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A HOLISTIC APPROACH TO COMPOSITES QUALITY USING ARTIFICIAL INTELLIGENCE-ENABLED AUTOMATIC INSPECTION

ABSTRACT

The advent of automatic inspection in composites fabrication has led to great progress in inspection speed and quality, and generates a large quantity of inspection data, which can serve as a rich data source for closed-loop manufacturing. These advances represent only the first wave of innovation made feasible by this technology. Not only is automatic inspection capable of quickly verifying key features of each ply in a large component, it also can be leveraged to inspect a multitude of material, process and component attributes not included in current quality programs. By viewing inspection as part of a holistic quality solution, fabricators can transition to an approach in which they monitor in-process key performance indicators (KPIs) and adjust process parameters in real time to reduce non-conformance events. Artificial intelligence is a critical enabling technology, speeding the development of analysis algorithms for each attribute, and also employing inspection data for Deep Learning and continuous process improvement. This paper explores the range of attributes that automatic inspection may monitor, the method for incorporating this new level of monitoring into a holistic quality approach, and the ways in which a holistic quality program might advance the state of the art in composites fabrication.

Author: Scott Blake

1. INTRODUCTION

In a paper on its automated inspection system used in large-scale automated fiber placement (AFP) cells, Electroimpact reports that inspection data can approach 1 TB (terabyte) per part for large complex composite parts [1]. In Electroimpact's initial application of AFP in-process automatic inspection, this raw inspection data is processed on the fly to verify overlap and gap width as well as ply boundary location, and to flag non-conformances and suspect locations.

The value of the large "data lake" produced by automatic inspection extends well beyond in-process inspection. It supports a holistic approach to quality in which the data is aggregated and contextualized as manufacturing intelligence. Continuous process and product improvement on an unprecedented scale, relying on this rich manufacturing intelligence, is in the offing. The capabilities of in-process automatic inspection technology, along with the untapped value of generated data lakes, may be leveraged to advance composites fabrication quality efforts in two ways, both of which rely on artificial intelligence (AI) for implementation. First, automatic inspection may be applied to a multitude of material, process and component attributes not included in current composites quality programs. AI-enabled application development opens this door and allows fabricators to monitor numerous in-process key performance indicators (KPIs) and adjust process parameters in real time to reduce non-conformance events. Second, AI Deep Learning mechanisms will employ the manufacturing intelligence aggregated from automatic inspection data to implement closed-loop continuous improvement, in which manufacturing insights fed back to design and engineering are used to improve product design and fabrication processes.

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1.1 Artificial Intelligence and Automatic Inspection

AI is defined as the ability of a device to perceive its environment and determine the best course of action to achieve intended goals [2]. 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 [3]. In relation to automatic inspection, Machine Learning is the AI mechanism used for application development while Deep Learning enables closed-loop product and process improvement.

1.2 Automatic Inspection Technology

Illustrative of the technologies available for in-process automatic inspection, the Electroimpact automated inspection system includes two elements. First, a laser profilometer is mounted to the AFP deposition head. From this position, it collects data in parallel with material lay down. By projecting a laser line and measuring the distance to points along that laser line, the profilometer creates a profile of the surface that is analyzed to identify and measure features, in this case, overlaps and gaps between tow lanes. Because the profilometer travels with the head, it is able to detect tow position relative to other tows, making it an effective means of verifying that the widths of overlaps and gaps between AFP tow lanes are within tolerance.

Second, to verify absolute position of tow ends — that is, their position relative not just to neighboring tow lanes but to the component's overall layout — a large-field automatic inspection system is mounted to a second gantry (Figure 1) [4]. This system is capable of inspecting in detail any area on the surface, independent of the deposition head. It consists of 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 3m by 3m (10 ft by 10 ft) field at a distance of 3m (10 ft) from the unit.

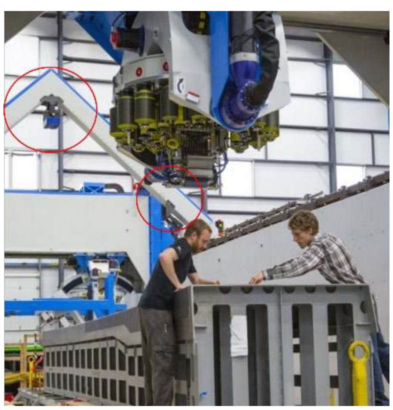


Figure 1. Large-field automatic inspection system mounted to a second gantry over a large AFP cell.
Two inspection units are circled in red.

