# Resolution Enhancement for Thermographic Inspection in Industrial Plant Using Deep Convolutional Networks

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**Abstract –**

**As the importance of maintainability for the energy efficiency of industrial plants is emphasized, thermographic inspection has been widely used as a key technique. However, the thermographic inspection cannot provide clear information due to the limitation of low resolution in inspecting wide areas where the worker cannot acquire data in close, such as hazardous environments and the ceiling with pipelines. Therefore, this paper proposes a resolution enhancement method for thermographic inspection in industrial plants based on deep convolutional network. The proposed network involves patch extraction and representation, non-linear mapping, and reconstruction. The proposed method was validated with 210 thermal images obtained from real cogeneration plants. Experimental results show that the method can provide the clear boundaries of instruments with an average PSNR of 32.51, which is superior than the bicubic interpolation of 29.92. The proposed method can be implemented in energy efficiency monitoring and automatic defect detection for thermal inspection in industrial plants by helping to detect defects that can be unchecked in low resolution images.**

**Keywords –**

**Thermographic inspection; Industrial plants; Resolution enhancement; Convolutional deep networks**

## 1 Introduction

As demand for electricity increases, the importance of the energy efficiency of an industrial plant becomes a critical issue. Chen et al. [1] demonstrate that the energy efficiency of industrial plants can be achieved through efficient maintainability. With emphasis on the importance of maintainability of industrial plants, many non-destructive evaluation techniques have been proposed as an efficient maintenance method to detect defects in industrial instruments. However, as industrial plants become larger and more complex, most non-destructive evaluation techniques require significant labor resources for maintenance. This may result in insufficient information for evaluation, which makes it difficult to achieve corrective action for defects at optimal times [1]. In addition, most non-destructive evaluation techniques expose the worker to hazardous environments by requiring them to closely approach and inspect the instrument [2]. In this context, thermographic inspection enables short but reliable inspection by allowing the worker to inspect energy efficiency for many areas at a distance without needing to access instruments during maintenance [3, 4].

Despite the advantages of thermographic inspection, thermal images have limitations due to their low resolution. When inspecting areas of industrial plants where a number of instruments are installed, a thermal image with insufficient resolution cannot provide clear information on critical defects. This problem can cause the inspector to be unaware of a critical defect and leave the defect unchecked. Unchecked critical defects cannot only lead to energy losses of industrial plants, but also have far-reaching consequences. In order to ensure the resolution of the thermal data, acquiring data from close to the instruments is inefficient and impossible in pipelines installed on the ceiling or in hazardous environments that people cannot approach. In this context, it is necessary to enhance the resolution of the thermal image for thermographic inspection in industrial plants.

Over the past few years, some studies have been carried out to enhance the resolution of thermal images to address these low-resolution limitations [5-8]. Recently, with starting with a study by Dong et al. [9], the deep learning method has been successfully applied to improve the resolution of a single image, so many studies using deep convolutional networks have been actively conducted [10-12]. Choi et al. [12] have demonstrated that a convolution neural network can be successfully applied to thermal image enhancement.

