ELEMENTS AND MECHANISMS FOR APPLYING ARTIFICIAL INTELLIGENCE TO COMPOSITES FABRICATION

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ABSTRACT

The composites industry will soon be in a position to apply artificial intelligence (AI) in ways that will accelerate manufacturing and inspection processes, and also will enable rapid process and quality improvement throughout the product lifecycle. AI-enabled technology has broad-ranging applications within composites, from a specific manufacturing process to an enterprise-wide Industrial Internet of Things (IIoT) program. In a developmental AI application in 2018, a convolutional neural network (CNN) successfully generated an analysis algorithm for an automatic inspection system to detect foreign objects and debris (FOD) on critical component surfaces. This AI application will eventually replace painstaking hand-engineering of algorithms. Its success highlights not only what AI might contribute to composites fabrication, but also how AI-enabled fabrication technology might be developed. For example, the CNN trial has uncovered an immediate need for large quantities of raw data and images, which are the necessary "raw materials" of AI application development. Other needed elements and advancements will be discussed. AI development as applied to composites lends itself to incremental implementation, with benefits being realized with each increment. Both near-term and long-term benefits will be described.

1. INTRODUCTION

By and large, the composites industry has not yet researched and developed, much less implemented, Industry 4.0 and the smart factory, but the operative term in this statement is "not yet." Composites fabrication is certain to benefit in the future from technologies and processes enabled by Artificial Intelligence (AI), and in this regard, the question is not whether AI will play a role in this industry. Indeed, even the question of when AI will be introduced has already been answered, as it is already making small inroads into composites fabrication, such as the one described herein. Instead, the questions to be addressed are: (1) where will AI be implemented; and (2) how will AI-enabled composites manufacturing be brought about.

AI is defined as the ability of a device to perceive its environment and determine the best course of action to achieve intended goals [1]. In industrial settings, two sub-categories of AI predominate: Machine Learning, which is the ability of a computer to use data to improve performance of a particular task without being explicitly programmed to do so; and Deep Learning, which also uses data to improve performance, but typically on larger data sets and more complex logic networks [2]. When AI is implemented in industrial operations in general and composites manufacturing in particular, two key benefits will be gained: (1) the acceleration of application development, and (2) accelerated product and process improvement. Just as

SAMPE Conference Proceedings. Charlotte, NC, May 20-23, 2019. Society for the Advancement of Material and Process Engineering – North America.

application, product and process pervade end-to-end composites manufacturing, so too the opportunities to employ AI.

1.1 Where AI Will Be Implemented

Points of entry for AI-enabled advancements in composites fabrication include material and asset tracking, process control, automatic inspection, the digital thread, the digital twin, and closed-loop process and quality improvement.

1.1.1 Material and Asset Tracking

As they help composite component manufacturers to minimize downtime for fabrication equipment and to avoid costly material waste, material and asset tracking systems record and/or generate large quantities of data regarding equipment age and key operating parameters over time, number of cycles performed, maintenance and repair procedures undertaken, incoming material quality, material storage location and conditions, material life and expiration dates, and kit locations and life. Manually preset values may be employed to initiate maintenance or to send an alert regarding recommended or required actions. A Machine Learning system might analyze the data collected by the material and asset tracking system, "learn" patterns within the tracked data, and detect anomalies that may prompt remedial action. A Deep Learning system might detect systemic patterns and uncover opportunities to improve supply chain efficiencies, minimize material backlogs, optimize equipment performance, better integrate material and production management, improve scheduling across the shop floor, and ultimately, reduce operational costs while better assuring the quality of the end product [3].

1.1.2 Process Control

New software solutions enable manufacturing engineers to generate comprehensive electronic work instructions for the entire composite fabrication process, including material layup, debulks, inspections and other intermediate procedures. Machine Learning may enable companies to automate the generation of work instructions. Deep Learning has the potential to analyze data generated over the course of multiple production cycles and uncover any bottlenecks or process points at which errors tend to be introduced. This gives the manufacturer the opportunity to adjust processes and minimize bottlenecks and end-product defects.

1.1.3 Automatic Inspection

The composites industry is just beginning a transition from manual inspection, with its attendant limitations, inaccuracies and lack of traceability, to automatic inspection with machine vision. For reasons discussed below, automatic inspection requires application development for each fabrication project and each work cell. Machine Learning will generate application-specific analysis algorithms and eliminate tedious and time-consuming hand-engineering of these algorithms. Deep Learning may employ inspection data to identify defect-prone plies or process steps, enabling modification to decrease reworking and scrap. Inspections also provide critical input data for the AI-enabled advancements below.