Figure 2. Large-field automatic inspection unit consists of laser projector with integrated machine vision system.

To perform automatic inspection, the vision component of the system directly accesses and applies manufacturing data to aim a high-resolution, high-magnification camera, 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.

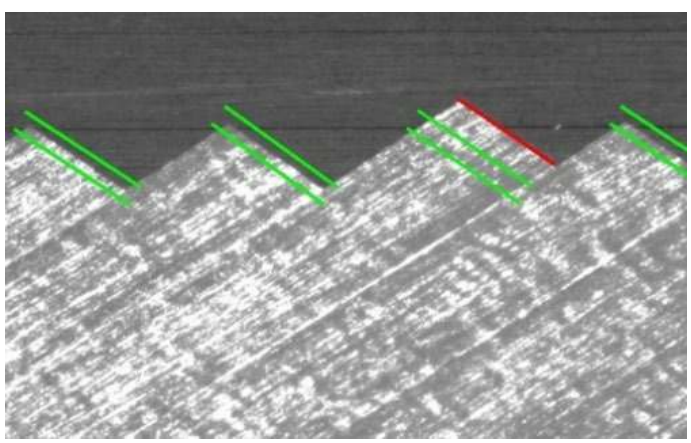
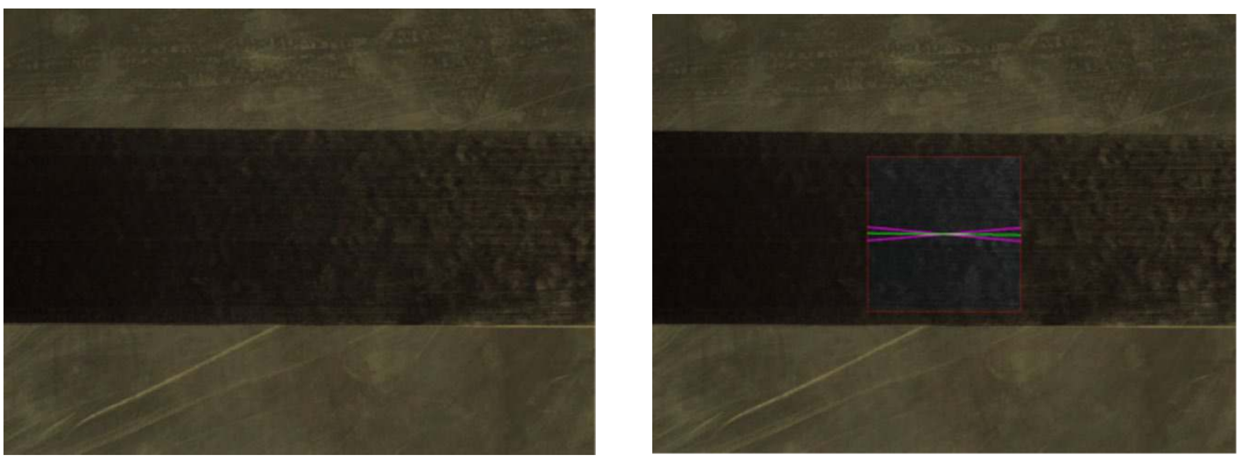


Figure 3. Analysis enabled by transform. Out-of-tolerance tow placement identified.

1.3 Currently Inspected Attributes

Tow end and edge positions define ply boundaries in AFP layup. Automatic inspection technology is also able to measure ply boundaries created through other layup methods (manual, Automated Tape Placement, etc.). As with many new technologies, the first attributes to which automatic inspection has been applied are those commonly inspected by the previous state of the art, in this case, manual inspection. In addition to gap and overlap widths, attributes to which laser profilometers have been applied include pits, bulges and distortions in filament-wound cylinders [5]; and automated dry material placement [6]. Large-field automatic inspection has been used to verify (or flag) material type (unidirectional versus woven plies, for example), fiber orientation (Figure 4), and foreign objects and debris (FOD).



