digital self-interference cancellation, which is particularly effective in denoising millimeter-wave signals. While these supervised methods excel in enhancing visible images, their performance often falls short when applied to thermal images due to the sophisticated degradation in the latter. However, these supervised methods provide robust supervisory signals during training, enhancing generalization across diverse domains. Based on these advancements, we advocate for the utilization of supervised learning methods.

In the realm of contrast improvement, various transform-based methods have been proposed over the past decades [34]. He et al. [20] propose a dark channel prior to estimate the haze transmission efficiently and improve the contrast of an image. Ling et al. [21] present saturation line prior for image dehazing and contrast improvement. Setiawan et al. [35] developed contrast limited adaptive histogram equalization (CLAHE) for fast contrast improvement. Petro et al. [36] presents Multi-Scale Retinex (MSR) to perform contrast improvement in various scales, which considers more comprehensive information. Zhang et al. [37] propose cognition-driven structural prior for label noise task. Luo et al. [38] propose a integrity verification scheme for cloud data improvement. Cai et al. [39] applied DehazeNet for end-to-end image dehazing with contrast improvement. However, despite significant progress in these image dehazing methods, their evaluation on noise-free or dehazed images may not account for the inevitable noise in natural images, potentially limiting their effectiveness in achieving satisfactory visual results.

**Methodology:** The comprehensive architecture of our network is visually presented in Fig.1. The network is composed of two major components: the denoising stage and the contrast improvement stage. Drawing inspiration from the U-Net framework known for its effectiveness in image modeling and transformation tasks, the denoising stage is designed. The encoder of the denoising stage extracts detailed information, which is seamlessly integrated into the decoder of the contrast improvement stage. In the contrast improvement stage, we decompose the denoised image into detail and contrast components, and two CNN branches concurrently to enhance global contrast and refine details.

**Denoising Stage:** Within the denoising stage, careful consideration has been given to the design of both encoder and decoder. The detailed

Table 1. Quantitative comparison with other image restoration methods on our dataset. The best and second best are indicated in **bold** and underline, respectively.

Classification	Methods	PSNR↑	SSIM↑
Denoising	NB2NB [41]	17.589	<u>0.5552</u>
	DnCNN [23]	17.475	0.4840
	IRCNN [25]	17.290	0.4609
	FFDNet [26]	17.611	0.5162
Contrast Improvement	SLP [21]	17.582	0.3805
	RefineDNet [27]	14.591	0.3428
	DCP [20]	15.754	0.3900
	DehazeNet [39]	16.729	0.4250
	CLAHE [35]	17.228	0.3205
Unified Way	U <sup>2</sup> D <sup>2</sup> Net [42]	<u>23.634</u>	0.5335
	<b>Ours</b>	<b>24.531</b>	<b>0.5634</b>

Table 2. Analysis of denoising stage and contrast improvement stage. *D* denotes denoising stage and *CI* denotes contrast improvement stage.

Variants	PSNR	SSIM
D Stage	16.309	0.4958
CI Stage	15.969	0.4877
CI Stage + D Stage	20.0487	0.4842
D Stage + CI Stage ( <b>Ours</b> )	<b>24.531</b>	<b>0.5634</b>

implementation is shown in our released code. Drawing inspiration from the effective FFDNet [26], known for its adeptness in balancing noise reduction and detail preservation by incorporating noise level maps into its input, denoising stage follows suit by concatenating the thermal image with the denoising guide map.

**Contrast Improvement Stage:** The contrast improvement stage takes the denoised thermal image and detail information from the preceding denoising stage as input and produces the final output after contrast restoration. In the contrast improvement stage, we initially decompose the input image  $I(x, y) \in \mathbb{R}^3$  into a low-frequency contrast component  $L(x, y) \in \mathbb{R}^3$  and a high-frequency detail component  $R(x, y) \in \mathbb{R}^3$  according to [40]. For detail restoration, our U-shaped model learns a mapping function  $F_R$  to enhance details by capturing the relationship between the original detail component  $D_{\text{original}}$  and the reference image's detail component  $R_{\text{ref}}$ . Extracted detail information from the denoising stage minimizes losses in the contrast improvement stage. For contrast improvement, we train a Contrast Improvement Encoder and Decoder to map the input low-contrast thermal image's  $C_{\text{original}}$  to that of the reference image.

