Compensation of temperature effects on imaging quality of thermal imaging objectives using deep learning techniques

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Received: 17 Sep. 2024; Revised 02 Nov. 2024; Accepted 12 Nov. 2024; Published 25 Nov. 2024.
DOI: https://doi.org/10.54939/1859-1043.j.mst.99.2024.89-98

ABSTRACT

Thermal imaging objectives are made from infrared materials with large thermal expansion coefficients, such as Ge, Si, and ZnSe. When the temperature changes, it leads to variations in the refractive index, curvature radius, and thickness of the lens, causing defocus shifts that degrade the image quality of the thermal imaging system. In this paper, we propose a novel method to compensate for the effects of temperature variations on the quality of thermal imaging objectives by using deep learning techniques. The temperature variations are measured using a thermal sensor. Subsequently, a U-Net network is employed to mitigate the impact of temperature on the imaging quality of the thermal imaging objectives without requiring any optical displacement or replacement of the lens. Simulation results show that the proposed method performs the effectively compensation for the influence of temperature changes on thermal imaging objective over a wide temperature range from -5 °C to 50 °C.

Keywords: Thermal imaging objectives; Temperature variation compensation; Deep learning technique.

1. INTRODUCTION

The thermal objective is a crucial optical component in thermal imaging systems, responsible for forming an image on the sensor plane within the infrared spectrum**.** Thermal imaging devices are enable to operate both day and night in the spectral range of 3-5 µm or 8-14 µm [1-3], thermal imaging objectives are typically made from crystalline materials such as Ge, ZnSe, and Si, which are highly sensitive to temperature changes [4, 5]. When the temperature changes, it alters parameters such as the refractive index, curvature radius, and lens thickness, which causes the image plane of the thermal imaging objectives to shift out to the sensor plane. This misalignment introduces a defocus aberration, which is the primary cause of image quality degradation due to temperature variations. Various methods have been employed to compensate for this defocus error, including mechanical compensation [6], optical compensation [7], and electromechanical methods [8].

Various methods that have been studied to compensate for the effects of temperature on thermal imaging objectives have their own advantages and disadvantages. The mechanical compensation method is a passive approach. The disadvantage of this method lies in the complex mechanical design and the limited availability of materials with high thermal expansion coefficients, as well as the difficulty in combining these materials to fabricate the frames of lens. Meanwhile, optical compensation methods are divided into two approaches. The first approach involves designing thermal imaging objectives that automatically compensate for the effect of temperature on image quality. However, this method's temperature compensation range decreases with higher numerical apertures. The second approach adds a phase mask to the thermal imaging objectives to produce a point spread function (PSF) invariant to temperature changes. Nevertheless, this method requires image processing, leading to the image quality near the diffraction limit and requires time-consuming computations. The electromechanical method, on the other hand, is an active approach. In this method, the temperature changes of the thermal imaging lens are measured by a temperature sensor. A lens within the thermal imaging objectives is shifted to correspond to each temperature in order to maintain the image plane and the sensor plane overlap. However, this method necessitates the production of highly precise and relatively complex components.

Recently, deep learning has become a key technique for improving the image quality of optical systems [9]. Its main advantage is to enhance image quality without changing the optical components [10]. In this paper, we first propose to use deep learning to compensate for temperature effects on thermal imaging objectives. This approach does not modify or add components to the thermal imaging objectives.

2. THEORETICAL BASIC

2.1. Deep learning models and the U-Net algorithm in image processing

Deep learning is a subset of artificial intelligence that uses artificial neural networks with multiple hidden layers to automatically learn and represent data at various levels of abstraction. Deep learning models incorporate essential components, including convolutional layers for feature extraction, pooling layers to reduce data dimensions while preserving important information, nonlinear activation functions to model complex relationships, and fully connected layers for output prediction. The training process involves calculating the loss function and applying backpropagation to adjust weights, thereby optimizing the model's predictions. Once trained, the model can predict new data with high accuracy and is widely used in image recognition, natural language processing, image quality enhancement, and other fields. Figure 1 illustrates a deep learning model designed to compensate for temperature effects on thermal imaging objectives. However, model parameter optimization must be tailored to specific temperature ranges.

