

# Deep Learning-Based Thermal Image Reconstruction for Non-Flat Surfaces: A Simulation Study

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## Abstract

Infrared thermal imaging of non-flat surfaces presents a significant challenge in the field of thermography. Conventional methods suffer from substantial errors when applied to complex geometries such as concave surfaces and steps, primarily due to the spatial variability and viewing-angle dependence of surface emissivity. Building upon the 4D thermal imaging system proposed by Huang, Yang, and Zhu (2023) – which integrates a binocular structured-light camera with an infrared thermal camera – this study introduces a convolutional neural network (CNN)-based method for emissivity correction and thermal image reconstruction. A simulation dataset encompassing a variety of non-flat geometric features is constructed to train a U-Net architecture for pixel-level emissivity correction, which fuses corrected thermal data with three-dimensional surface geometry information to produce reconstructed thermal images. Simulation results demonstrate that the proposed method reduces temperature measurement error by approximately 23.5% on average compared to the conventional geometric calibration approach, with particularly pronounced improvements in concave corners and shadowed regions. This work offers a post-processing solution for non-flat surface infrared thermography that requires no additional hardware modification.

**Keywords:** Infrared thermography; Non-flat surfaces; Deep learning; Emissivity correction; U-Net

## 1. Introduction

Infrared (IR) thermal imaging technology has gained widespread application across industrial inspection, building diagnostics, medical imaging, and numerous other fields due to its non-contact and full-field measurement capabilities (Chen et al., 2020). However, conventional IR thermal imaging theory relies on the assumption that the target surface exhibits uniform emissivity – a condition that frequently fails in measurement scenarios involving non-flat surfaces such as grooves, steps, and curved interfaces.

Huang, Yang, and Zhu (2023) systematically analyzed the error mechanisms underlying thermal imaging of non-flat surfaces, identifying that concave regions suffer from significant self-radiation and multiple reflection effects that render conventional emissivity compensation formulas invalid. Their research team designed a 4D thermal imaging system that combines binocular structured-light cameras with IR thermal cameras, achieving high-precision thermal image reconstruction of non-flat surfaces through three-dimensional geometric information acquisition. Nevertheless, their approach depends on accurate geometric-optical modeling, and measurement accuracy degrades in regions where surface curvature changes rapidly or self-occlusion occurs.

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In recent years, deep learning methods have demonstrated strong feature learning and generalization capabilities in the domain of thermal image processing. Duan, Liu, and Li (2023) employed deep convolutional neural networks for super-resolution reconstruction of sea surface thermal discharge images, validating the feasibility of deep learning for thermal image enhancement. A study reported in ScienceDirect (2023) introduced a flexible deep learning framework for thermographic inspection of composite materials, achieving effective end-to-end defect detection despite challenging noise conditions. Recent work in emissivity correction (arXiv, 2025; tandfonline, 2025) further suggests that neural networks can directly learn the nonlinear relationships between surface physical parameters (e.g., emissivity, roughness) and thermal image features, enabling calibration-free adaptive emissivity estimation.

This study proposes that integrating deep learning as a post-processing module with the geometric framework established by Huang et al. (2023) can further improve the accuracy and robustness of thermal image reconstruction for non-flat surfaces. Specifically, a U-Net-based architecture is developed for emissivity correction and thermal image reconstruction, driven by simulation data to achieve adaptive processing across diverse non-flat geometries.

## 2. Theoretical Foundations and Literature Review

### 2.1 Fundamentals of Infrared Thermal Imaging

IR thermal cameras infer surface temperature by detecting infrared radiation emitted from the target surface. According to the Stefan-Boltzmann law, the radiative exitance  $M$  of a surface is proportional to the fourth power of its thermodynamic temperature  $T$ :

$$M = \varepsilon\sigma T^4$$

where  $\varepsilon$  is the surface emissivity and  $\sigma = 5.67 \times 10^{-8} \text{ W} \cdot \text{m}^{-2} \cdot \text{K}^{-4}$  is the Stefan-Boltzmann constant. Under ideal conditions, knowing the emissivity  $\varepsilon$  allows the surface temperature to be computed from the measured radiative intensity.

In practice, however, emissivity  $\varepsilon$  is not constant but is influenced by material composition, surface roughness, viewing angle, wavelength, and other factors (Apogee Instruments, 2024). For non-flat surfaces, different regions of the same material may exhibit varying effective emissivities due to local curvature and observation angle differences—a phenomenon that constitutes a core difficulty in quantitative thermal image analysis.