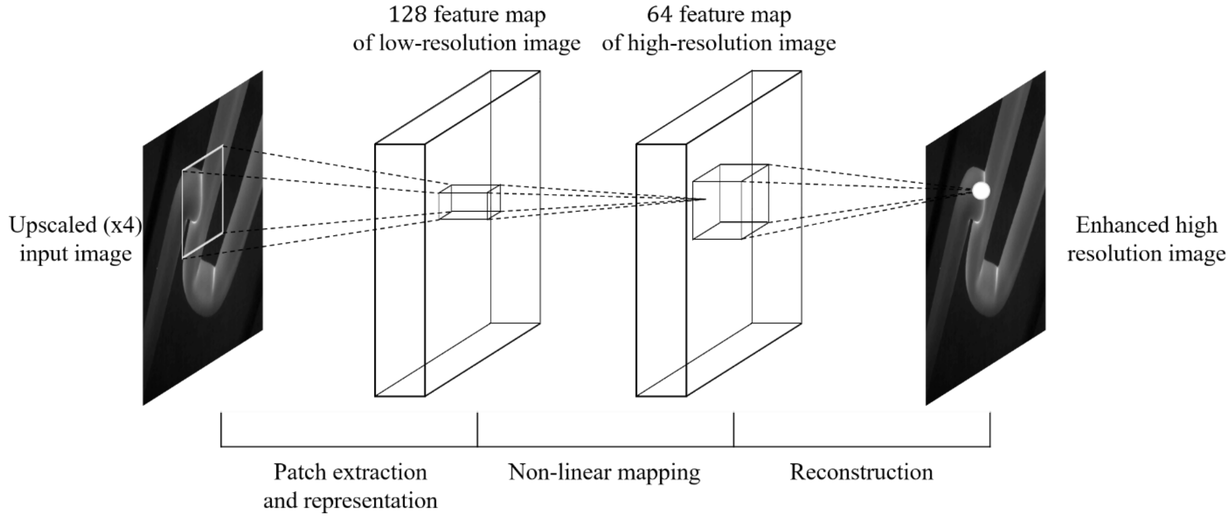


Figure 1. Network structure for super-resolution of thermographic inspection

However, Choi et al. [12] used an RGB (red-green-blue) dataset converted to gray scale as a training dataset. This process cannot be applied to thermographic inspection that utilizes the thermal value of acquired data, because it can distort acquired thermal values guided by the RGB image. Therefore, none have studied the method that can enhance the resolution of the thermal image for thermographic inspection in industrial plants. This study proposes a thermal image enhancement method for efficient thermographic inspection of industrial plants based on deep convolutional networks. The proposed method was evaluated by using a thermal dataset obtained from actual industrial plants.

## 2 Methodology

For resolution enhancement of thermographic inspection, this study uses a deep convolutional network inspired by C. Dong et al. [9, 10]. The configuration of the network is outlined in Fig. 1.

### 2.1 Proposed Networks

In pre-processing, the input image with low resolution is upscaled to the desired size of the high-resolution image using bicubic interpolation. This study used only gray channel for the input image by extracting temperature value from raw images. After pre-processing, there are three convolution layers that are patch extraction and representation, non-linear mapping, and reconstruction separately.

In the first layer, patch extraction and representation operation extracts overlapping patches from the upscaled image and represent each as high-dimensional vectors. In this paper, we use a larger network with the filter number of the first and second layers, because a superior performance can be achieved by a larger network [10]. We applied 128 filters with a size of $9 \times 9$ in the first layer. Therefore, output is generated as a 128-dimensional feature map. In this layer, the Rectified Linear Unit (ReLU) [13] is used as an activation function. In the second layer, each of the high-dimensional vectors from the first layer is mapped onto another high-dimensional vector. This operation is equivalent to applying filters with the size of $1 \times 1$. We set the number of filters as 64 in this operation. In the last layer, the enhanced output image is generated by aggregating the representations from the second layer. This layer operates as like the average pooling layer in traditional methods.

### 2.2 Training

This study used the 205 thermal images with resolution $640 \times 480$ taken from a cogeneration plant as training dataset. Figure 2 shows some examples of the training dataset. For training, the high-resolution ground truth images are cropped as sub-images with the size of $33 \times 33$ and the stride of 14. The sub-images are blurred using Gaussian kernel and sub-sampled by the upscaling factor of four. Finally, sub-images are generated by upscaling using bicubic interpolation with the same factor.

In the training phase, the parameters as weights and biases of filters are optimized in a way that minimizes loss. In this paper, mean squared error (MSE) is used as the loss function between input low-resolution images and the high-resolution images that are ground truths.

