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Abstract

Infrared thermography is a valuable non-destructive tool for inspection of materials. It measures the surface temperature evolution, from which hidden defects may be detected. Yet, thermal cameras typically have a low native spatial resolution resulting in a blurry and low-quality thermal image sequence and videos.
In this study, a novel adversarial deep learning framework, called Dual-IRT-GAN, is proposed for performing super-resolution tasks. The proposed Dual-IRT-GAN attempts to achieve the objective of improving local texture details, as well as highlighting defective regions. The generated high-resolution images are then delivered to the discriminator for adversarial training using GAN's framework.
The proposed Dual-IRT-GAN model, which is trained on an exclusive virtual dataset, is demonstrated on experimental thermographic data obtained from fibre reinforced polymers having a variety of defect types, sizes, and depths. The obtained results show its high performance in maintaining background colour consistency and removing undesired noise, and in highlighting defect zones with finer detailed textures in high-resolution.

KEYWORDS: Deep learning; Super-resolution; GAN; Infrared thermography; Composite; Defect detection; Non-destructive testing

1. Introduction

Nowadays, carbon fibre reinforced polymer (CFRP) and glass fibre reinforced polymer (GFRP) composites are widely used in a range of applications, with a focus on the aerospace and automotive industries. Therefore, Non-Destructive Testing (NDT) has become a crucial tool for guaranteeing the structural integrity of composite components.
Active InfraRed Thermography (IRT) is an attractive non-destructive testing (NDT) technique for diagnostic purposes that utilizes an IR camera to monitor the heat response promptly and precisely in order to discover and quantify defects [1]. The information of high-frequency textures, however, tends to be lost in the received thermal images due to the nature of an infrared imaging system having a limited number of pixels and pixel size. As a result, the obtained thermal images become blurry and fuzzy. This forms a hot research topic termed single image super-resolution (SISR).

In recent years, CFRP and GFRP have gained popularity in recent years due to their high strength and low weight. Numerous signal post-processing approaches [2-4] have been used to determine the presence of defects in CFRP and GFRP specimens. These approaches, however, are restricted in resolution and are susceptible to noise, regardless of the capability in defect identification.
In order to overcome the difficulties presented by low resolution (LR), we propose a defect-aware deep adversarial learning framework, as a continuation of previous work IRT-GAN [5], termed Dual-IRT-GAN, to enhance the SR image quality of real LR infrared images by leveraging the defect information.

