QIRT'2022
10.21611/qirt.2022.3029
16th Quantitative InfraRed Thermography Conference

IRT-GAN: A GAN framework for automated defect segmentation in composites using infrared thermography

by Liangliang Cheng*, Zongfei Tong*,**, Shejuan Xie** and Mathias Kersemans*

* Mechanics of Materials and Structures (MMS), Ghent University, Technologiepark 46, B-9052 Zwijnaarde, Belgium, *liangliang.cheng@ugent.be, mathias.kersemans@ugent.be*
** State Key Laboratory for Strength and Vibration of Mechanical Structures, Xi'an Jiaotong University, 710049, Xi'an, China, *zongfei.tong@ugent.be*

Abstract

Infrared thermography (IRT) for non-destructive testing of fiber reinforced polymers is becoming increasingly popular in industrial applications. However, conventional post-processing techniques often require intervention by experienced operators to confirm and evaluate defects. To further enhance the detectability of defects and alleviate operator-intervention, this study proposes a deep learning generative adversarial network (GAN) framework, termed IRT-GAN. IRT-GAN takes six pre-processed thermal images as input and progressively fuses them through a multi-headed fusion strategy. As such, the developed IRT-GAN method yields a single segmented defect map in an automated manner. It is worth mentioning that the presented IRT-GAN model has been exclusively trained on virtual data, and it is applied on experimental datasets of fiber reinforced polymers having different defect types, sizes, and depths. A high prediction accuracy is demonstrated, showing the good generalization capacity of the developed IRT-GAN.

1. Introduction

Active infrared thermography (IRT) uses infrared (IR) cameras to quickly and accurately measure thermal responses in order to detect and quantify defects in materials. With the aim of moderating the effects of noise and enhancing the detectability of defects in composites, several post-processing techniques have been developed, such as thermographic signal reconstruction (TSR) [1], principal component thermography (PCT) [2], and pulsed phase thermography (PPT) [3]. What all these techniques have in common, nevertheless, is that they compress the recorded IR data set into a few representative images. Yet, even so, the selection and interpretation of post-processed images in order to detect the presence of defects is not always straightforward. Often, human intervention and experienced operators are needed to perform a proper diagnosis and evaluation of defect profiles.

In this study, a deep learning segmentation model, termed IRT-GAN, is proposed for automatic defect detection in thermal imaging data. The proposed IRT-GAN aims to generate a single unique segmented defect map via a progressive fusion strategy. In contrast to end-to-end deep learning approaches [4], our approach focuses on post-processing images, such as TSR, PCT, or PPT images, and fuses them into a unique segmented defect map. Additionally, our IRT-GAN is solely trained on a virtual database, and then transferred for application on experimental data.

2. IRT-GAN architecture

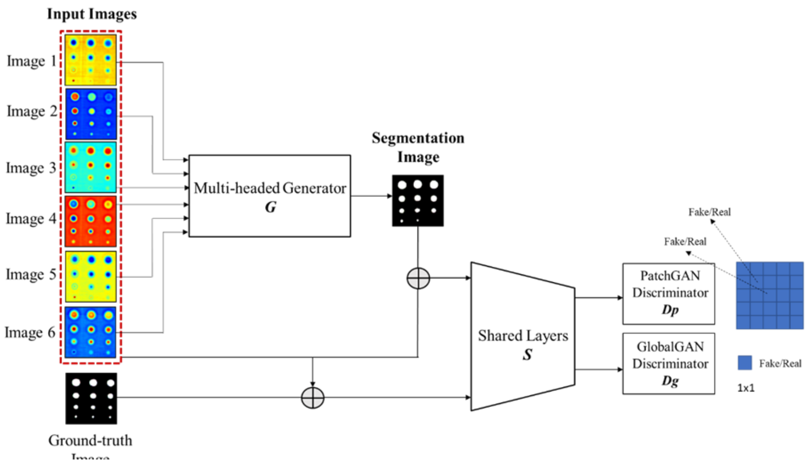


***Fig. 1.** The overall architecture of the developed IRT-GAN method*

The overall architecture of IRT-GAN consists of a multi-headed generator and a dual-path discriminator, as shown in Figure 1. The generator in IRT-GAN uses U-Net [5] as the backbone structure, and consists of an encoder with multiple encoding paths and a decoder. To integrate the features of the six post-processed images (in our case TSR images), the multi-headed encoder first extracts the feature maps independently from the original images and fuses them progressively into a bottleneck feature involving a spatial grouping enhancement layer [6]. It is further passed to the decoder, which generates a unique segmentation defect map together with the skip connection strategy of the encoder. Then, the segmented and ground truth images are concatenated with the original six TSR images to form a 21-channel image matrix and sent to the discriminator to make a judgment on their authenticity. Specifically, the architectures of the generator and discriminator are presented in Fig.2 and Fig.3.

The IRT-GAN is implemented using PyTorch framework in the platform Python (Python 3.7.10 and CUDA v11.0.221). The IRT-GAN model employs the Adam optimizer with an initial learning rate $lr = 1e^{-4}$, and momentum parameters $\beta_1 = 0.5$, $\beta_2 = 0.999$. The batch size for training is 16. The training epoch is set to be 100, empirically shown to yield a good performance.