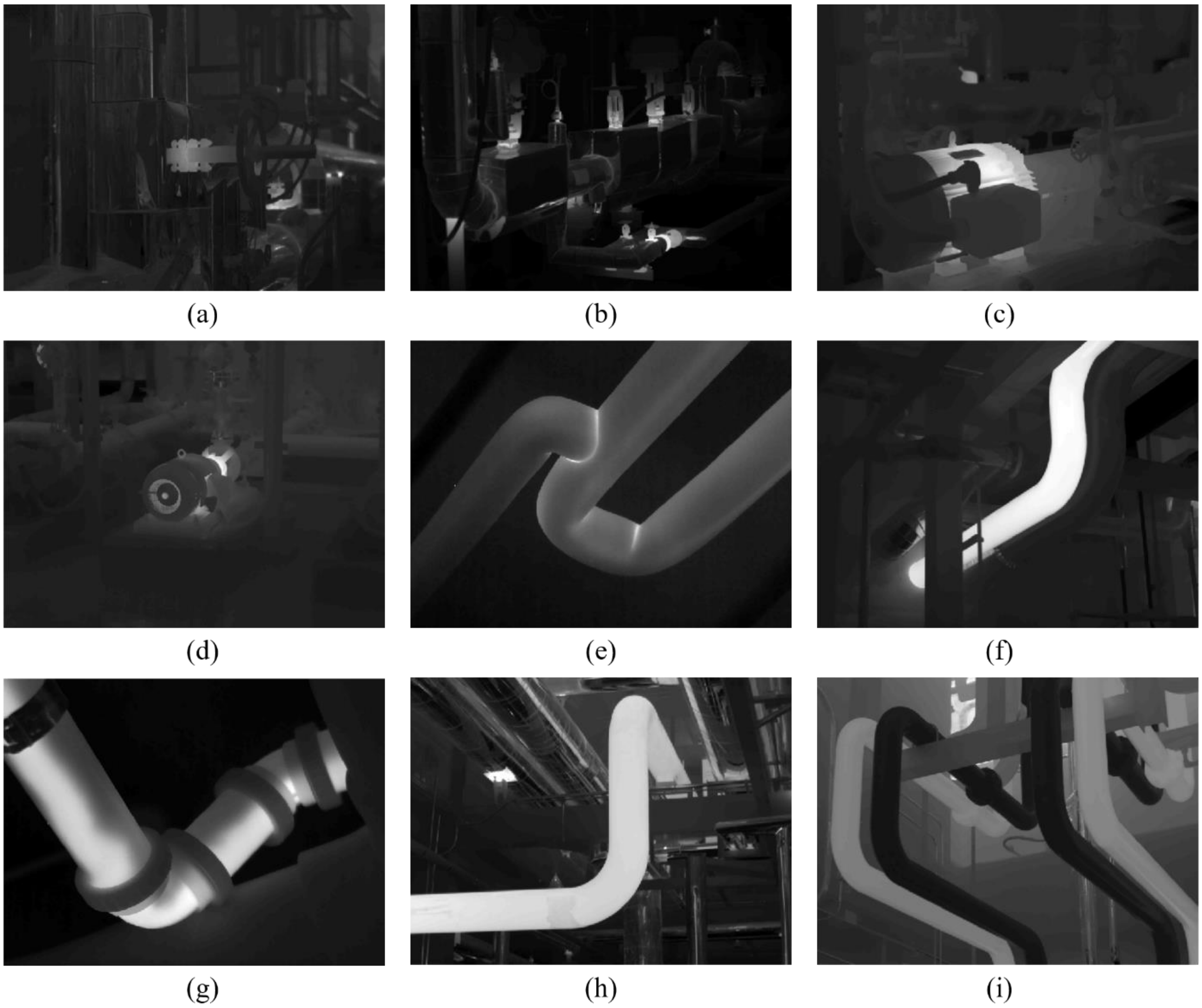


Figure 2. Examples of thermal image from cogeneration plant: (a) – (d) instruments; and (e) – (i) pipelines.

The loss function of MSE is below:

$$L(\theta) = \frac{1}{n}\sum_{i=1}^{n} \| F(X^i;\theta) - G^i \|^2 \qquad (1)$$

where $\theta$ is the parameters consisting weights and biases of filters, $n$ is the number of training samples, $F(X^i;\theta)$ is $i$-th reconstructed image and $G^i$ is a ground truth image. Therefore, the parameters are updated so that $F(X^i;\theta)$ is reconstructed close to $G$ by calculating the loss every time it iterates from end to end. The parameter optimization is held by using stochastic gradient descent with back-propagation. We used a learning rate of $10^{-4}$ for the first and second layers. The smaller learning late of $10^{-5}$ is used for the last layer as suggested in Dong et al. [9].

## 3 Experimental Results

To measure the performance of the resolution enhancement, we employed peak signal-to-noise ratio (PSNR). The PSNR is the most common quantitative evaluation of resolution enhancement [11,12]. For evaluating the proposed method, five thermal images from real industrial plants were used a test dataset (Figure 3 (a)). We compared the performance of the proposed method with bicubic interpolation which is one of the baseline method in resolution enhancement [12,14].