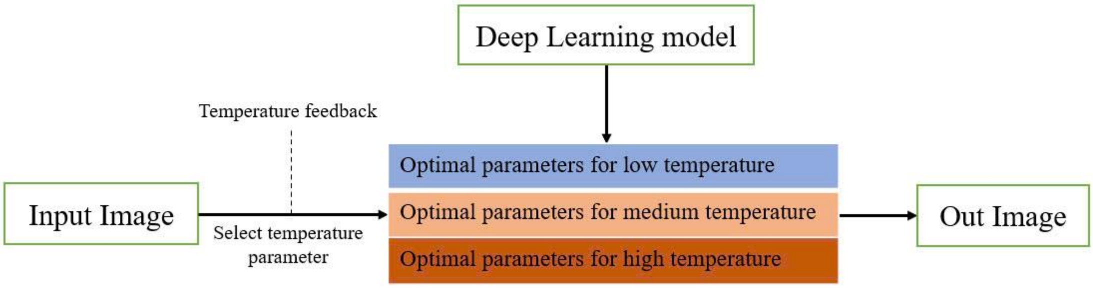


Figure 1. *Diagram of the deep learning model that compensates for the temperature effects on thermal imaging objectives.*

This paper employs the U-Net deep learning model, designed for image segmentation with a U-shaped architecture consisting of an encoder and decoder (figure 2). The encoder uses 3x3 convolutional layers and 2x2 average pooling to extract features from the input image (256x256x1). At each encoding step, the image is processed through convolutional layers with ReLU activation to detect basic features like edges, followed by pooling to reduce spatial dimensions while preserving key features. The number of feature channels doubles at each downsampling step, allowing the model to extract increasingly complex features and the encoder outputs a 16x16x256 image.

The decoder employs 2x2 upsampling layers to restore the image's spatial dimensions. At each decoding step, a 2x2 up-convolution is used to halve the number of feature channels, followed by concatenating feature maps from the encoder through skip connections. These connections enhance image resolution and ensure the preservation of critical information from the encoding phase. Convolutional layers in the decoder relearn features as the image is expanded back to its original size. Both the encoder and decoder use 3x3 convolutions with ReLU activation, resulting in a total of 23 convolutional layers. A final 1x1 convolution reduces each 16-dimensional feature vector to a single output, yielding a 256x256x1 output image. This process enables U-Net to accurately segment images by labeling each pixel. The model is particularly effective in applications such as healthcare and defense. Figure 2 illustrates the basic U-Net architecture.

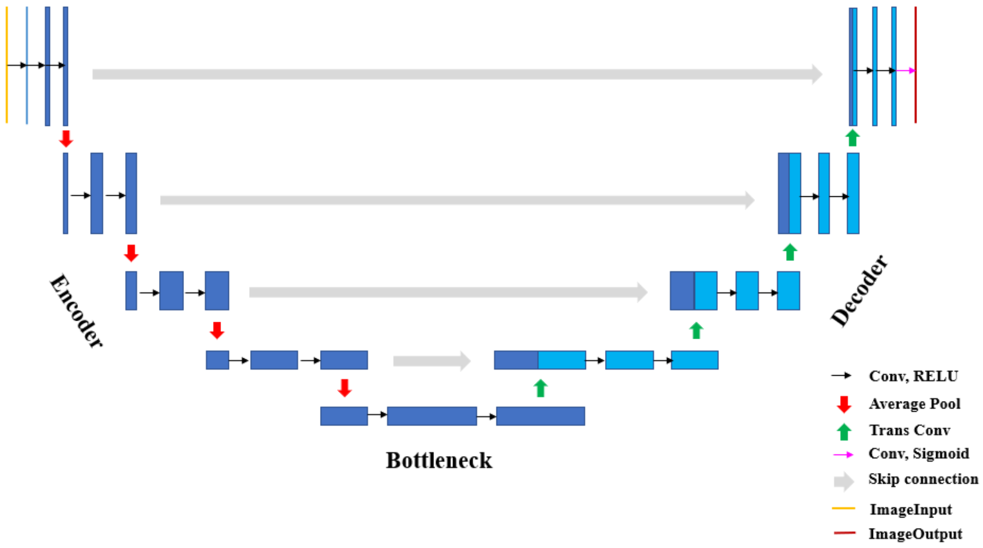


Figure 2. *U_net algorithm model.*

2.2. Principle of temperature variation compensation using deep learning

The image represented by the intensity of the optical system is given by the following equation:

$$g = o \otimes h + n \tag{1}$$

where, o is the object; h is the point spread function, PSF, n is the noise, denoted by $\otimes$ as the convolution operator.

Thus, the imaging quality can be evaluated through the PSF function. When there is a change in temperature, it leads to a change in parameters such as refractive index, radius of curvature, and thickness of lenses, leading to a change in the PSF function. The deep learning method in this paper is a new solution that does not shift any components when compensating for the influence of temperature on the image quality. First, a dataset is built to determine the low-quality images of the thermal imaging system corresponding to each specified temperature value, in which the image at the ideal working temperature of 20 ^{o}C is a high-quality image.

This dataset will be used to train in order to restore the low-quality images at other temperatures to the high-quality image at the reference temperature, in this process the algorithms will find the corresponding weights and use them for the next restorations. When thermal imaging objectives work in an environment with changing temperatures, the temperature sensor will measure the actual temperature value to determine the used U_net to restore the desired quality image. Figure 3 shows the schematic diagram for the temperature compensation principle of the proposed method.

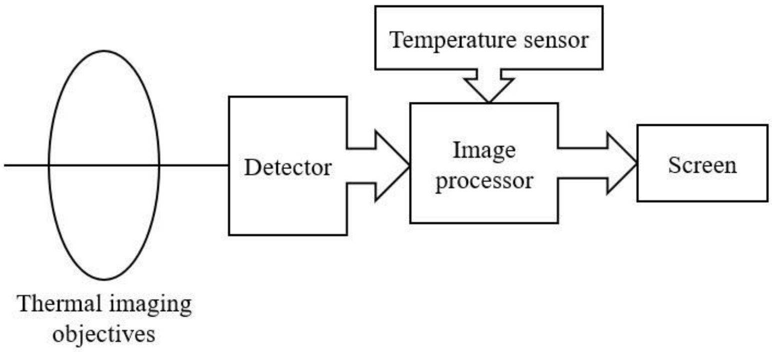


Figure 3. *Schematic diagram of the proposed method.*

3. DEEP LEARNING METHOD COMPENSATES FOR THE INFLUENCE OF TEMPERATURE

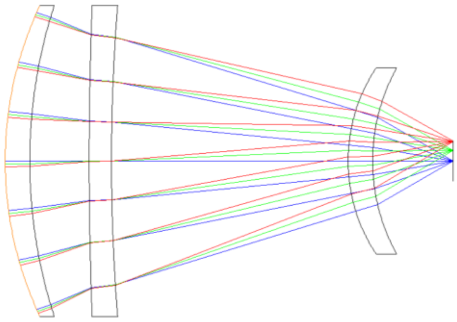
3.1. Study of the effect of temperature on thermal imaging objectives

In this paper, a thermal imaging objective is used to demonstrate the effectiveness of the proposed method. It is composed of three single Germanium (Ge) objective lenses with a pupil diameter of 20 mm. The parameters of the thermal imaging objectives are shown in table 1.

