NDE INSPECTION OF AFP MANUFACTURED CYLINDERS USING AN INTELLIGENT SEGMENTATION ALGORITHM

Christopher Sacco, Anis Baz Radwan, Andrew Anderson, Ramy Harik
University of South Carolina
Columbia, South Carolina

ABSTRACT

This article will discuss the approach and results for the identification of defects on an Automated Fiber Placement (AFP) manufactured cylinder. While the increase in productivity in AFP manufactured structures has allowed for the large-scale production of composite parts, imprecision in process can lead to the production of defects. A comprehensive platform for the inspection of AFP manufactured cylinders for utilizing a profilometry-based data collection approach was used. This data is then processed by a novel machine learning method. The machine learning method is based on the creation of fully convolutional neural networks and is used to fully characterize defects developed on cylindrical parts. Defect information was used to inform the repair of the cylinders and capture defects on cylinders that were intended to have hand placed defects. Cylinders were then used for validation of structural analysis tools.

Keywords: Inspection, AFP, Machine Learning
Corresponding author: Ramy Harik

1. INTRODUCTION

1.1 Purpose

The gaining popularity of AFP and its many emerging subsets has led to the need to generate expert knowledge in the field. A particular concern for those attempting to create composite structures using the AFP process is the potential for the inclusion of manufacturing induced defects in a part. The time considerations produced by manual inspection are notorious [1]. Cemenska et al. [2] suggests that as much as 20% of part manufacturing time is occupied in inspection of parts for defects. A study by Electroimpact has demonstrated that 32% of cycle time during manufacturing is from inspection and rework [3].

In service of improving this process, the authors have developed an automated inspection system to be used to aide AFP operators in the process of identifying defects for rework. This system has been outlined in detail in three previous works and demonstrated on a number of small-scale structures [4]–[6]. The inspection process developed differs from other approaches in a distinct way: the defect data produced includes precise boundary data necessary for a comprehensive evaluation for the significance of the defects. In this document, we will demonstrate the use of our system on the manufacturing of several large cylinders and demonstrate the capability for our system to inform the repair of a large structure using the precise data obtained through the

Copyright 2020. Used by the Society of the Advancement of Material and Process Engineering with permission.

inspection process. Through this, the overall repair time was improved, and targeted repair strategies could be implemented.

1.2 Cylinder Design and Testing

The development of an analysis tool at the McNair Center for the rapid prediction of the structural performance impact of manufacturing defect necessitated the development of test structures to test the model. Cylinders were manufactured on-site at the McNair Center utilizing the Ingersoll Machine Tools Lynx AFP Machine in conjunction with our inspection system. In service to the task, two cylinder dimensions, a 1219.2mm diameter cylinder and a 609.6mm diameter cylinder, were produced in both a defective and pristine configuration. For the defective configuration, defects were hand-placed such that a significant degradation in structural performance could be produced. In both the areas of the defective cylinders that were not intended to be affected by the hand-placed defects and the entirety of the pristine cylinders required large scale inspection and repair for the development of an appropriate test article. Figure 1 shows how the repair process of the cylinders is influenced by the inspection of each ply.