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visionuni version 20180105

All read in: 0.547000
 Calcs done: 1.687000
angle expected -89.727594
angle found -89.283803
angle diff 0.443792  tol 5.000000
REFERENCE_ANGLE -89.727594
IMAGE_RESULT?ORIENT+ANGLE+-89.283803+PASS
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Figure 4. Raw (left) and analyzed (right) image from large-field automatic inspection system verifying that fiber orientation is within tolerance.

To detect FOD, 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 draws a boundary around the FOD on the surface (Figure 5). FOD detection extends to specific kinds of FOD and application areas. For example, detecting peel ply in critical bonding applications requires the development of algorithms specific to the environment in which bonding will take place, the kinds of composite surfaces to be bonded, and the type of peel ply being used. More about algorithm development is discussed under Section 2, Quality Approaches, below.

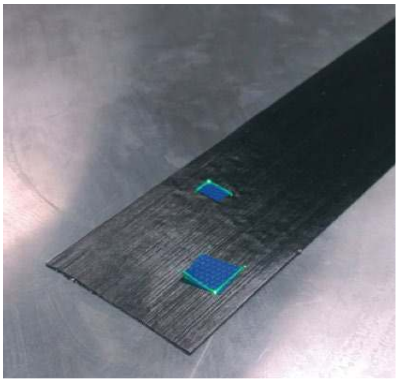

Figure 5. Detected Foreign Objects and Debris (FOD) detected by automatic inspection are pinpointed on the surface by laser outline.

In addition to extending the specific attributes to which automatic inspection is applied (e.g. type of FOD), developments also continue regarding the mechanisms by which automatic inspection occurs; and this too increases the demands on algorithm development. For example, new camera technology improves the ability to recognize edges, layers, fiber orientation and FOD before processing an image with analysis algorithms (Figure 6).

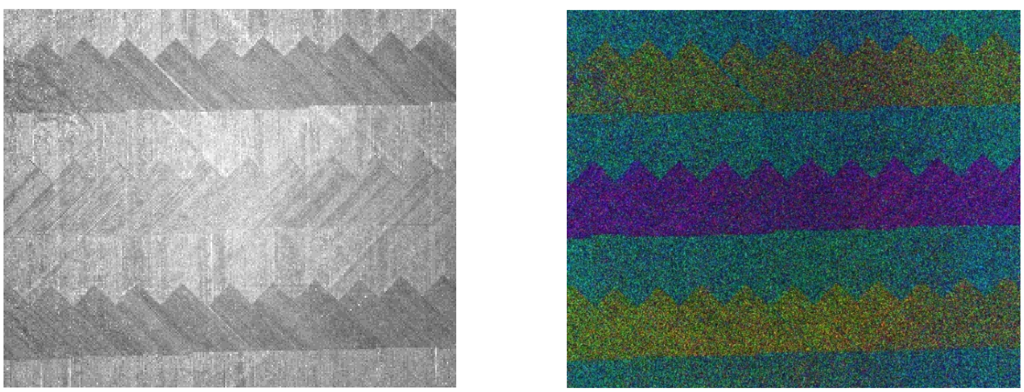

Figure 6. Camera advancement improves image capture and also places new demands on application development.

1.4 Additional Attributes to Inspect

Automatic inspection systems are capable of verifying other important attributes of composites fabrication, attributes that are critical to part performance and that are extremely difficult to detect through human visual inspection. Prior to automatic inspection, the only alternative has been metrology, which is infeasible for most applications because it is so labor- and time-intensive. (Additionally, some metrology systems provide a costly and unnecessary level of precision.) To measure some of these attributes with metrology, a "point cloud" comprised of hundreds of thousands or millions of points has to be captured and converted into a surface. The modeled surface must then be aligned with a nominal surface and the two compared. In contrast, the large-field automatic inspection system uses much less data-intensive expectation-driven analysis: it generates an acceptable pattern and its tolerances directly from the CAD model. The system's machine vision captures an as-built laser pattern from the actual surface being inspected. Automatic image analysis then compares the CAD-generated and as-built patterns, producing a go/no-go metric.

One significant area for which automatic inspection has the potential to markedly improve quality is raw material inspection. In high performance composites applications, flaws in raw materials may diminish critical attributes. Yet currently, common practice is to inspect raw material manually or not at all. Manual inspection here faces the same difficulties as in the fabrication cell: human limitations such as distractedness, fatigue and verification bias decrease inspection effectiveness. Moreover, manual inspection is very time consuming. In the holistic quality approach outlined below, automatic inspection and material tracking systems could work together on the same software platform, making raw material inspection an easily streamlined and beneficial process.