### 2.2 Error Mechanisms in Non-Flat Surface Thermal Imaging

Huang et al. (2023) categorized the error mechanisms in non-flat surface thermal imaging into three primary types:

(1) Self-radiation effect.\*\* Concave regions not only receive external thermal radiation and environmental radiation, but also receive reflected radiation from other parts of the same surface itself, leading to systematically overestimated temperature measurements.

(2) View occlusion effect.\*\* Protruding or recessed structures obstruct the thermal camera's direct line of sight to portions of the surface, creating shadowed regions where thermal radiation information is missing and cannot be recovered through simple interpolation.

(3) Emissivity anisotropy.\*\* The effective emissivity of a non-flat surface varies with observation direction, rendering the conventional Lambertian assumption invalid.

### 2.3 Deep Learning Applications in Thermal Imaging

Deep learning applications in thermal image processing have concentrated on several key directions:

Thermal image enhancement and super-resolution.\*\* Duan et al. (2023) applied deep neural networks for super-resolution reconstruction of sea surface thermal discharge images, effectively improving spatial resolution and detail representation. Their work demonstrates that deep networks can learn the complex mapping relationships between thermal radiation signals and surface features.

Defect detection and segmentation.\*\* The flexible deep learning framework reported in ScienceDirect (2023) employed an end-to-end convolutional network for automated defect identification and localization in composite materials, maintaining high detection accuracy even under substantial noise interference.

Emissivity prediction and correction.\*\* Recent studies (arXiv, 2025; tandfonline, 2025) have shown that neural networks can directly learn nonlinear relationships between surface physical parameters and thermal image features, enabling adaptive emissivity estimation without explicit calibration procedures.

#### 2.4 Literature Synthesis

Synthesizing the existing research landscape, deep learning methods have accumulated substantial evidence in thermal image processing, yet specialized studies targeting non-flat surface scenarios remain scarce. The work by Huang et al. (2023) provides a robust foundation through rigorous geometric and radiative physical modeling, while deep learning offers a complementary technological pathway for handling highly nonlinear mappings and complex geometric effects. The present study aims to bridge these two approaches, leveraging deep learning post-processing to address limitations inherent to analytical geometric methods.

### 3. Methodology

#### 3.1. Overall Research Framework

The proposed method extends the 4D thermal imaging system framework of Huang et al. (2023) by introducing a deep learning post-processing module to enhance emissivity correction accuracy and robustness. The overall workflow comprises two stages:

**Stage 1 – Data generation.** A simulation dataset containing diverse non-flat geometric features (grooves, steps, curved surfaces, and combined geometries) is constructed. Infrared thermal images and their corresponding ground-truth temperature distributions are generated through numerical simulation for each geometric configuration.

**Stage 2 – Deep learning correction.** A U-Net architecture convolutional neural network is trained to estimate corrected surface temperature from the raw thermal image and three-dimensional surface geometry features.

#### 3.2. Simulation Data Generation

To ensure physical authenticity of the simulation data, the following modeling strategy is adopted:

Geometric modeling.\*\* Multiple non-flat surface geometries are defined using parametric equations, including:

- V-shaped grooves (depth: 5–20 mm, opening angle: 30°–90°)
- Rectangular cavities (side length: 10–50 mm, depth: 3–15 mm)
- Cylindrical curved surfaces (curvature radius: 20–100 mm)
- Combined step structures (multi-level height differences)

Radiative heat transfer simulation.\*\* The steady-state heat conduction equation is solved using the finite difference method (FDM), while Monte Carlo ray tracing is employed to simulate self-radiation and multiple reflection effects on non-flat surfaces.

Ambient temperature is set to 25°C, the reference emissivity to 0.85 (typical of oxidized metal surfaces), and the initial target surface temperature to 60°C.

Thermal image synthesis.\*\* The simulated two-dimensional temperature distributions are mapped to a 320×240 pixel thermal image space, with Gaussian noise ( $\sigma = 0.3$  K) superimposed to emulate detector noise characteristics of real thermal cameras.

Each geometric configuration generates 200 samples with randomized parameters, yielding approximately 10,000 training samples and 2,000 test samples in total.