**Experiments:** For the purpose of thermal image restoration, we gathered high-quality thermal images utilizing the InfiRay M600F thermal imager to construct our dataset. The implementation of our network was carried out in the Python programming language and the PyTorch framework. The system employed for this task was equipped with an NVIDIA GeForce RTX 3090 and ran on Ubuntu 20.04. All our implementations can be found here: <https://github.com/ChickenEating/Two-stage-TIR>.

**Quantitative Comparison:** In Table 1, denoising techniques improve PSNR but compromise SSIM. Our network excels with the highest PSNR and second-highest SSIM. Compared to the second-highest PSNR on our dataset, there's a 0.897 dB improvement. our network's SSIM decreases marginally by 0.0082, negligible compared to the highest value.

**Qualitative Comparison:** In Fig.2, noisy and low-contrast input images are addressed by contrast restoration and denoising methods. While contrast restoration methods (e.g., SLP [21], DehazeNet [39]) improve contrast, they retain noise artifacts. Denoising methods (e.g., FFDNet [26],

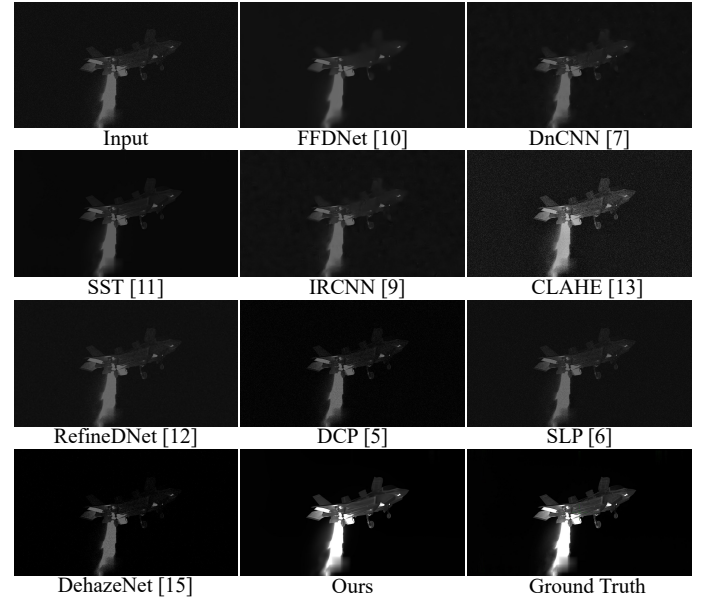


Fig 2 Qualitative comparisons on our Dataset.

DnCNN [23]) effectively reduce noise but may compromise detail. Our network outperforms, consistently delivering a visually favorable impact with a noise-free appearance and well-suited contrast.

**Ablation Studies:** Table 2 presents the statistical results of the ablation studies on denoising stage and contrast improvement stage. It is evident from the table that our network outperforms single denoising stage and single contrast improvement stage, highlighting the synergistic effectiveness of both modules. Notably, the performance of Contrast Improvement Stage before denoising stage appears less robust compared to our network, affirming our hypothesis that arranging the sequence of denoising before contrast restoration yields superior results.

**Conclusion:** This letter presents an innovative strategy for enhancing infrared (IR) images, effectively addressing the challenge of detail loss during concurrent denoising and contrast improvement procedures. Our proposed network consists of two distinct stages: the denoising stage and the contrast improvement stage. Both stages are meticulously designed to capture intricate interactions and correlations between noise and contrast within thermal images. Through extensive experimentation, our approach demonstrates superior performance when compared to existing methods dedicated to denoising, contrast restoration, and unified approaches on the our dataset.

**Acknowledgments:** This work was funded by the STI 2030—Major Projects under grant 2022ZD0209600, the National Natural Science Foundation of China under grant 62201058, the Beijing Institute of Technology Research Fund Program for Young Scholars under grant 6120210047, and the China Postdoctoral Science Foundation under grant 2021M700399.

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Received: 10 January 2024 Accepted: 4 March 2024  
doi: 10.1049/ell2.10001

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