Figure 3 shows the resolution enhancement results of the proposed method. We used the model obtained at $2 \times 10^6$ iteration of the proposed networks. As can be seen in Figure 3 (d), a much sharper image is produced using the proposed method compared to input image (b)

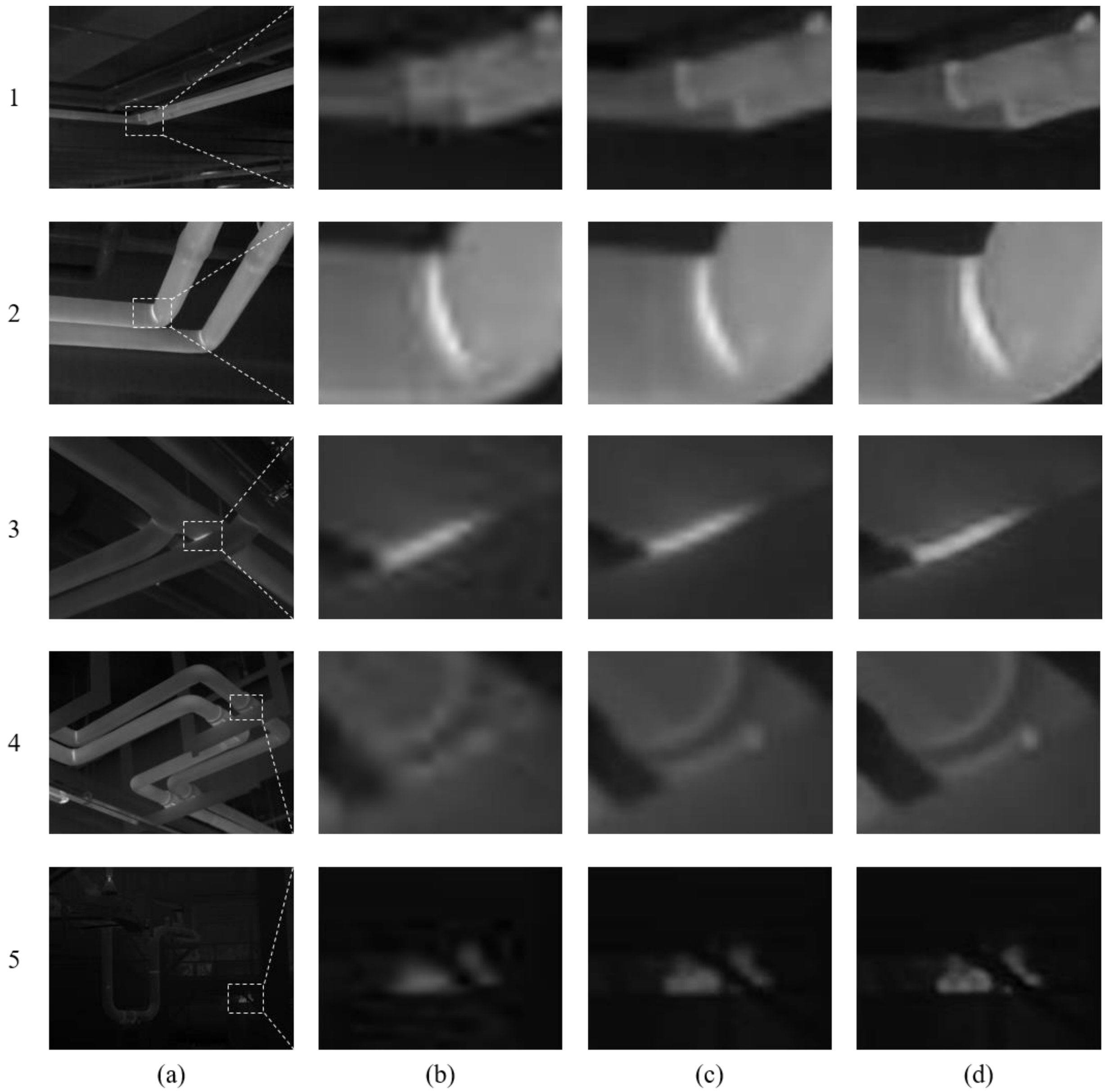


Figure 3. Resolution enhancement results of five test images: (a) ground truth; (b) input; (c) bicubic interpolation; and (d) proposed method

and bicubic interpolation (c). This shows that blurry boundaries of defects and other instruments in input low-resolution thermal images can changed to clear boundaries through the method proposed in this study. Table 1 shows the quantitative results as average PSNR for test dataset. For each test image, the PSNR of the proposed method shows the superior performance over bicubic interpolation. Therefore, the results show that the proposed method for resolution enhancement can be effectively applied in thermographic inspection for industrial plants.