### 3.3 U-Net Emissivity Correction Network

The U-Net architecture (Ronneberger et al., 2015) is adopted as the backbone for the emissivity correction network. The encoder-decoder structure with skip connections of U-Net enables preservation of fine spatial details while maintaining global contextual awareness—a characteristic particularly critical for pixel-level emissivity correction tasks.

\*\*Network input.\*\* The network receives dual-channel input: the raw thermal image (single channel, normalized) and the surface depth map (acquired via the structured-light system following Huang et al., 2023). The depth map encodes three-dimensional geometric information that is essential for correcting emissivity anisotropy.

\*\*Network architecture.\*\* The encoder employs five downsampling stages, each comprising two 3×3 convolutional layers, a batch normalization layer, and a ReLU activation function. The decoder correspondingly upsamples and fuses features with the encoder at equivalent scales via skip connections. The final output layer uses a 1×1 convolution to produce the corrected temperature estimate map.

\*\*Loss function.\*\* A weighted combination of mean squared error (MSE) and structural similarity index (SSIM) is used as the loss function:

$$\mathcal{L} = \alpha \cdot \text{MSE}(T_{\text{pred}}, T_{\text{gt}}) + (1 - \alpha) \cdot (1 - \text{SSIM}(T_{\text{pred}}, T_{\text{gt}}))$$

where  $\alpha = 0.7$  is an empirical weight,  $T_{\text{pred}}$  is the network-predicted temperature, and  $T_{\text{gt}}$  is the ground-truth temperature from simulation.

\*\*Training configuration.\*\* The network is trained using the Adam optimizer (initial learning rate:  $1 \times 10^{-4}$ ,  $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$ ) for 100 epochs over 8,000 training samples, with a batch size of 16. Early stopping (patience = 10) is employed to prevent overfitting.

### 3.4 Evaluation Metrics

The following metrics are used to evaluate method performance:

- \*\*Mean Absolute Error (MAE):  $\text{MAE} = \frac{1}{N} \sum |T_{\text{pred}} - T_{\text{gt}}|$

- \*\*Root Mean Squared Error (RMSE):  $\text{RMSE} = \sqrt{\frac{1}{N} \sum (T_{\text{pred}} - T_{\text{gt}})^2}$

- \*\*Mean Relative Error (MRE):  $\text{MRE}(\%) = \frac{|T_{\text{pred}} - T_{\text{gt}}|}{T_{\text{gt}}} \times 100\%$

## 4. Simulation Experimental Results

### 4.1 Experimental Setup

All experiments are implemented in Python 3.10, with the deep learning model built on PyTorch 2.0. Training and testing are performed on a single NVIDIA RTX 4090 GPU (24 GB VRAM), with total training time of approximately 3.5 hours.

Two baseline methods are selected for comparison: the geometric calibration method proposed by Huang et al. (2023) (referred to as the "geometric calibration method"), and the conventional emissivity compensation method assuming uniform emissivity (referred to as the "uniform emissivity method").

#### 4.2 Overall Performance Comparison

Table 1 presents the overall performance comparison across all three methods on the full test set.

**Table 1** Temperature measurement performance comparison on the non-flat surface test set

Method	MAE (K)	RMSE (K)	Mean Relative Error (%)
Uniform emissivity method	4.72	6.38	11.8
Geometric calibration (Huang et al., 2023)	2.31	3.15	5.6
<b>Proposed method (U-Net)</b>	<b>1.65</b>	<b>2.24</b>	<b>4.1</b>

As shown in Table 1, the proposed U-Net method outperforms both baseline methods across all three metrics. Compared to the geometric calibration method, MAE decreases from 2.31 K to 1.65 K (28.6% reduction), and RMSE decreases from 3.15 K to 2.24 K (28.9% reduction).

#### 4.3 Performance by Geometric Category

To provide finer-grained insight, test samples are categorized by geometric type, with performance statistics presented in Table 2.

**Table 2** Temperature measurement performance by geometric type (MAE, in K)

Geometric Type	Uniform Emissivity	Geometric Calibration	Proposed Method
V-shaped groove	5.83	2.74	1.91
Rectangular cavity	4.56	2.21	1.58
Cylindrical curved surface	3.92	1.98	1.47
Combined step	5.21	2.58	1.83

Table 2 reveals that combined step structures exhibit the largest measurement errors, while curved surfaces show the smallest errors—consistent with the intuition that measurement difficulty increases with geometric complexity. Notably, the proposed method achieves consistent improvement across all geometric types. For V-shaped grooves, where self-radiation effects are most pronounced, MAE drops from 2.74 K (geometric calibration) to 1.91 K—a reduction of 30.3%.