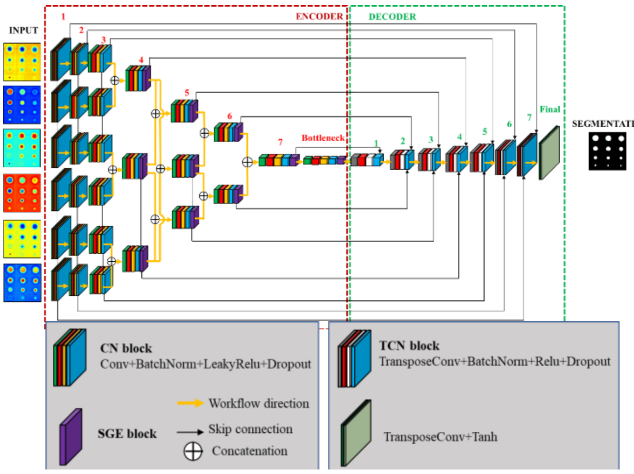


***Fig. 2.** The architecture of the generator G*

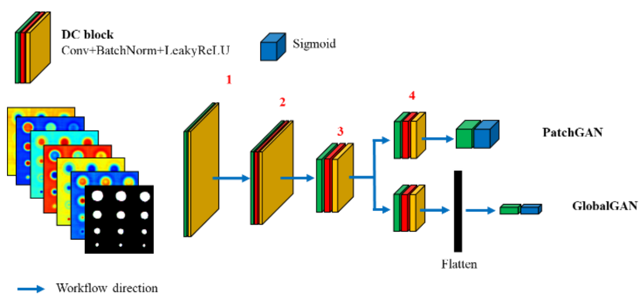
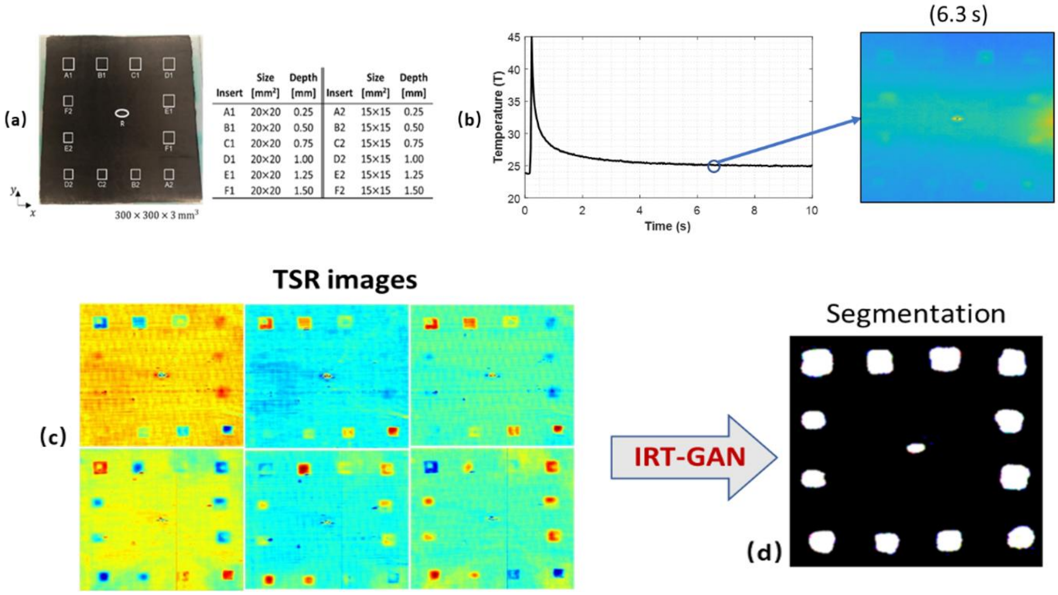


***Fig. 3.** The architecture of the Discriminator D*

3. Results

To demonstrate the performance of the proposed IRT-GAN model, the model is first trained on augmented TSR images from a large virtual dataset (obtained from an in-house developed FE methodology, implemented in Fortran), and then validated on several experimental datasets. As an example, the obtained segmentation result for a carbon fiber reinforced polymer plate, having insert defects with different sizes and depths, is presented in Fig.4.



Insert	Size [mm²]	Depth [mm]	Insert	Size [mm²]	Depth [mm]
A1	20×20	0.25	A2	15×15	0.25
B1	20×20	0.50	B2	15×15	0.50
C1	20×20	0.75	C2	15×15	0.75
D1	20×20	1.00	D2	15×15	1.00
E1	20×20	1.25	E2	15×15	1.25
F1	20×20	1.50	F2	15×15	1.50

Fig.4. *(a) Photograph of CFRP plate and its defect parameters, (b) thermogram at time 6.3s, (c) six processed images from TSR, and (d) segmentation result using our developed IRT-GAN.*

Acknowledgments

Zongfei Tong is a joint Ph.D. student between Ghent University and Xi'an Jiaotong University and is supported by the China Scholarship Council by grant number 202006280481, and is co-funded by Bijzonder OnderzoeksFonds Ghent University (BOF 01N01719).

REFERENCES

[1] Shepard, S. M., & Beemer, M. F. (2015, May). Advances in thermographic signal reconstruction. In Thermosense: thermal infrared applications XXXVII (Vol. 9485, p. 94850R). International Society for Optics and Photonics.
[2] Rajic, N. (2002). Principal component thermography for flaw contrast enhancement and flaw depth characterisation in composite structures. Composite structures, 58(4), 521-528.
[3] Maldague, X., & Marinetti, S. (1996). Pulse phase infrared thermography. Journal of applied physics, 79(5), 2694-2698.
[4] Ruan, L., Gao, B., Wu, S., & Woo, W. L. (2020). DeftectNet: Joint loss structured deep adversarial network for thermography defect detecting system. Neurocomputing, 417, 441-457.
[5] Ronneberger, O., Fischer, P., & Brox, T. (2015, October). U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention (pp. 234-241). Springer, Cham.
[6] Li, X., Hu, X., & Yang, J. (2019). Spatial group-wise enhance: Improving semantic feature learning in convolutional networks. arXiv preprint arXiv:1905.09646.