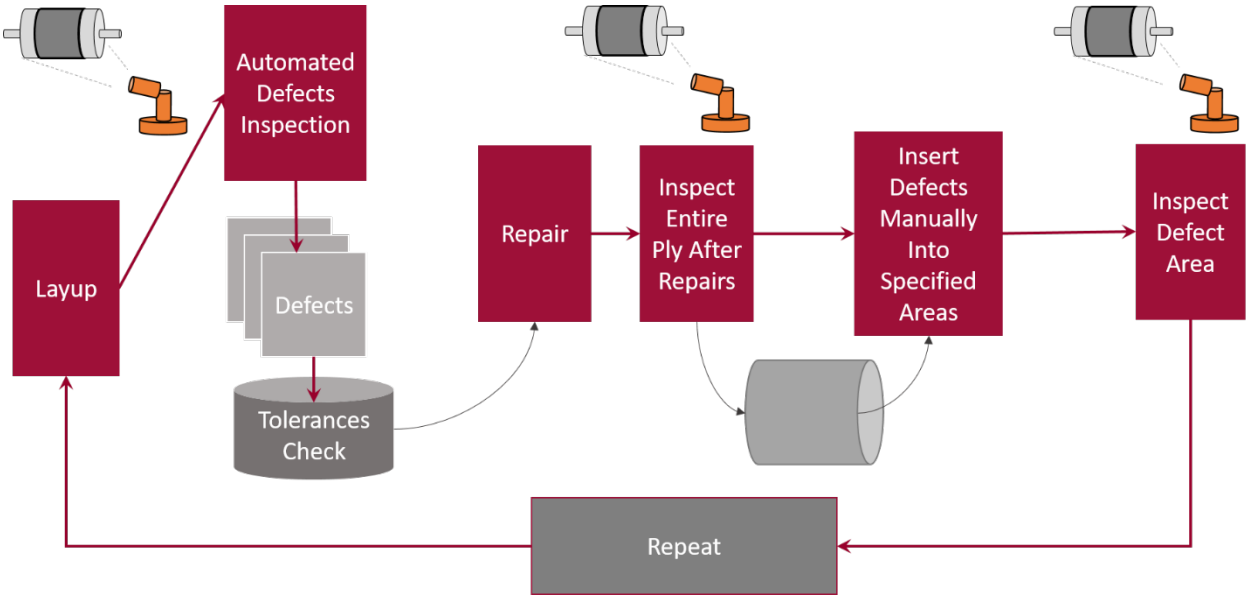


Figure 1: Workflow of Inspection in Manufacturing Process

2. LITERATURE REVIEW

In service of facilitating a discussion on automated inspection of the AFP process, it is useful to discuss composite inspection techniques both during and post-manufacturing. In addition, an introduction to a few key works in the machine learning and computer vision space will also be introduced. In general, the process for automated inspection of composite structures is clustered into two principle domains of research: (1) the physical data collection hardware and (2) the analysis algorithms for processing said data. When combining these two systems together, an automated inspection system for composite parts can be fully realized. To date, there have been a number of key approaches across each domain, with an assorted selection of systems attempting to make the leap towards full automation.

The low visual contrast nature of composite materials implies that traditional imaging techniques are, under most circumstances, ineffective. Therefore, novel alternatives to traditional optical imaging have emerged for the collection of data both across the surface and through a composite part. Thermography uses a source of thermal excitation to monitor the propagation of heat through a part [7]–[11]. Traditionally, halogen bulbs have been used to accomplish the excitation process, though LED sources have shown some positive benefits in the application [12]. By noting the reference propagation of heat through a structure, deviations from this reference can imply a change in material properties or structure. These deviations can denote common composite laminate defects such as voids or delaminations. In the context of AFP, thermography has been used as an in-situ method for the identification of common manufacturing errors, including gaps, overlaps, and twists [13].

Ultrasonic techniques are popular for post-manufacturing inspection, especially with respect to the identification of major sub-surface defects. Ultrasonic inspection uses concentrated sound waves propagated through a material to create an internal mapping of the object. Similar to thermography, where sound propagates differently against a reference, changes in structure are indicated [14]. Common variants of ultrasonic imaging include through transmission and pulsed-echo techniques [15].

While the acquisition of inspection data is a key parameter, the unsorted feature lists produced only push the manual sorting of data through a proxy rather than with human eyes. This improves some of the issues with visual inspection of low contrast composites. However, to move towards an automated system, most or all of this feature extraction and defect identification must happen automatically. One potential solution for this process is the increasingly prevalent use of machine learning (ML) in the analysis of data. A subset of ML, denoted as supervised learning, uses hand-labeled training data to create models that can infer the relationships between data without explicitly modeling the underlying principles connecting said data. This makes ML a strong tool for problems that lack clear definitions for analysis.

ML has become an incredibly useful tool for applications ranging from object detection [16] to natural language processing [17]. The introduction of AlexNet [18] and the massive improvements in image classification accuracy ushered in with it mean that industry ready computer vision tools can be generated readily. Thus, in the creation of our inspection system, ML became a natural tool for the identification of AFP defects.