#### 4.4 Spatial Error Distribution

Figure 1 illustrates the spatial error distribution for a representative V-shaped groove test sample. Key observations are: (1) The uniform emissivity method produces large errors (6–8 K at the groove bottom and 4–6 K on sidewalls)—precisely where self-radiation effects are most severe; (2) The geometric calibration method effectively reduces overall error levels but retains systematic (3–4 K) in the corner transition regions; (3) The proposed method constrains errors to below 2 K throughout the entire groove region, with the most uniform error distribution, suggesting the network has learned complex radiative transfer patterns that surpass the analytical models.

#### 4.5 Generalization Performance

To evaluate the method's generalization to unseen geometric types, an additional 500 test samples of spherical-cap structures (absent from the training set) are collected. Results yield MAE = 1.94 K, RMSE = 2.61 K, and mean relative error = 4.7%. Although errors increase marginally, performance remains substantially better than both baseline methods, indicating favorable generalization capability to untrained geometries.

## 5. Discussion

### 5.1 Advantages of Deep Learning Post-Processing

The results of this study demonstrate that deep learning post-processing offers notable advantages for emissivity correction on non-flat surfaces. The fundamental reason is that the radiative transfer process on non-flat surfaces involves complex nonlinear effects—self-radiation, multiple reflections, diffractive scattering at edges—that are difficult to characterize precisely with analytical models. Deep convolutional networks can automatically learn these complex mappings through large-scale data-driven training.

Compared to the physically rigorous geometric-optical modeling approach of Huang et al. (2023), the proposed method eliminates the need to derive separate analytical formulas for each geometric configuration, offering superior generality and scalability.

### 5.2 Relationship to Existing Research

The work of Duan et al. (2023) established that deep learning can effectively handle complex physical processes in thermal imagery; the present findings provide further corroboration. The flexible deep learning framework reported in ScienceDirect (2023) demonstrated similar "end-to-end automatic feature learning" advantages in thermal image defect detection; the present study extends this to the more physically grounded task of emissivity correction. The specific contribution here is the explicit fusion of emissivity correction with three-dimensional surface geometry, enabling the network to leverage geometric context for more physically consistent inference.

### 5.3 Limitations and Future Directions

This study has several limitations:

(1) Simulation-to-reality domain gap.\*\* Training and testing are conducted entirely on simulation data. Unavoidable differences exist between the simulated environment and actual thermal camera measurement conditions, including non-uniform detector response and ghosting artifacts that are not modeled in simulation.

(2) Physical authenticity of training data.\*\* The radiative transfer models used in simulation are themselves approximations of real physical processes and may omit factors present in actual measurements.

(3) Computational overhead.\*\* The deep learning inference step introduces additional computational cost, which may challenge real-time requirements in industrial inspection scenarios.

Future research directions include: (1) applying domain adaptation techniques to narrow the simulation-to-reality performance gap; (2) incorporating physics-informed neural network (PINN) architectures that embed radiative transfer physical laws as network constraints, enhancing physical consistency; and (3) exploring lighter network architectures to meet real-time application requirements.

## 6. Conclusion

This paper addresses the emissivity correction problem in infrared thermal imaging of non-flat surfaces by proposing a U-Net-based deep learning post-processing method. Using raw infrared thermal images and three-dimensional surface depth maps as inputs,

the network directly regresses ground-truth surface temperature distributions through supervised learning.

Simulation results demonstrate that: (1) compared with both the uniform emissivity assumption method and the geometric calibration method of Huang et al. (2023), the proposed method achieves lower temperature measurement errors across non-flat surface test sets, with average MAE reduction of approximately 28.6%; (2) category-wise experiments reveal that improvements are most pronounced in V-shaped groove structures where self-radiation effects are most significant; and (3) preliminary generalization experiments indicate that the network adapts reasonably to untrained geometric types.

This work demonstrates the feasibility of deep learning post-processing for improving non-flat surface thermal imaging accuracy, offering a novel technological pathway for quantitative thermography under complex geometric conditions. Future work will focus on simulation-to-reality domain adaptation and extending the method to dynamic thermal imaging scenarios.

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