INTEGRATING AI-ENABLED AUTOMATIC INSPECTION OF COMPOSITES FABRICATION WITH AUTOMOTIVE QUALITY PROCESSES

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Abstract

As advanced composites move into high-volume automotive applications, critical enabling technologies include automatic inspection systems developed and tailored to the unique demands of composites inspection. The kinds of attributes and anomalies to monitor in advanced composites production far outpace those monitored in the materials with which automotive manufacturers are more familiar, making inspection much more complex and application specific. Advanced composites inspection systems have matured in the aerospace market, but to accommodate automotive production speeds and cycle times, they must be capable of (1) rapid application development despite great complexity and (2) integration with the automotive factory's existing quality management system (QMS) or other manufacturing operations management (MOM) system. This paper will discuss the role of artificial intelligence/machine learning (AI/ML) in accelerating application development, including low-code AI/ML that enables manufacturing engineers, rather than data scientists, to generate analysis algorithms for modified and new applications. It will also describe and report on the status of a recently initiated research study that is applying a low-code AI/ML platform to automatic inspection of a production composite component. Finally, the paper will present several options for integrating the composites automatic inspection system with the existing QMS or MOM system.

Background and Requirements

For more than a decade, machine vision-based automatic inspection technology has been implemented in automotive and other industrial production settings [1]. However, application to the manufacture of components made from advanced composite materials, which consist of plies of continuous oriented fiber reinforcement in a matrix material (usually a resin), has been hampered by the complexity of these materials. Machine vision systems represent a mature inspection technology as applied to visual attributes of works-in-progress (WIPs) made from metals, plastics, composite sheet molding compounds (SMCs), bulk molding compounds (BMCs), and other materials. What all these materials have in common is an isotropic or quasi-isotropic internal structure. That is, their physical properties are not dependent on material orientation. On the other hand, the anisotropic internal structure and ply buildup of advanced composite materials result in a much higher number of attributes requiring inspection: ply edge location, fiber orientation, absence of wrinkles, and absence of foreign objects and debris (FOD) that could be trapped between plies, to name a few.

Additionally, manufacturing processes for advanced composite components are markedly different from those used in conventional automotive component manufacturing, and the differences lead to new potential defects that must be detected. For example, parts with concave surfaces must be inspected for bridging of the composite material that would leave a void between the ply and tool surface or previous ply.

Automatic inspection for WIPs made from advanced composites has been developed in the aerospace industry, but so far it has been limited to R&D facilities, pilot production lines, and a handful of low-volume applications (<1,000 units annually). Before an automatic inspection system using currently available technologies is able to perform inspections in live production of advanced composite WIPs, the system must be programmed to recognize all the features to be verified and all anomalies or nonconformances that may occur. This inspection engineering has been accomplished by (1) using machine vision to capture calibrated images of each feature to be inspected and tagging these images as displaying passing or failing attributes (e.g. edge located inside or outside tolerance band); and (2) hand engineering analysis algorithms that correctly classify the tagged images. Only after completing this process is the automatic inspection system ready to inspect features in a production operation. As an example of this slower inspection engineering, an application of in-process automatic inspection using hand-engineered algorithms has been implemented at Electroimpact for its manufacture of Boeing 777X composite spars and wing skins. [2] Using this system involves application development that takes weeks – sometimes months – to complete, and any change in component design, raw materials or fabrication processes requires this application development to be repeated. High-volume advanced composites fabrication simply cannot accommodate this lengthy inspection engineering cycle.

To accelerate inspection engineering, artificial intelligence/machine learning (AI/ML) has been employed to replace the tedious and time-consuming hand engineering of algorithms. However, AI/ML efforts have required highly specialized resources and expertise, including AI/ML data scientists, vast computing power, and hundreds or thousands of images to train the ML model. These requirements make automatic inspection of advanced composites impractical for production applications, and so they must be surmounted. To achieve the speed and efficiency required in high-volume production operations, two advancements must be developed:

1. The means and methodology to capture a database of calibrated images that display all the features and anomalies that the automatic inspection system must detect and/or measure; and
2. A low-code AI/ML platform and robust ML tools to develop the algorithms that analyze the captured images.

Work presented in this paper promises to move automatic inspection technology of advanced composite components along the development curve so that it can achieve the efficiencies required by high-volume aerospace and automotive applications. These efforts will accelerate the generation of application-specific analysis algorithms from a weeks-long process of hand-engineering to a one- to two-day process using low-code AI/ML technology. Low-code AI/ML also enables automotive manufacturers to have their own manufacturing engineers, rather than third-party data scientists, generate analysis algorithms for additional applications, making it a faster and lower cost engineering task.

Automatic inspection of advanced composite components represents a digital technology capable of integration into a manufacturer's digital ecosystem. As it reaches the efficiencies required on an automotive manufacturing floor, such an inspection system will offer manufacturers several options for digital configuration. These are presented at the end of this paper.

Enabling Technologies

Inspection engineering for a commercially ready composites automatic inspection system involves interactions between three essential technologies. First is the automated fabrication technology used to make advanced composite components in high volume. Production systems that employ automated fiber placement (AFP), filament winding, automated tape laying (ATL), resin transfer molding (RTM), dry preforming, 3D printing and other additive manufacturing operations have matured to a point that automotive production speeds are in sight (albeit for a limited variety of components). Because these machines produce the features that an automatic inspection system must be trained to classify, they are both the subject of inspection and the source of input data needed to train the inspection system (Figure 1). The two other essential technologies – a machine vision system and AI/ML – have been developed individually but require joint development to achieve production-ready in-process automatic inspection for advanced composite components.