1.1.4 Digital Thread

The Digital Thread provides connectivity between previously siloed functional systems, raising visibility of processes and outcomes across the enterprise [4]. The Digital Thread is a key element of the Industrial Internet of Things (IIoT) and so is part of Industry 4.0 in and of itself. In composites fabrication, functional systems that will be fully integrated via the Digital Thread include CAD and laminate design data; nesting, cutting and kitting data; layup, course, pick-and-place and/or steering data; inspection data; post-processing data; and end product data. Machine Learning may streamline the process of enabling functional systems to communicate with each other. Deep Learning has the potential to increase communication efficiencies and make user interfaces more intuitive to raise the productivity and effectiveness of human assets.

1.1.5 Digital Twin

A Digital Twin is a digital representation of an individual end product. It may include visual elements, such as ply-by-ply images collected by an automatic inspection system. It also includes quantified data specific to that particular fabricated component, including data about the raw material used, equipment status during fabrication, process parameters, time stamps, buyoffs, and both in-situ and post-completion inspection data. Machine Learning has the potential to be used to develop the specific elements and format of the Digital Twin. Deep Learning may help to improve the usefulness of a Digital Twin. Like the Digital Thread, Digital Twins are part and parcel to the IIoT and therefore, Industry 4.0.

1.1.6 Closed Loop

When fully implemented, Industry 4.0 culminates in the closed loop (Figure 1). In composites manufacturing, this means that data infrastructure of the Digital Thread would provide for the seamless flow of data from design, simulation and analysis to manufacturing engineering and generation of fabrication guidance, then to process control and automatic inspection, then to documentation (Digital Twin) and back to design. Machine Learning could enable accelerated completion of the closed loop for a particular smart factory. Deep Learning would employ data from the manufacturing floor to improve design as well as process and product quality outcomes.

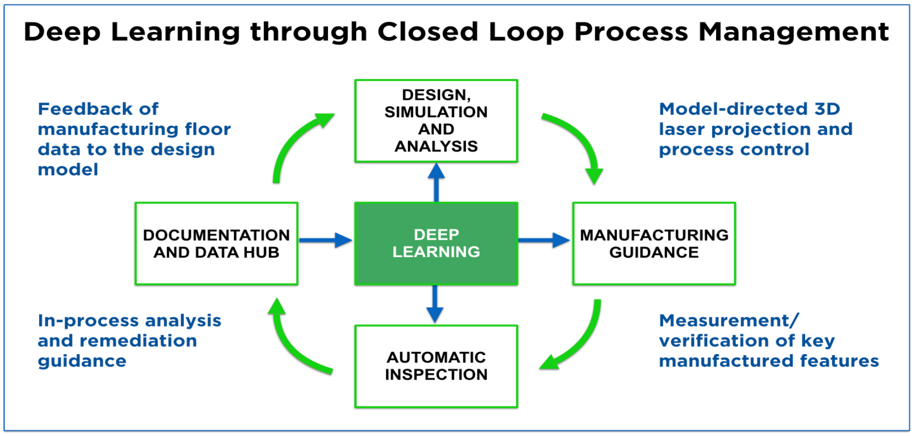

Figure 1. Closed-loop manufacturing with Deep Learning

1.2 How AI Will Be Implemented

With some forethought, AI can be implemented in composites fabrication in an incremental, minimally disruptive manner. In fact, it is reasonably straightforward to perform application development via Machine Learning in a way that is nearly invisible to shop floor personnel. For example, the data that a material and asset tracking system is generating and/or recording can be collected in the background while normal operations proceed. The Machine Learning system would then be trained with these harvested data sets outside of production operations. New functions or modified tracking programs generated by the Machine Learning system potentially could be implemented in the same manner that software updates are made, which frequently means during normal production downtime. Just as software updates usually are a familiar and minimally disruptive occurrence on the shop floor (or on one's cell phone, for that matter), so too the AI-generated updates.

More significantly, AI-enabled application development would accelerate the expanded use of a tracking system from one production line to multiple production lines within a facility, or from one facility to multiple manufacturing sites, or from manufacturing operations to the entire supply chain, including vendors, OEMs and other interconnected operations. Notice that each of these advancements or expansions can be implemented one at a time, incrementally; yet each increment yields productivity, efficiency and/or quality benefits.

Deep Learning can also be conducted while regular production operations continue. In the closed loop, advancements developed via Deep Learning can be implemented at the appropriate point in the loop, then create a "domino effect" of improvements throughout the loop. Deep Learning may establish that a particular manufacturing parameter (e.g. winding tension) varies less on the manufacturing floor than assumed in design and simulation, and a key performance parameter of the end product that is related to the manufacturing parameter (e.g. impact resistance) is consistently better than the required specification. This knowledge would enable the design to be modified, which may lead to a lighter structure, which may lower demands on a key piece of equipment (e.g. the filament winder), which may yield even less variation in the manufacturing parameter … and so on through what may be called a "cycle of virtue." Once again, each improvement or advancement would create benefits and could be implemented one at a time.