Within the composites fabrication cell, attributes to which automatic inspection may be applied include wrinkles, bridging and shear. Inspection of these attributes has been assessed at the Advanced Composites Centre for Innovation and Science (ACCIS), University of Bristol, U.K. [7]. Wrinkles occur when material does not conform completely to the tool surface. To detect wrinkles, the automatic inspection system's analysis algorithm identifies discontinuities in a laser reference pattern that would not be expected when viewing an unwrinkled surface. The approximate size of a detected wrinkle is determined through the defined geometric relationships among the projection source and pattern, the camera, and each surface (Figure 7).

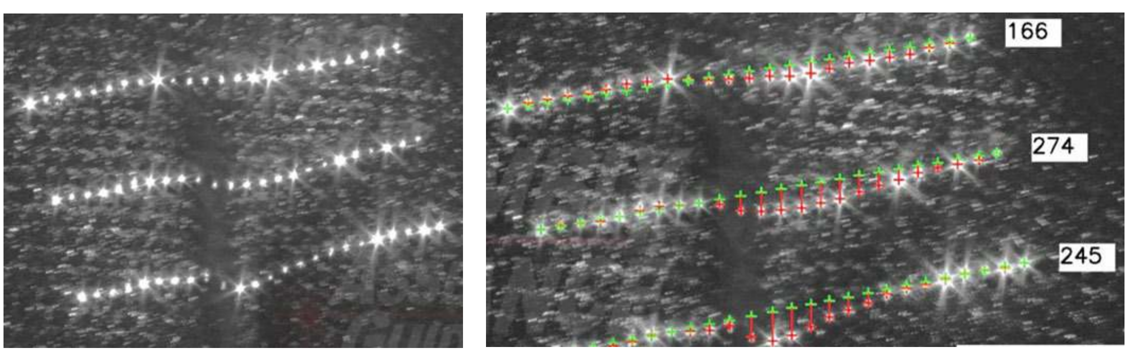

Figure 7. Automatic detection of 0.8mm wrinkle in robotic layup system

Bridging occurs when material does not conform fully to the tool surface in a concave region. With secondary bridging, material that initially conforms is pulled out of conformity as material is draped or creased elsewhere. The automated inspection system may be programmed not only to detect bridging but also to automatically re-inspect areas that are susceptible to secondary bridging (Figure 8).

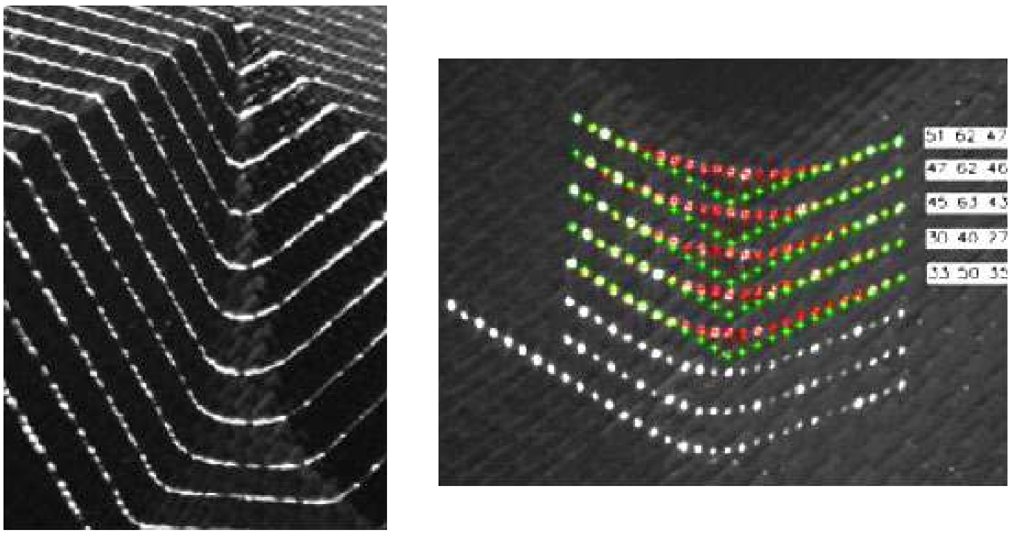

Figure 8. Difference between expected and actual location of projected reference points indicates proportion of bridge displacement.