Table 1. *Structural parameters of thermal imaging objective.*

Obj	Radius	Thickness	Glass	Semi-diameter
Stop	49.341	3.30	Ge	21.00
2	68.089	8.00		21.00
3	550.180	3.00	Ge	21.00
4	265.661	31.846		21.00
5	22.807	3.30	Ge	12.56
6	25.964	10.84		12.56

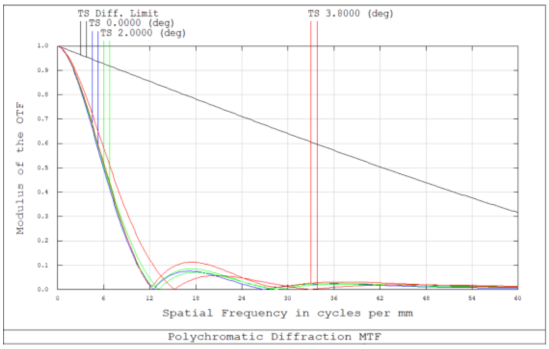
Figure 4 shows the shape of the thermal imaging objective and the technical parameters. Firstly, the image quality is evaluated by the MTF function corresponding to several temperature points. The lower the MTF function, the worse the image quality. Therefore, the higher the MTF values, the better the image quality. Moreover, the smaller the cut-of frequency, the worse the image quality. The cut-of frequency is the first zero value when the line of MTF meets the horizontal axis. With a temperature range from -5 ^{o}C to 50 ^{o}C, the MTF functions at different temperature values are shown in figure 5. It can be seen that thermal imaging objectives is designed at 20 ^{o}C, so the MTF function at this temperature is the best, the further the temperature value is from the reference temperature value of 20 ^{o}C, the lower the MTF function. The MTF function at -5 ^{o}C and 50 ^{o}C has the lowest value, corresponding to the poor-quality image at these temperature points.



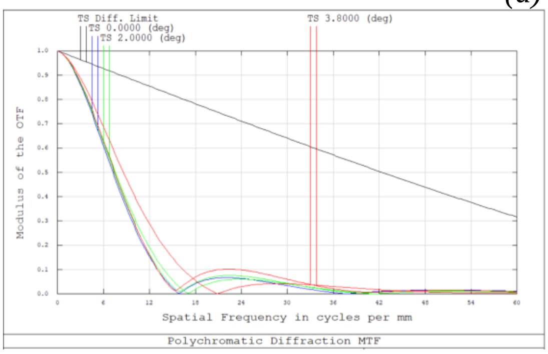
Some technical parameters:

- Active spectral range: 8-11 μm
- Focal length: 40 mm
- Field of view: 7.6°
- Aperture number: F/1
- Design temperature: 20 °C

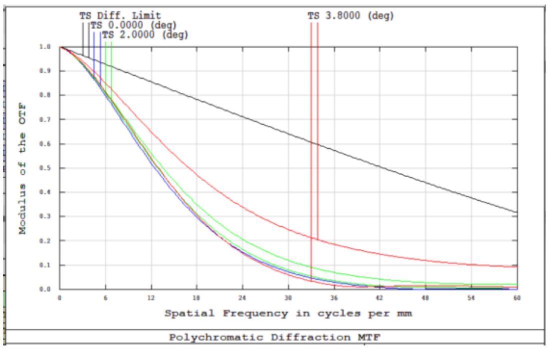
Hình 4. *Objective configurations and technical parameters.*