Table 1 Resolution enhancement results (PSNR)

| Test images | Bicubic | Proposed |
|---|---|---|
| 1 | 38.88 | 41.23 |
| 2 | 38.33 | 40.94 |
| 3 | 42.52 | 44.39 |
| 4 | 39.03 | 40.89 |
| 5 | 45.59 | 46.33 |
| Average | 40.87 | 42.75 |

## 4 Conclusion

This study proposed a method for thermal image resolution enhancement using deep convolutional networks, with the goal of providing clear information about instruments installed in areas where it is impossible for workers to acquire data from nearby, such as pipelines on the ceiling or instruments in a hazardous environment. The experimental results show that the proposed method could produce a far clearer thermal image of actual industrial plants. The proposed method is expected to help identify the defects of instruments that may not show up in low-resolution thermal images. In future research, we will focus on automatically detecting defects based on the improved data using the proposed method.

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## References

[1] Chen, K. Y., Chen, L. S., Chen, M. C., and Lee, C. L. Using SVM based method for equipment fault detection in a thermal power plant. *Computers in industry*, 62(1):42–50, 2011.

[2] Burri, M., Nikolic, J., Hürzeler, C., Caprari, G., and Siegwart, R. Aerial service robots for visual inspection of thermal power plant boiler systems. In *Proceedings of Applied Robotics for the Power Industry 2012 2nd International Conference*, page 70–75, Zurich, Switzerland, 2012.

[3] Fox, M., Coley, D., Goodhew, S., and de Wilde, P. Thermography methodologies for detecting energy related building defects. *Renewable and Sustainable Energy Reviews*, 40:296–310, 2014.

[4] Junga, P., & Trávníček, P. Diagnostics of the thermal defects of the walls on the solid-state biogas plant. *International Journal of Sustainable Energy* 35(6):554–565, 2016.

[5] Lai, R., Yang, Y. T., Wang, B. J., and Zhou, H. X. A quantitative measure based infrared image enhancement algorithm using plateau histogram. *Optics communications* 283(21):4283–4288, 2010.

[6] Bai, X., Zhou, F., and Xue, B. Infrared image enhancement through contrast enhancement by using multiscale new top-hat transform. *Infrared Physics & Technology*, 54(2) 61–69, 2011.

[7] Zhao, J., Chen, Y., Feng, H., Xu, Z., and Li, Q. Infrared image enhancement through saliency feature analysis based on multi-scale decomposition. *Infrared Physics & Technology*, 62:86–93, 2014.

[8] Yuan, L. T., Swee, S. K., and Ping, T. C. Infrared image enhancement using adaptive trilateral contrast enhancement. *Pattern Recognition Letters* 54:103–108, 2015.

[9] Dong, C., Loy, C. C., He, K., and Tang, X. Learning a deep convolutional network for image super-resolution. In *Proceedings of European Conference on Computer Vision*, page 184–199, Amsterdam, Netherlands, 2016

[10] Dong, C., Loy, C. C., He, K., and Tang, X. Image super-resolution using deep convolutional networks. *IEEE transactions on pattern analysis and machine intelligence*, 38(2):295–307, 2016.

[11] Kim, J., Kwon Lee, J., & Mu Lee, K. Accurate image super-resolution using very deep convolutional networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, page 1646–1654, Las Vegas, USA, 2016.

[12] Choi, Y., Kim, N., Hwang, S., and Kweon, I. S. Thermal Image Enhancement using Convolutional Neural Network. In *Proceedings of the IEEE Conference on Intelligent Robots and Systems*, pages 223–230, Daejeon, South Korea, 2016..

[13] Nair, V., and Hinton, G. E. Rectified linear units improve restricted boltzmann machines. In *Proceedings of the 27th international conference on* machine learning, pages 807–814,(ICML-10), Haifa, Israel, 2010.

[14] Shao, Wen-Ze, Hai-Song Deng, and Zhi-Hui Wei. A posterior mean approach for MRF-based spatially adaptive multi-frame image super-resolution. *Signal, Image and Video Processing*, 9(2):437–449, 2015.