3. SOLUTION

3.1 Data Acquisition

The hardware for data acquisition was provided by Ingersoll Machine Tools (IMT) in the form of the Advance Composite Structures Inspection System (ACSIS). ACSIS is an AFP inspection system that utilizes profilometry, or rapid 3-dimension height profiling [19], to scan an AFP manufactured part ply-by-ply. The profilometers are actuated on a Kuka KR120 robotic arm that can reach across the entire width of the AFP tooling [Figure 1].

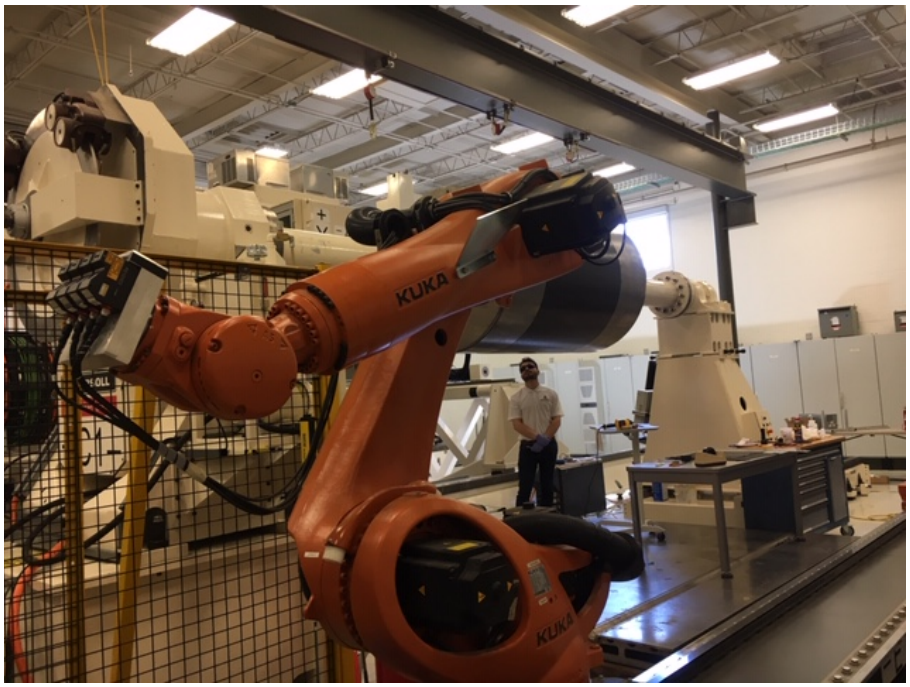


Figure 2: IMT ACSIS Inspection System

The height profiles generated by the profilometers are gated, and then scaled such that each point on the height profile can be embedded into a greyscale image, with the pixel intensity encoding the height information [Figure 2]. The result is a rapidly profiled and generated image that is capable of conveying high resolution surface features along the surface of a ply.