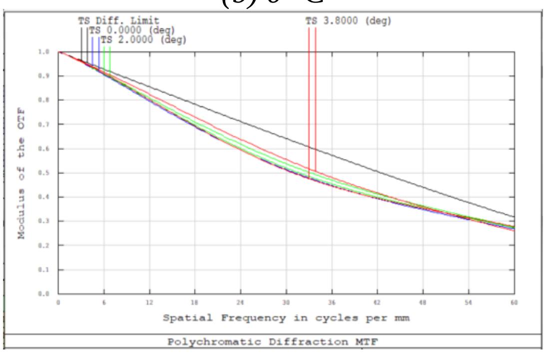
(a) -5 °C



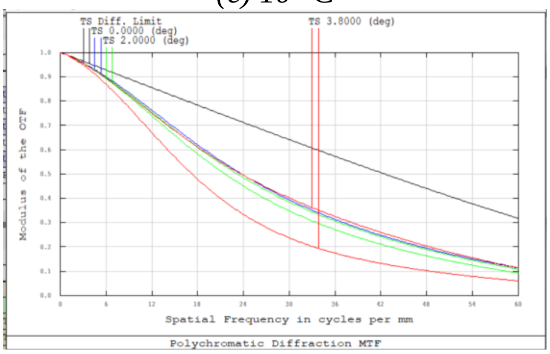
(b) 0 °C



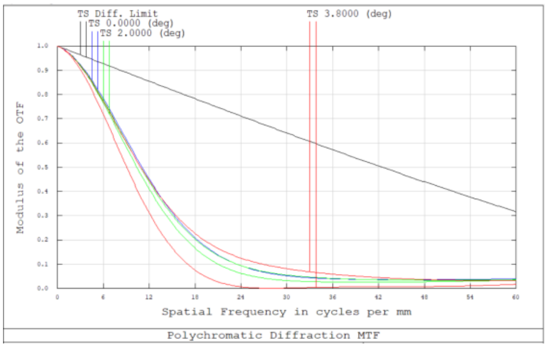
(c) 10 °C



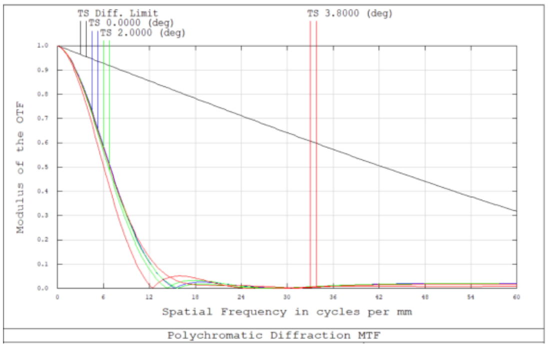
(d) 20 °C



(e) 30 °C



(f) 40 °C

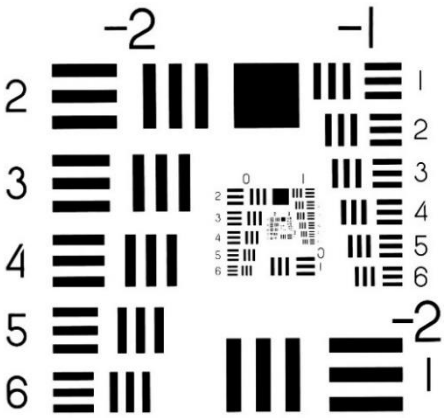


(g) 50 °C

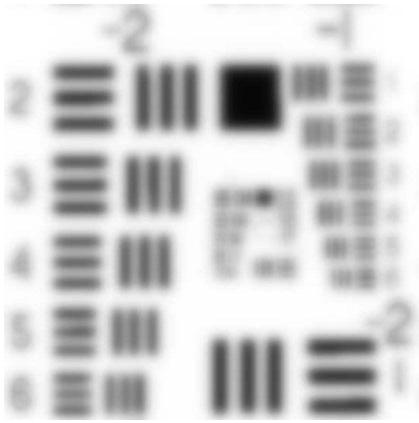
Figure 5. *MTF function of thermal imaging objectives at different temperatures.*

3.2. Building dataset

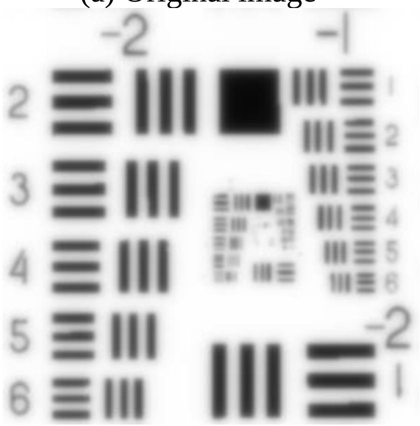
The PSF function data is obtained by using the Zemax software. The Zemax software is the famous software with optical systems. The Zemax software generates the PSFs at different temperature values. After, images obtaned from thermal imaging objectives were obtained using equation (1). In this paper, bias is not considered. An original image used for simulation is shown in figure 6(a) as an example of a used original image. Simulated images at different temperatures are shown in figure 6. We do not employ these images in the training processing.