2. The Dual-IRT-GAN architecture

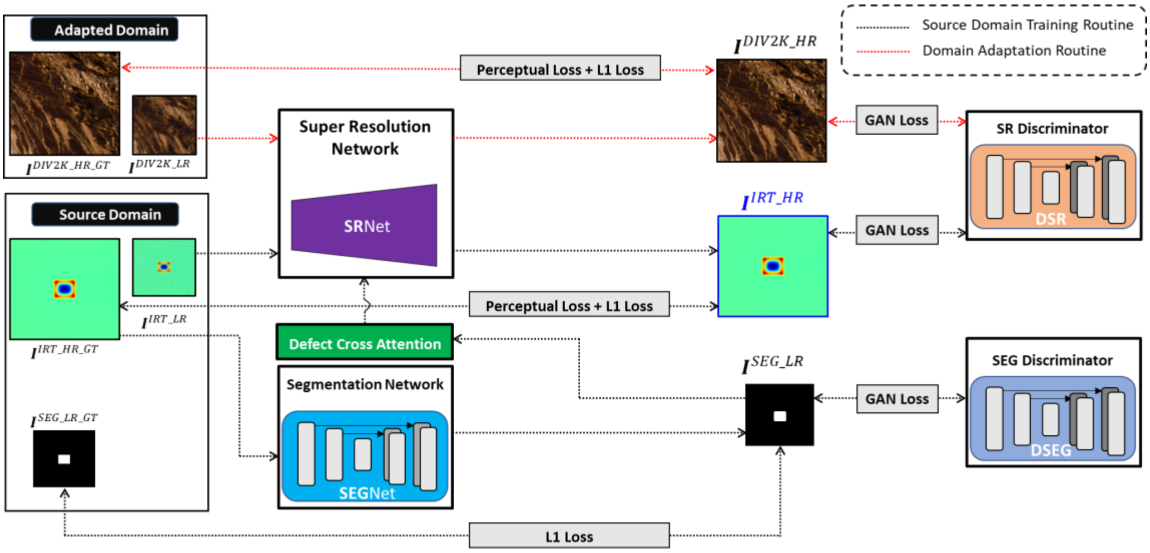


Figure 1. The overview of the proposed Dual-IRT-GAN framework

The overview of the proposed Dual-IRT-GAN model at the general architecture level is displayed in Figure 1. In general, it consists of two generators: SRnet and SEGnet and two discriminators DSR and DSEG, with SRnet attempting to generate plausible photo-realistic HR infrared images I^{IRT_HR} with a scaling factor of 4 from LR infrared images $\boldsymbol{I}^{IRT\_LR}$, and SEGnet aiming to segment the defects $\boldsymbol{I}^{SEG\_LR}$ from ground-truth LR infrared images $\boldsymbol{I}^{IRT\_LR}$ in composites. To determine their authenticity, the generated HR infrared images from SRnet and segmentation maps from SEGnet are fed into two discriminators, DSR and DSEG, respectively.
To compensate for the domain gap between the infrared images and realistic real-world images, a domain adaptation process is incorporated into the Dual-IRT-GAN training process to bias the parameters in SRnet and ensure SRnet learning to reconstruct with realistic textures and maintain color consistency. The SRnet is additionally trained on LR/HR ($\boldsymbol{I}^{IRT\_LR}$/$\boldsymbol{I}^{IRT\_HR\_GT}$ in Figure 1) image pairs from the DIV2K dataset [6], containing 1000 real-world 2k resolution images.
A detailed description of the generator and discriminator network architectures is described in the Figure 2 and Figure 3.
The proposed Generator, inspired by ESRGAN [7], unifies two subnets SRnet and SEGnet to jointly learn both tasks of SR image generation and defect segmentation,

respectively, in an end-to-end training framework via the trade-off between reconstruction loss and segmentation loss.

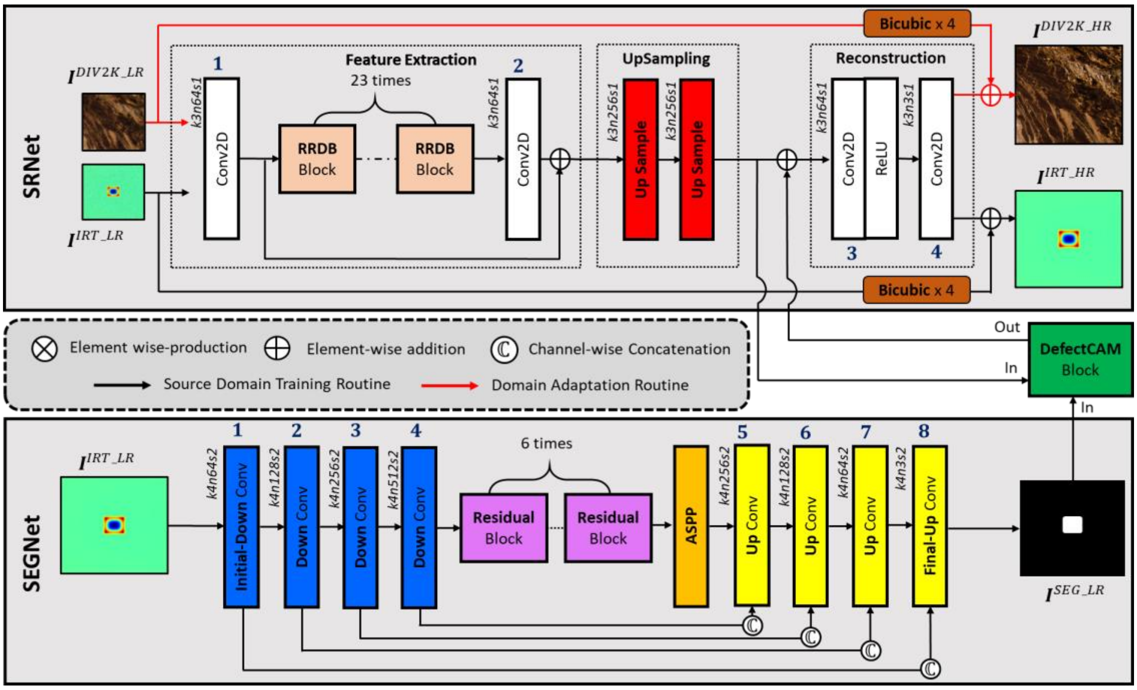


Figure 2. The network architecture of the generators (SRnet and SEGnet)