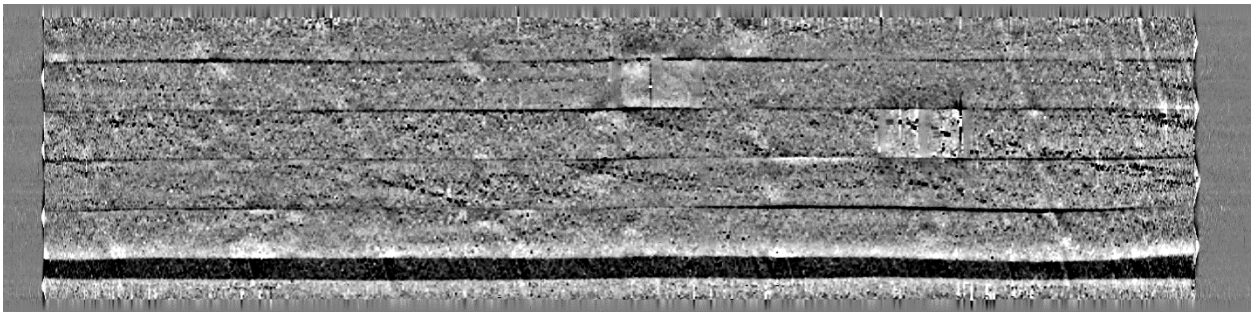


Figure 3: ACSIS Scan Image

3.2 Image Analysis

The essential nature of the analysis algorithms presented in the inspection system have been covered extensively in previous works. For the convenience of the reader, a detailed discussion of the machine learning engine and the user interface developed for operator integration will be left to further reading of the authors previous publications. Rather, a brief discussion of key concepts will be presented with an overview of how the inspection system outlined integrates with the larger AFP manufacturing environment.

3.2.1 Fully Convolutional Neural Network

One key element in the development of an AFP inspection system is the fidelity of defect details provided. While the sliding window approach utilized in a number of previous attempts at machine learning-based inspection can provide high classification accuracy and general location information, more precise information is elusive. For integration into finite element solvers or other third-party applications, precise boundary and location information may be necessary.

To accomplish this, the concept of semantic image segmentation was used as an ML task to derive a blob of pixels locating a defect rather than a patch of image. A Fully Convolutional Network (FCN) has been demonstrated to be an ideal tool for this application [20]. FCNs are entirely consisting of convolution layers that down-sample and then up-sample input vectors to have output vector size match input vector size. This creates a network capable of one-shot pixel-by-pixel classification [Figure 3]. The result embeds semantic meaning into entire pixel regions of an image and generate output with precise boundaries for each object class in an image.

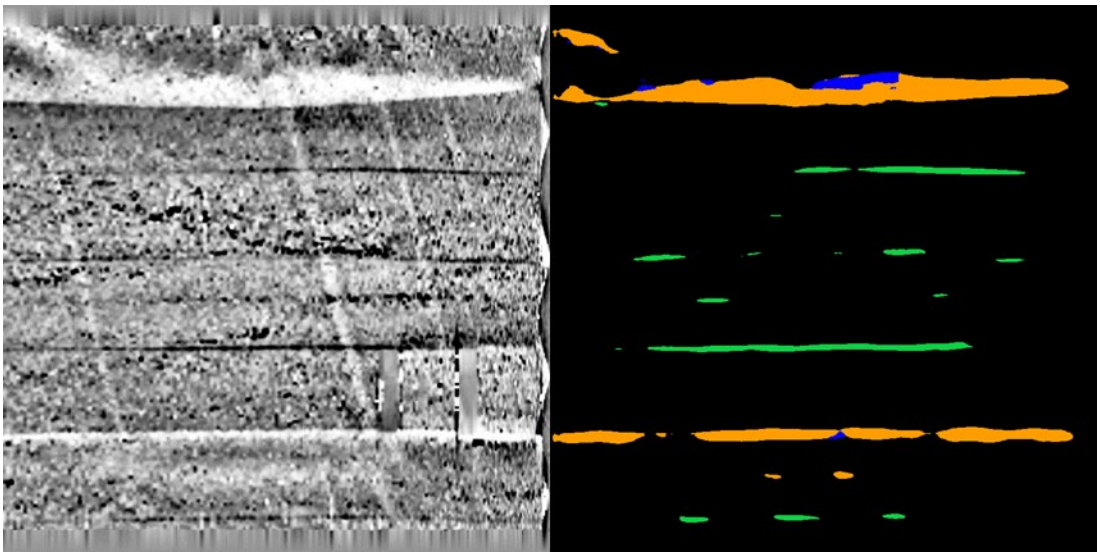


Figure 4: Pixel Output of Network

3.2.2 Operator User Interface

The increased detail afforded by the FCN structure of our ML algorithm also requires an equally elegant strategy for the display of this data to an operator. The large amount of data provided by the inspection system implies that observing defects from raw output is not feasible. Therefore, a user interface was created to improve the interaction between the operator and the system.