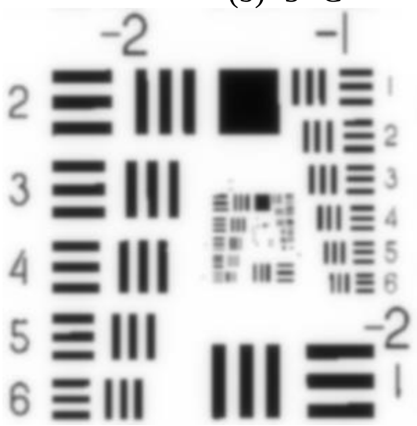
(a) Original image



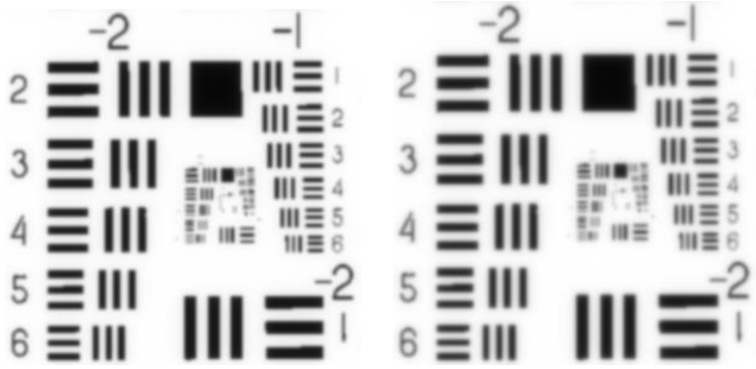
(b) -5 °C



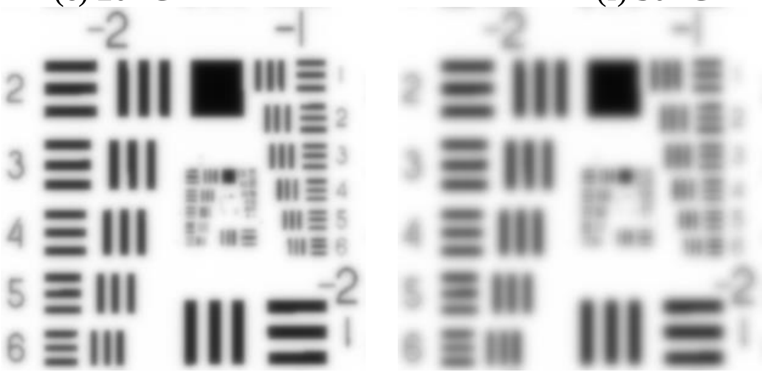
(c) 0 °C



(d) 10 °C



(e) 20 °C (f) 30 °C



(g) 40 °C (h) 50 °C

Figure 6. *The obtained images of the optical system at different temperature values.*

It can be seen that as the temperature changes further from 20 °C, the image quality is reduced compared to that at 20 °C, the larger the temperature change, the worse the image quality. The image dataset of thermal imaging objectives at these different values is used to train the parameters in the U_net network to restore images at different temperatures to images at 20 ^{o}C. Building an image set for training is an important task in optimization using deep learning techniques. In this paper, high-quality and low-quality image sets need to be built to train the deep learning network. In this paper, the high-quality image set will correspond to the images at 20 ^{o}C. Meanwhile, the low-quality image set will correspond to images at temperatures in the range from -5 ^{o}C to 50 ^{o}C. Data sets are generated with a temperature jump of 5 °C. In this paper, the low-quality image set includes 1600 images.