Shear — the distortion of the material's fiber orientation as it is deformed in three dimensions — often occurs by design in composite fabrication. Excessive shear, however, may weaken the finished product. To detect shear, the automatic inspection system illuminates the surface to maximize the visibility of each tow. Analysis algorithms track the appearance of each tow in images captured by the system's aimed camera and calculate the angular change in direction along the length of the tow. Maximum positive and negative angular changes are automatically calculated (Figure 9).

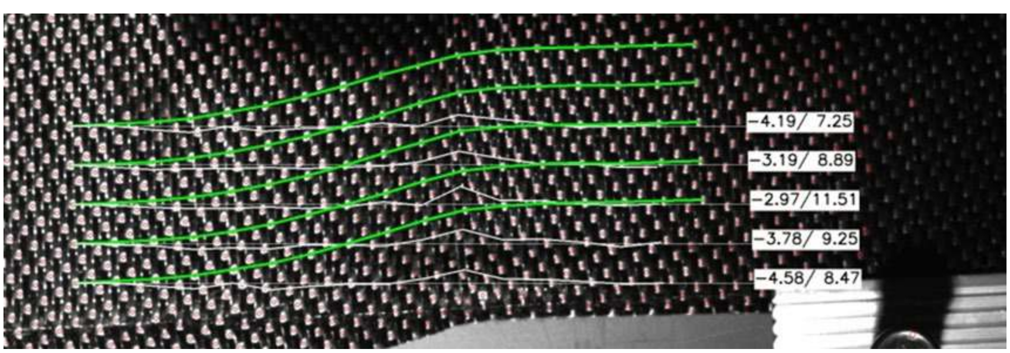

Figure 9. Automatic discovery of fiber paths in material sheared in press

Beyond composites fabrication, automatic inspection technologies are applicable to post-processing steps like machining, as well as assembly and other manufacturing processes. The large-field automatic inspection system described here has the capability to inspect for any visible feature's presence or absence, as well as its location on a surface. For example, it may be used to verify not only the position of fasteners in an assembly, but also the type of fasteners being used (Figure 10).

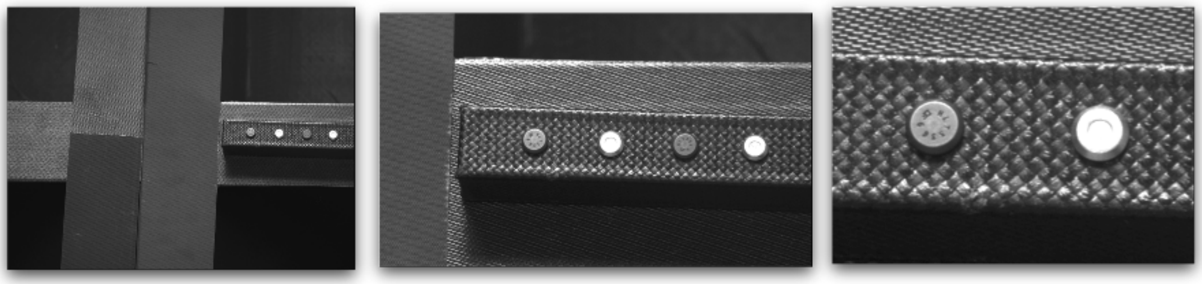

Figure 10. Automatic inspection detects fastener position and type. The captured image (left, from 10 ft away) is high resolution and shows excellent detail under zoom (center and right).

2. QUALITY APPROACHES

The automation of inspection tasks is one of numerous areas in which digitalization is driving fabrication quality and speed to new levels. Digitalization should not be confused with digitization: the latter simply takes analog information and converts it to digital form (e.g. scanning a physical surface to create a digital model) while the former generates, analyzes and manages data. Ultimately, digitalization leads to the complete Digital Factory, also known as Smart Manufacturing or Industry 4.0. Digitalization typically is implemented in a step-by-step fashion. Major phases of this implementation include digital point solutions, integrated manufacturing operations management (MOM) solutions, and closed-loop manufacturing operations. As a key element of quality efforts, automatic inspection is following this stepwise path toward a holistic quality approach, sometimes referred to as Quality 4.0.