Defect boundaries were translated into bounding polygons through the Marching Squares Algorithm [21]. The location of the vertices of the bounding polygons were recorded and then displayed over the original scan image [Figure 4]. The operator has the capability to delete, change the class of, or define their own defects. When the operator is satisfied with the inspection data, they can automatically embed the data in a JavaScript Object Notation (JSON) file and export it to a remote server to be processed by third-party applications.

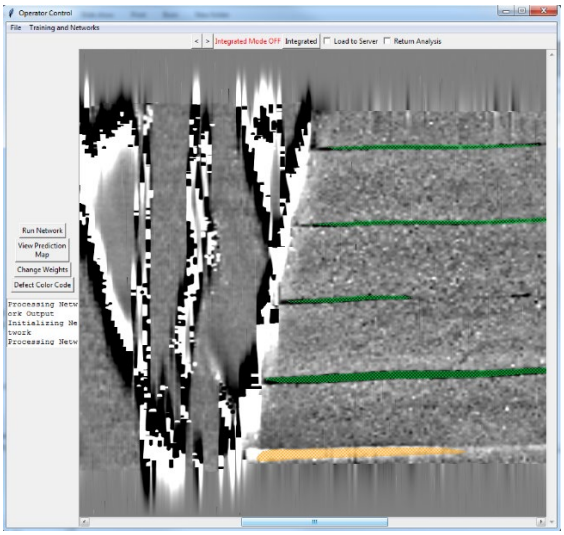


Figure 5: UI Display of Gaps and Overlaps

4. RESULTS

4.1 Inspection Informed Rework

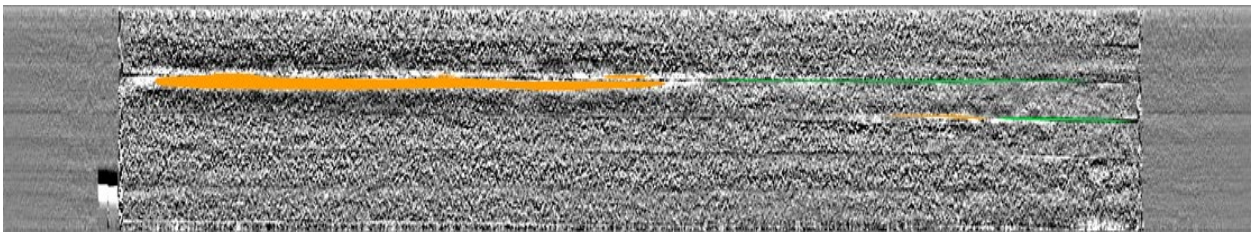
For each ply produced on a given cylinder, inspection was performed, and defects were identified. Defect information was used to identify locations requiring rework, thus creating a system by which inspection directly influenced the rework process. Cylinder repair and rework is demonstrated in