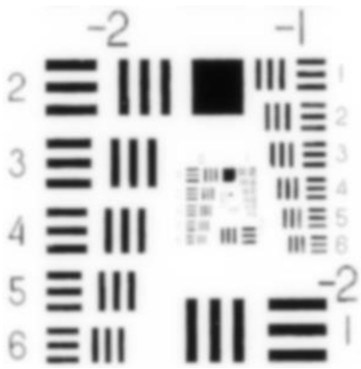
4. SIMULATION RESULTS

In U_net model, two important parameters that need to be considered are Batch size and Learning rate. Batch size is the number of data samples that are fed into training in one computation. When the data is too large, using the entire data can cause memory overflow, so it is necessary to divide the data into small parts (batches) to process each part in each epoch. Although it helps avoid memory overflow and maintains the system's performance, calculating the loss function based on each batch can lead to not covering the entire data, affecting the training speed and the decreased of loss function. Meanwhile, the learning rate is a coefficient in the training process, between 0 and 1, controlling the rate of loss function’s decrease. This is an important parameter that needs to be optimized to achieve the best convergence of the model. To optimize the learning rate, it is often started from a large value and gradually decreased until the smallest loss point is reached.

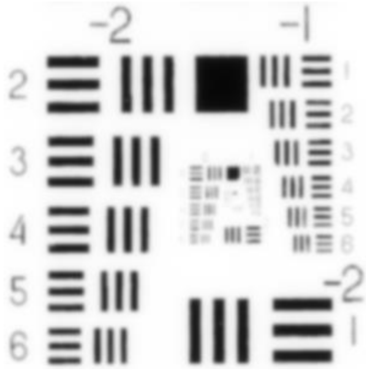
The computer configuration used to train the network is Google Colab with 15GB GPU RAM, 12.7 GB system RAM. The deep learning network will optimize the parameters in the network to restore low-quality images to high-quality images. The training time of the deep learning network for uneven temperature ranges is because the farther away from the design temperature at 20 ^{o}C, the longer the training time will be because the image loses many restored features.

Two functions are used to evaluate the quality of restored images, including SSIM (Structural Similarity Index Measurement) and PSNR (Peak Signal-to-Noise Ratio). SSIM is used to measure the similarity between two images. The value of SSIM ranges from 0 to 1, where SSIM =1 represents the level of complete similarity between two images. Meanwhile, PSNR is also used to measure the quality of the restored signal. PSNR is expressed in decibels units (dB). The higher PSNR value, the better the restored image quality.

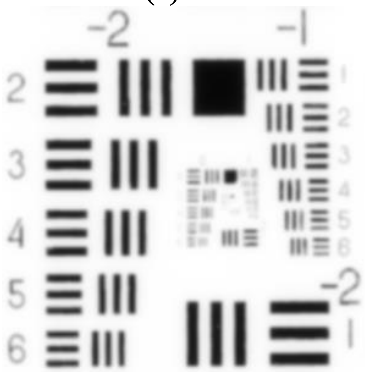
The restored images by using the U_net deep learning network is shown in figure 7. The obtained image quality at different temperatures has improved in comparison with images at the same temperature in figure 6, except at temperature 20. The SSIM and PSNR indices at different temperatures are shown in table 2 for the set of 200 original images. Table 2 shows that the quality of the restored images has significantly improved SSIM and PSNR values compared to the SSIM and PSNR values of the images before restoration. That means the proposed new method compensates for temperature changes for thermal imaging objectives.