2.1 Automatic Inspection as a Digital Point Solution

Automatic inspection technology is often introduced to a fabrication floor as a stand-alone technology. The system imports needed data from CAD and composites-specific CAM files (such as Fibersim or CPD). In the case of the large-field automatic inspection system discussed here, these files direct the system to aim the laser projector/machine vision unit and capture the desired images. The system's computer then performs image analysis and provides confirmation of analyzed features, or sends an alert regarding a non-conformance (Figure 11).

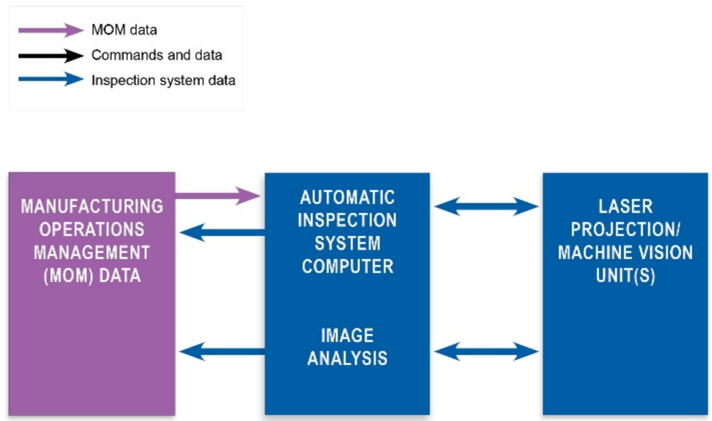

Figure 11. As a digital point solution, an automatic inspection system operates as a stand-alone, importing design and control data from the manufacturing operations management (MOM) system and exporting as-built data back to the MOM system.

Application of automatic inspection to each specific fabrication effort is unique. As with virtually all automated technologies and contrary to a common misconception, application is not as simple as setting up the equipment and switching it on. Because of the relatively high number of variables associated with fabrication of composite materials — fiber and resin type, fiber form, fiber orientation, ply schedules, resin infusion or prepregging method, layup mechanism and cure mechanism, to name a few — application development for automated manufacturing processes has been a tedious and time-consuming process. This is no less true of automatic inspection, for which the analysis algorithms used to assess digital images collected via machine vision have been hand-engineered.

With the high number of composites fabrication variables, plus additional factors like lighting within the work cell, developing an analysis algorithm for a particular application via hand-engineering typically takes several weeks of dedicated effort. To accelerate implementation of automatic inspection to each application, recent experimentation suggests that Machine Learning is an effective and accurate approach to application development [8]. In a matter of one to two days, a Machine Learning program may be trained on a set of images to detect a particular attribute.

Machine Learning for automatic inspection applications can be conducted away from manufacturing floor, which means that manufacturers may be able to transition to automatic inspection quickly and with little to no disruption of shop floor activities. Manufacturers employing laser templating could replace a standard unit with a laser projection/machine vision 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.

To create an algorithm that is ready to detect all potential flaws, the fabricator would create artifacts containing those flaws, as well as correctly fabricated regions. Then in an environment similar to the manufacturing floor, the machine vision system would capture images that would be used to train the Machine Learning system.

2.2 Integration of Automatic Inspection into Manufacturing Operations Management

Using a software development kit or other integration process, automatic inspection can be integrated into a manufacturing operations management (MOM) system (Figure 12), and more specifically, into the quality management functionality of a MOM system. On an integrated MOM platform, automatic inspection becomes a critical function within the quality ecosystem, maximizing a fabricator's ability to respond to real-time manufacturing quality events. To illustrate, an integrated MOM system performs machine and work cell monitoring alongside in-process inspection of components as they are built. When a non-conformance event is detected by an automatic inspection system, a machine operational parameter related to that non-conformance may be adjusted by an operator, or even by the system itself. For example, a gap between tow lanes that is outside of tolerance may point to a dropped tow, which can be corrected in real time on the AFP.