Figure 6: Rework on Cylinder from Inspection Data

4.2 Inspection Generated Data

A selection of scans from the cylinders is displayed in



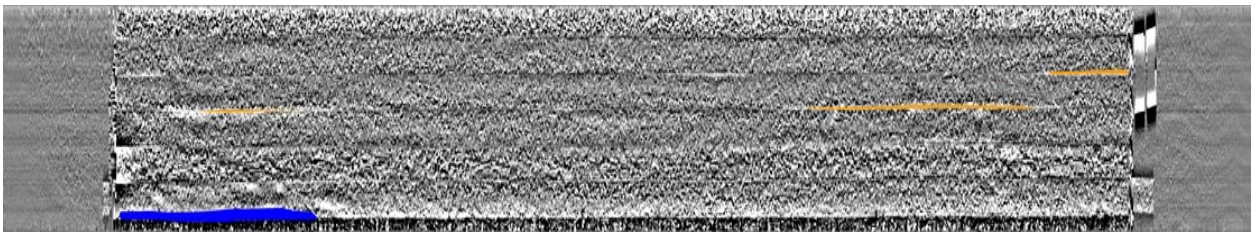


Figure 7: Defect Identified on Cylinder

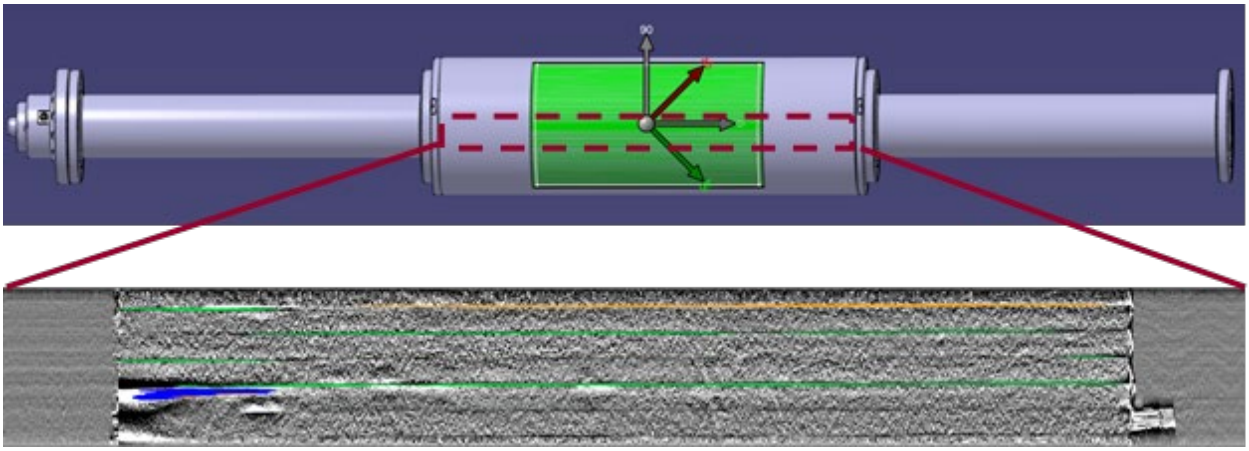


Figure 8: Defects Located on Cylinder

Custom code was written to translate the pixel positions into coordinates from the output of the CAM tool used to program the robot. With paths determined on the cylinders, it is relatively simple to determine spatial coordinates for each defect. From this point, defect data was transferred onto the remote server for use with third-party applications.

5. CONCLUSIONS

In this document a comprehensive inspection system developed in previous works was outlined and demonstrated to inform the repair of AFP manufactured cylinders. The data was logged and exported to a remote server for use with FE tools for the determination of the significance of each defect. In addition, cylinders were processed and tested at NIAR to validate the rapid analysis FE tools.

5.1 Future Work

In exercising the inspection system, it has become clear that a significant advantage in rework and repair could be derived by eliminating the need to interface directly with the inspection computer. A great deal of time is used in the process of translating what is seen on the screen of the inspection software UI to the physical part, even with coordinate positions to rely upon. Thus, it might behoove future work to eliminate this time expensive step.

One potential solution involves the use of an augmented reality system to overlay the defects on the physical part, making location and identification significantly faster. This interface could theoretically be accomplished using data already presented in the inspection solutions coupled with

off-the-shelf hardware and software. The authors have taken several steps in the process of accomplishing this next phase.

Further, the ready identification of defects on a layup has developed to a point that the construction of quality metrics is becoming possible. Soon the days of qualitative analysis of layups in a research setting will likely be gone, and with a new paradigm of quantifiable defect data reliable metrics of layup quality will need to be developed. Integration with AFP systems will require it, as the increased knowledge associated with a quality metric will precede the identification of processing windows or machine parameters that increase part quality.

5.2 Acknowledgements

The material is based upon work supported by NASA under Award Nos.515 NNL09AA00A and 80LARC17C0004.

6. REFERENCES

[1] D. Maass, "Progress in automated ply inspection of AFP layups," *Reinf. Plast.*, vol. 59, no. 5, pp. 242–245, 2015. 10.1016/j.repl.2015.05.002.

[2] J. Cemenska, T. Rudberg, and M. Henscheid, "Automated In-Process Inspection System for AFP Machines," *SAE Int. J. Aerosp.*, 2015.