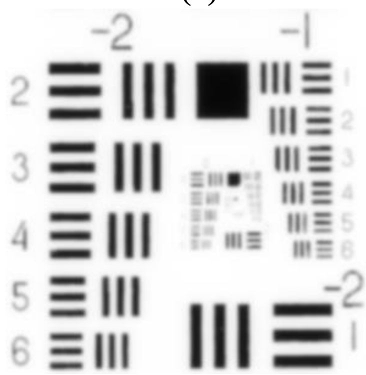
(a) -5 °C



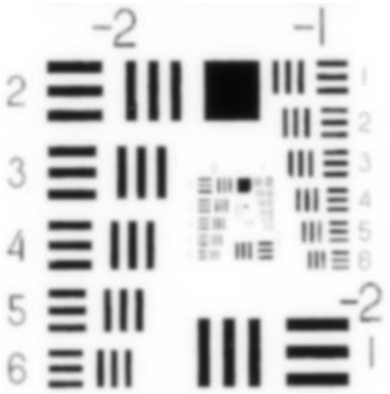
(b) 0 °C



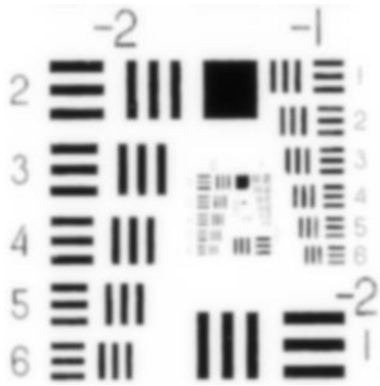
(c) 10 °C



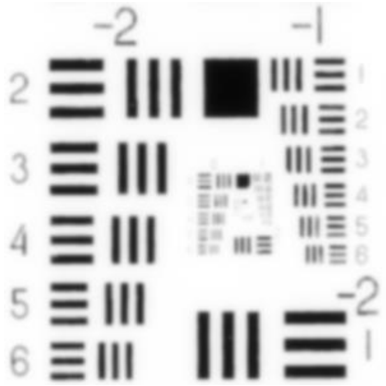
(d) 20 °C



(e) 30 °C



(f) 40 °C



(g) 50 °C

Figure 7. *The Recovered image obtained by the proposed method.*

Table 2. *Some comparison results for the deep learning networks.*

	Temperature	-5 °C	0 °C	10 °C	20 °C	30 °C	40 °C	50 °C
Before restoration	SSIM	0.48	0.64	0.72	1.00	0.71	0.65	0.45
	PSNR	17.30	21.54	27.36		28.04	22.19	16.72
After restoration	SSIM	0.85	0.89	0.92	0.95	0.92	0.88	0.84
	PSNR	28.20	29.12	30.07	34.10	31.02	29.78	28.12

Deep learning techniques offer advantages in image processing. However, it also faces difficulties in practical application, such as requiring strong machine configuration and high cost. However, with the current strong development of semiconductor chips, this solution can be applied in real systems that require fast signal processing speed.

5. CONCLUSIONS

The paper introduced a new method to overcome the influence of temperature changes on the quality of thermal imaging systems. The method to compensate for thermal changes in the image quality by applying deep learning techniques is presented. The U_net deep learning algorithm has been built and applied to restore images with good quality when the temperature changes. The optical system simulation model has been built demonstrating that our method not only maintains outstanding image quality over a temperature range of -5 °C to 50 °C but is also capable of expanding wide to accommodate wider temperature ranges.

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TÓM TẮT

Bù ảnh hưởng nhiệt độ đến chất lượng tạo ảnh của vật kính ảnh nhiệt bằng sử dụng kỹ thuật học sâu

Vật kính ảnh nhiệt được làm từ các vật liệu hồng ngoại có hệ số giãn nở nhiệt lớn như Ge, Si, ZnSe,... Khi nhiệt độ thay đổi dẫn đến sự thay đổi chiết suất, bán kính cong và độ dày của vật kính mà gây ra lượng dịch chuyển defocus làm giảm chất lượng tạo ảnh của vật kính ảnh nhiệt. Trong bài báo này, chúng tôi đề xuất một phương pháp mới giúp bù lại sự ảnh hưởng của sự thay đổi nhiệt độ đến chất lượng của vật kính ảnh nhiệt bằng kỹ thuật học sâu. Sự thay đổi nhiệt độ của vật kính ảnh nhiệt được đo bằng cảm biến nhiệt. Sau đó, một mạng U_net được dùng để khử ảnh hưởng nhiệt độ đến chất lượng tạo ảnh của vật kính ảnh nhiệt mà không cần dịch chuyển, thay thế quang học nào vào vật kính ảnh nhiệt. Kết quả mô phỏng chỉ ra rằng phương pháp được đề xuất có kết quả tốt, có thể bù lại ảnh hưởng của sự thay đổi nhiệt độ lên vật kính ảnh nhiệt trong dải nhiệt độ biến thiên rộng từ -5 °C đến 50 °C.

Từ khoá: Vật kính ảnh nhiệt; Bù sự thay đổi nhiệt độ; Kỹ thuật học sâu.