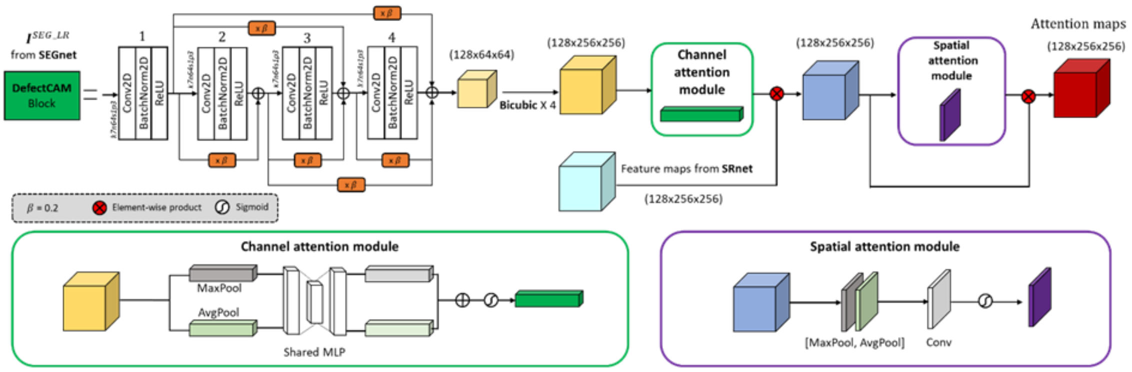


Figure 3. The proposed defect cross-attention module (DefectCAM) for the Dual-IRT-GAN

To customize our SR task, modifications are designated in an effort to generate more photorealistic HR images with finer textures, as shown in Figure 2. As an auxiliary network, SEGnet attempts to investigate all potential defects in the IRT dataset of composites, thereby guiding and assisting SRnet in concentrating on defect areas via a proposed DefectCAM block, see Figure 3, inspired by Convolutional Block Attention Module(CBAM) [8].

Inspired by real-ESRGAN [9], the discriminators DSR and DSEG in this study employ the identical Unet architecture with spectral normalization to determine the authenticity or falsity of generated HR images ($\boldsymbol{I}^{IRT\_HR}$ and $\boldsymbol{I}^{DIV2K\_HR}$) and segmentation maps ($\boldsymbol{I}^{SEG\_HR}$), respectively. Rather than focusing exclusively on local textures originating from PatchGAN [10], a modification to the discriminator in real-ESRGAN by paying extra attention to a global structure is formulated to the original PatchGAN output. The framework of the discriminators DSR and DSEG is displayed in Figure 4.

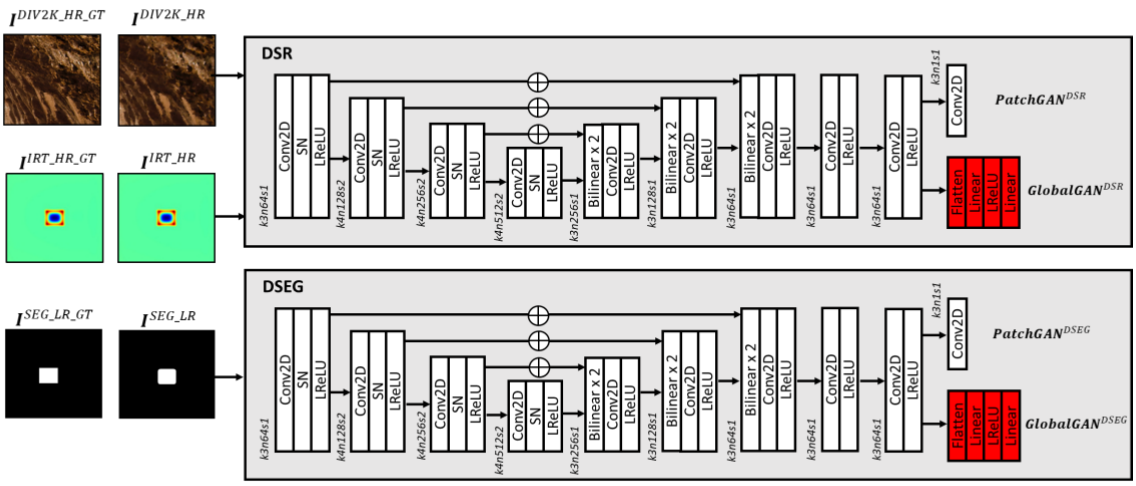


Figure 4. The architecture of DSR and DSEG

3. Training

3.1 Loss function

In this work, three types of loss functions are used concurrently to achieve the desired result: Content loss $\boldsymbol{L_1}$, Perceptual loss $\boldsymbol{L_{VGG}}$ and Adversarial loss $\boldsymbol{L_{ADV}}$. The total loss $\boldsymbol{L_{tot}}$, therefore, can be therefore concluded as

$$L_{tot} = \alpha\, L_{VGG} + \beta\, L_1 + \gamma\, L_{ADV} \tag{1}$$

Where $\boldsymbol{\alpha}, \boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are the loss weights. For more details, the readers are referred to [11].