2. EXPERIMENTATION

Automatically inspecting a part as it is being fabricated involves the capture of data – in this case, images captured via machine vision – and analysis of that data via algorithms. Because each application varies in significant ways relative to digital images – lighting, material composition, surface geometry, fiber orientation, laps and gaps, etc. – each application requires tailored algorithms, and non-AI algorithm development requires painstaking hand engineering. The trials conducted helped to determine whether a Machine Learning system could successfully generate an application-specific analysis algorithm without requiring explicit manual programming.

2.1 Automatic Inspection System

The base technology on which these applications run is an automatic guidance and inspection system that includes laser projection and machine vision hardware, and laser templating and automatic inspection software. The system (Figure 2) is designed to inspect detailed regions of interest anywhere on a large complex surface (typically 5m by 5m). Each unit of the system projects its laser and captures images within a 60˚ (±30˚) angle. Meeting Boeing D6-55902 requirements, the unit achieves an accuracy of 0.38 mm (0.015 in.) in a standard field of $9m^2$ ($10 ft^2$) at a distance of 3m (10 ft) from the unit.

Figure 2. Laser projector with integrated vision system

To perform automatic inspection, the vision component directly accesses and applies manufacturing data to aim a high-resolution, high-magnification camera system, which captures “calibrated images” under data control. “Calibrated imaging” refers to the images being captured along with a photogrammetric transform that defines the relationship between the camera and the feature being imaged. This enables measurements in the image that correspond accurately to features on the surface of the part. That is, the transform enables each pixel in the 2D image to be dimensioned relative to the 3D surface and in the coordinate system of the part. The analyzed images support a “gauging” function, in which the surface containing the features being imaged is assumed to be correct and the location of features on that surface are assessed for translations and rotations. Any features found to be out of tolerance are flagged and highlighted on the surface by the laser projector (Figure 3), enabling near-real-time assessment and repair before any flaw is covered by subsequent plies.

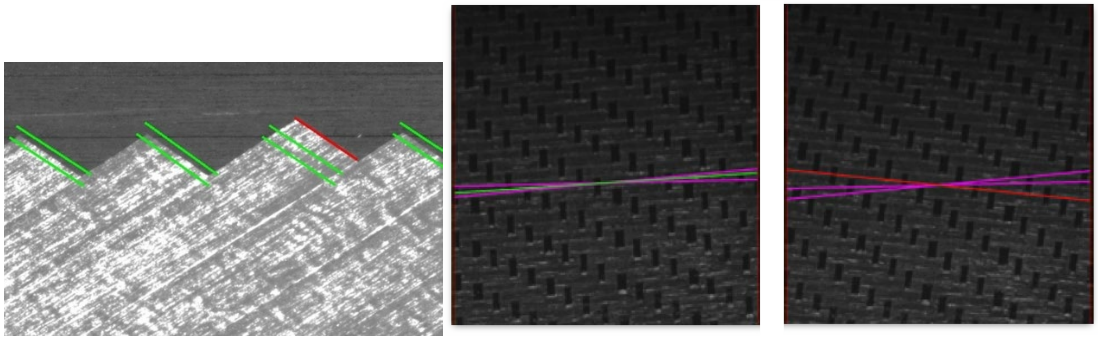

Figure 3. Analysis enabled by transform. Out-of-tolerance tow placement (left) and fiber orientation (center and right) identified.

A recent Automated Fiber Placement (AFP) application of fully automatic inspection demonstrated the ability to detect and locate 90 percent of all tow ends when initially implemented, with an anticipated increase (through fine-tuning of analysis algorithms) to a 99 percent detection rate in production. This application has received full certification from a major OEM and is qualified to be within ±1.5 mm of the true position in a gantry-mounted setup [5]. It is being used to inspect first-article wing panels and wing spars for Boeing's first 777X test aircraft. Inspection on one area of the surface can be conducted while material laydown continues elsewhere. Large, complex plies take only 3 to 5 minutes to be imaged and processed [6]. The system also automatically captures a series of adjacent images, which it combines to document features and details over the full surface of each ply in a single image [7].

Figure 4. Automatic inspection of Boeing 777X component. Two guidance/inspection units circled in red.

To detect foreign objects and debris (FOD), such as poly liner, insects that find their way into large production bays, or peel ply not properly removed, the automatic inspection system's analysis algorithm identifies any abrupt changes in optical surface characteristics where none is expected. Such changes prompt the system to flag the location, and the laser projector pinpoints the location on the surface (Figure 5). In a 2015 study of peel ply detection using the automatic inspection system, 6100 inspections correctly detected peel ply present (3010 instances) or peel ply absent (3090 instances) with no false positives or false negatives [8].