[3] T. Rudberg, J. Nielson, M. Henscheid, and J. Cemenska, "Improving AFP Cell Performance," *SAE Int. J. Aerosp.*, 2014. 10.4271/2014-01-2272.

[4] C. Sacco, A. B. Radwan, T. Beatty, and R. Harik, "Machine Learning Based AFP Inspection : A Tool for Characterization and Integration," *SAMPE Conf. Proc.*, 2019.

[5] C. Sacco, A. B. Radwan, R. Harik, and M. Van Tooren, "Automated fiber placement defects: Automated inspection and characterization," in *International SAMPE Technical Conference*, 2018, vol. 2018–May.

[6] C. Sacco, "Machine Learning Methods for Rapid Inspection of Automated Fiber Placement Manufactured Composite Structures," University of South Carolina, 2019.

[7] J. Y. Wu, S. Sfarra, and Y. Yao, "Sparse Principal Component Thermography for Subsurface Defect Detection in Composite Products," *IEEE Trans. Ind. Informatics*, vol. 51, no. 24, pp. 855–860, 2018.

[8] X. Meng, Y. Wang, J. Liu, and W. He, "Nondestructive inspection of curved clad composites with subsurface defects by combination active thermography and three-dimensional (3D) structural optical imaging," *Infrared Phys. Technol.*, vol. 97, no. February, pp. 424–431, 2019.

[9] A. P. Chrysafi, N. Athanasopoulos, and N. J. Siakavellas, "Damage detection on composite materials with active thermography and digital image processing," *Int. J. Therm. Sci.*, vol. 116, pp. 242–253, 2017.

[10] V. Kalyanavalli, T. K. A. Ramadhas, and D. Sastikumar, “Long pulse thermography investigations of basalt fiber reinforced composite,” *NDT E Int.*, vol. 100, no. December 2017, pp. 84–91, 2018.

[11] M. Jolly *et al.*, “Review of Non-destructive Testing (NDT) Techniques and their Applicability to Thick Walled Composites,” *Procedia CIRP*, vol. 38, pp. 129–136, 2015.

[12] S. G. Pickering, K. Chatterjee, D. P. Almond, and S. Tuli, “LED optical excitation for the long pulse and lock-in thermographic techniques,” *NDT E Int.*, vol. 58, pp. 72–77, 2013.

[13] E. D. Gregory and P. D. Juarez, “In-situ thermography of automated fiber placement parts,” in *AIP Conference Proceedings*, 2018.

[14] M. Meng, Y. J. Chua, E. Wouterson, and C. P. K. Ong, “Ultrasonic signal classification and imaging system for composite materials via deep convolutional neural networks,” *Neurocomputing*, vol. 257, pp. 128–135, 2017.

[15] A. Wronkowicz, K. Dragan, and K. Lis, “Assessment of uncertainty in damage evaluation by ultrasonic testing of composite structures,” *Compos. Struct.*, vol. 203, no. July, pp. 71–84, 2018.

[16] A. R. Jac Fredo, R. S. Abilash, R. Femi, A. Mythili, and C. S. Kumar, “Classification of damages in composite images using Zernike moments and support vector machines,” *Compos. Part B Eng.*, vol. 168, no. December 2018, pp. 77–86, 2019.

[17] M. Sharp, R. Ak, and T. Hedberg, “A survey of the advancing use and development of machine learning in smart manufacturing,” *J. Manuf. Syst.*, 2018.

[18] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” *Adv. Neural Inf. Process. Syst.*, pp. 1–9, 2012.

[19] S. Van der Jeught and J. J. J. Dirckx, “Real-time structured light profilometry: A review,” *Opt. Lasers Eng.*, vol. 87, no. 2016, pp. 18–31, 2015.

[20] J. Long, E. Shelhamer, and T. Darrell, “Fully convolutional networks for semantic segmentation,” *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. 07–12–June, pp. 3431–3440, 2015.

[21] C. Maple, “Geometric design and space planning using the marching squares and marching cube algorithms,” in *Proceedings - 2003 International Conference on Geometric Modeling and Graphics, GMAG 2003*, 2003.