3.2 Implementation details

The proposed Dual-IRT-GAN model is trained entirely in the absence of experimental data using a virtual dataset implemented in the Fortran90 environment, see [11] for more details. Prior to training the Dual-IRT-GAN, the pre-processing of virtual numerical IRT dataset in source-domain training and DIV2K dataset in domain-adaptation training is conducted to obtain the original training HR image set $\boldsymbol{I}^{IRT\_HR\_GT}$ and $\boldsymbol{I}^{DIV2K\_HR\_GT}$ by randomly cropping with a size of 256×256 and the corresponding training LR image set $\boldsymbol{I}^{IRT\_LR}$ and $\boldsymbol{I}^{DIV2K\_LR}$ with a size of 64×64 are obtained following a second-degradation process [8]. The Dual-IRT-GAN is implemented using the PyTorch framework in Python (Python 3.7.10 and CUDA v11.0.221) using an NVIDIA Quadro RTX 6000 GPU card with 24GB of RAM. The IRT-GAN model employs the Adam optimizer with an initial learning rate lr = 2×10^{-4}, and momentum parameters β_1=0.9, β_2=0.999. The batch size for training is 8. The training epoch is set to be 1500, empirically shown to yield a good performance.

4. Validation on experimental IRT dataset

A schematic diagram of the thermographic setup is displayed in Figure 5(a). The optical energy input is supplied by a Hensel linear flash lamp with 6 kJ energy and 5 ms flash duration, and a FLIR A6750sc infrared camera is used to capture the sample's surface temperature.

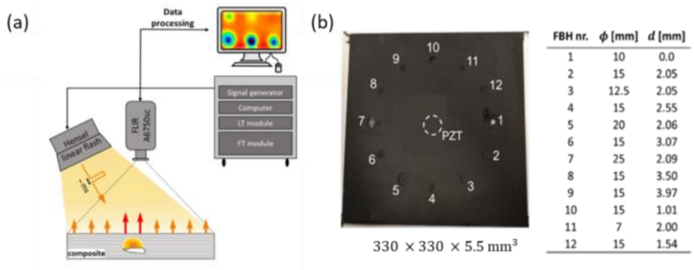
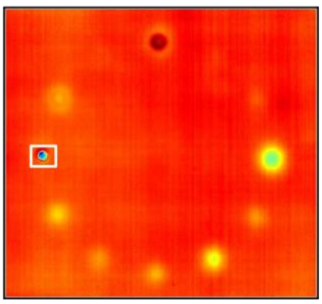
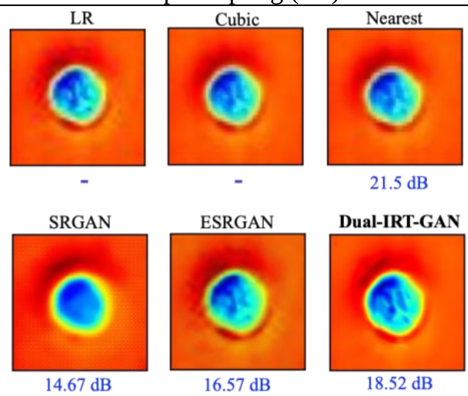


Figure 5: (a) Schematic of the experimental setup for flash thermography, (b) photograph and defect parameters of $\mathrm{CFRP_{FBH}}$

The testing sample, referred to as $\mathrm{CFRP_{FBH}}$, is a 5.5 mm thick compression-moulded CFRP plate with a quasi-isotropic stacking sequence of [(+45/0/-45/90)3]s. From the backside of the sample, 12 circular FBHs with diameters ranging from 7 to 25 mm and a remaining thickness of up to 4 mm were milled.

Table.1 The inference outcomes for $\mathrm{CFRP_{FBH}}$ dataset utilizing the Bicubic interpolation, Nearest interpolation, SRGAN, ESRGAN, and Dual-IRT-GAN models

Sample	Up-sampling (×4)
$\mathrm{CFRP_{FBH}}$ (512 X 512) 	

From Table.1, we observe that the proposed model is capable of producing relatively cleaner and sharper edges and accurately preserving finer textures, resulting in HR images that are perceptually plausible to humans. In order to evaluate the quality of HR images that were generated, a widely-used metric known as peak signal-to-noise ratio (PSNR) [12] was employed. However, due to the absence of a ground-truth reference, a cubic image was used as a reference instead. This poses a challenge because the resulting PSNR values, expressed as blue values in Table.1, may not accurately reflect the true quality of the generated images. For instance, from Table.1, the highest PSNR value can be observed for Nearest up-sampling image.

5. Conclusions

Dual-IRT-GAN, a novel deep learning model, is presented. It consists of a generator with two subnets, SRnet and SEGnet, to jointly perform super-resolution and defect segmentation tasks for infrared images, and two discriminators, DSR and DSEG, to determine the veracity (or falsity) of the generated high-resolution images and segmentation maps, respectively. The Dual-IRT-GAN model can be directed toward learning plausible realistic high-resolution solutions, improving the visibility of defected regions and in-depth textures. This is made possible by the implementation of the DefectCAM Module, which extracts and fuses the attention maps into the feature maps. On the basis of thermographic data obtained from a CFRP sample with FBH defects, the performance of the Dual-IRT-GAN is assessed.

Acknowledgements

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