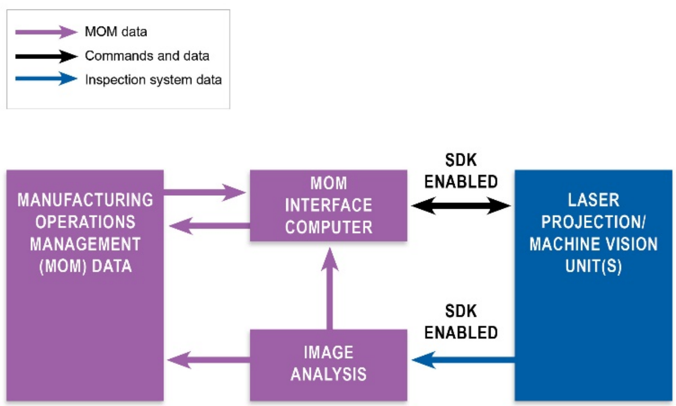

Figure 12. Integrated into a manufacturing operations management (MOM) system, automatic inspection becomes one of the critical functions within a quality ecosystem

2.3 Manufacturing Intelligence and Closed-Loop Manufacturing

Automatic inspection systems generate detailed, as-built data for each part — an as-built Digital Twin, or virtual representation of each individual part's specific attributes. The Digital Twin includes quantitative data as well as the image set captured by automatic inspection. While the automatic inspection system captures detailed images of small regions within the surface of a large component, it has the capacity to combine these images and produce a single image of a complete ply surface (Figure 13). As a result, the as-built Digital Twin provides both visual and quantitative traceability for each individual part — documentation of critical attributes that can accompany the part throughout its operational life.

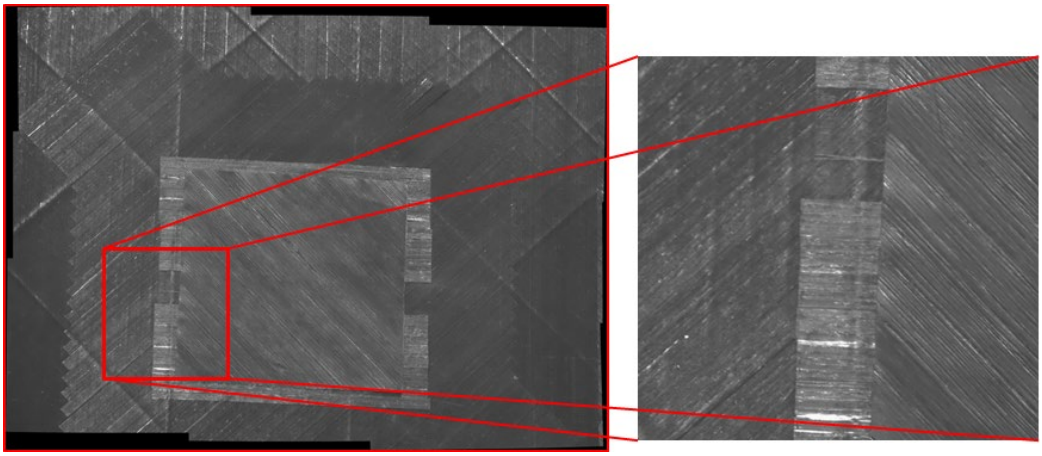

Figure 13. Nine captured images combined into one (left). Algorithm in the automatic inspection system aligns images seamlessly.

Comprehensive quality documentation is one outcome of automatic inspection. In a fully integrated system and with the availability of Deep Learning processes, this detailed, as-built data also feeds predictive and prescriptive analysis, as well as root cause analysis. Applying Deep Learning to a large database of inspection data and feeding the insights gained back to product design and process engineering will lead to improvements in simulation, modeling, product quality and process efficiency and efficacy.

3. CONCLUSIONS

In composites manufacturing, a holistic quality program places all quality-related data — from material lot and out-time to post-processing component features and attributes — on the same software platform. Data generated by in-process automatic inspection on this platform enables real-time corrective actions that extend beyond rework of a detected non-conformance to adjustment of operational parameters related to that non-conformance. An immediate increase in part quality and decrease in scrap rate are the first outcomes of this integrated approach. Beyond improved quality of individual components, closed-loop manufacturing utilizes the manufacturing intelligence aggregated from multiple component data and contextualized within the full set of operational parameters. This manufacturing intelligence feeds Deep Learning efforts, which in turn enable continuous improvements to product design, process engineering, operational conditions and settings, and resulting product quality.

4. REFERENCES

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