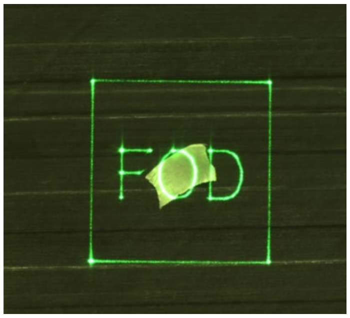

Figure 5. Foreign Objects and Debris (FOD) detected by the automated system are highlighted by the laser projector for correction.

2.2 Procedures

The first trial used a convolutional neural network (CNN), which is an AI computational model commonly employed in facial and other image recognition. The goal was to a create a binary classifier that would identify images with FOD present or FOD absent. About 700 images captured by the automatic inspection system described above were used as input to the CNN. All of the images were similar in content except that some contained FOD consisting of peel ply with print on it. The number of images is relatively small for building and testing a classifier, since neural networks typically are trained on thousands of images or more. However, a publicly available pre-trained network was able to be repurposed for this new classification task, enabling its completion with the small number of training images.

To ensure that the CNN did not “overfit” (focus too closely on the particular training set with the result that it does not generalize well), the dataset was augmented by feeding variations of the training images into the training process. This was accomplished with slight random shifts of rotation, zoom, crop, etc., and by introducing a “dropout” layer in the CNN, which prevents the model from incorporating weak patterns.

In an iterative process, the CNN was trained and evaluated. The images were divided into three subsets: the initial training set, consisting of about 80% of the images; a validation set, which used about 10% of the images to evaluate the work-in-progress model during construction and tweaking; and a test set of about 10% of the images to evaluate the model in its completed form.

The second trial employed a third-party AI-based development program for machine-vision applications. The data set consisted of 868 automatic inspection images of a hat stiffener with and without peel ply. Each image was between 9 in^2 (3 by 3 in.) and 25 in^2 (5 by 5 in.), and these were divided into sub-images of 200 by 200 pixels, usually 9 per image, for a total of 7,909 sub-images. The program was trained on 3,907 sub-images divided between those with and those without peel ply.

3. RESULTS

In the first trial, when the CNN’s classification model was applied to the test image subset, which it had not previously analyzed, the model achieved 100% accuracy. In the second trial, when the classifier was tested, only 13 sub-images were mis-classified, representing a raw accuracy of 99.8%. On any images for which the classifier returned mixed results (i.e. some sub-images classified as peel ply present and some classified as peel ply absent), a statistical process determined classification of the full image. On this level, the classifier achieved 100% accuracy.

The two trials have demonstrated the feasibility of AI-enabled application development. Both AI systems (the CNN and the third-party system) proved highly capable of correct image analysis and verification of a process parameter (or identification of a process flaw).

It is important to note that training of the AI system in these trials required considerably less time and staff hours than hand engineering using conventional image analysis software. Once images were collected and prepared, training and testing of the classifier required about a half-day.

4. CONCLUSIONS

The trials of AI-enabled application development for automatic inspection demonstrate the feasibility of using Machine Learning to accelerate the implementation of automatic inspection to composites manufacturing cells. One initial concern about using Machine Learning in this manner was that the relatively small set of images available would be insufficient to generate an accurate classifier. As it turns out, the small data set – which is tied to the fact that many composites manufacturing operations are low volume – does not appear to be problematic. In fact, another industrial AI experiment reportedly used only five product images to successfully perform visual inspection, though the complexity of the product and parameters being inspected was not disclosed [9]. While a five-image data set is unlikely to be adequate given the complexity of composites manufacturing, AI-based application development may prove viable even for component prototyping, which would be especially helpful given the short time required to generate a successful classifier via AI.

Conducting the trials successfully away from manufacturing floor means that manufacturers may be able to transition to automatic inspection quickly and with little to no disruption of shop floor activities. The laser projection capability of the system described here is identical to that provided by a standard laser templating system. Manufacturers employing laser templating could replace a standard unit with the automatic inspection unit, and continue to conduct laser templating operations while Machine Learning uses harvested images to develop the specific application. The only additional requirement would be the deliberate creation of flaws to provide a full data set for the Machine Learning system. Otherwise, production activities would continue, including manual inspection procedures, until AI application development was completed.

Though field trials are not yet scheduled, discussions have commenced on Deep Learning-based process and quality improvement, for which an automatic inspection system would serve as a "smart sensor." As such, it would generate input data for the Deep Learning system, and then implement process changes uncovered through Deep Learning. The potential for reduced scrap and rework, better defined design allowables, and systemic improvements to component weight, production rate and end-product quality would seem to make the employment of AI in composites engineering not only inevitable, but also highly attractive with little apparent downside.

5. REFERENCES

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