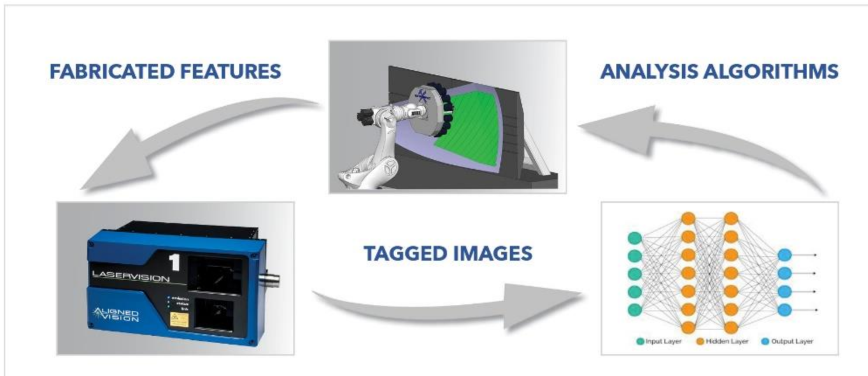

Figure 1. A high-volume automatic inspection system feeds fabricated feature information from the automated fabrication machine to machine vision, which captures a tagged image database that machine learning employs to enable image analysis.

Status of AI/ML-Enabled Automatic Inspection

Beginning in 2019, AI/ML has been applied on a rudimentary level to create application-specific analysis algorithms for automatic in-process inspection of composite components. Two recent trials [3] have demonstrated the advantage of AI/ML-enabled algorithm development over hand engineering. The experiments focused on identification of FOD on various composite surfaces, which typically requires several weeks of dedicated effort when hand engineering of analysis algorithms is performed. AI/ML-enabled development of similar analysis algorithms in the experiments required only one to two days.

Feasibility of AI/ML-enabled inspection engineering is confirmed by a recent project at Oak Ridge National Laboratory. The ORNL team led a successful effort to apply resources to the development of algorithms for 3D printing anomaly detection [4]. An ORNL lead researcher confirms that developmental work of the kind that this paper reports can leverage lessons learned in the cited ORNL project, and he anticipates that classifier development for high-volume automatic inspection of composite components is feasible and straightforward [5]. ML technology has experienced great advancement in recent years, especially with the availability of high-capacity computing power. The generation and hardening of application-specific ML models capable of operating successfully outside the laboratory and in the less controlled environment of the production floor is an essential part of the developmental path.

Experimental

The research study that is the subject of this paper was initiated in February 2021. It is a joint effort between Aligned Vision, which is providing the machine vision-based automatic inspection system, and Sway AI, which is generating the low-code AI/ML platform and ML tools. The study's objectives are to:

1. Identify a candidate composite component currently in production to which the automatic inspection technology and methodology can be applied;
2. Capture a database of calibrated images using a machine vision system installed at the production line as well as production artifacts that can be imaged at an offsite laboratory;
3. Use the low-code AI/ML platform to develop analysis algorithms for the candidate composite structure;
4. Install, operate and compare the results of this automatic inspection system with existing inspection protocols; and
5. Evaluate the applicability of the automatic inspection system when the composite structure or fabrication process is modified.

The goal of the study is to demonstrate rapid inspection engineering, as well as continuing application of machine learning through the low-code ML tool to enable the inspection system to continually improve as production images are processed, and to quickly adjust to design and engineering changes.

To conduct the study, the team from Aligned Vision and Sway AI first assembled the equipment and technologies to be used. Next, a composites fabrication partner and a specific production component were identified. Currently, Aligned Vision and Sway AI are working with composite WIP artifacts to create an image database and develop and fine-tune the AI/ML platform to be used in this application. Next, Aligned Vision will produce an image database of actual production features and anomalies to be inspected on the identified production component, and Sway AI will generate a robust ML classifier to analyze inspection images. The composites fabricator will implement the automatic inspection system, operating it in parallel with current manual inspection protocols, and inspection data from the two inspection approaches will be compared. Finally, the ML classifier will be used by the composites fabricator's engineers in conjunction with Sway AI personnel to verify that inspection engineering can be performed by non-specialists.

Study Equipment and Technologies

Machine Vision System

The machine vision system used in this research study captures detailed, calibrated images anywhere within a large field of view (FOV) on a large complex surface (typically 3m by 3m). It incorporates machine vision and laser projection in one unit. Independent of automated fabrication equipment, this system is mounted on a truss or gantry at a standoff distance from the work surface typically of 3m. This independence means that the system is able to measure the position and orientation of features relative to the tool or part surface and the work cell's coordinate system. (Profilometers and other inspection systems are limited to measurements relative to other plies or features.) Unlike inspection devices connected to a deposition head, this machine vision system is able to inspect any visible point on the surface at any time before it is covered by another ply. Each unit of the system (Figure 2) captures images and projects its laser within a 60˚ (±30˚) angle. Exceeding Boeing D6-55902 requirements, the unit achieves an accuracy of ±0.25 mm (±0.010 in.) in a standard 3m by 3m (10 ft by 10 ft) FOV at a standoff distance of 3m (10 ft).

Figure 2. A large-FOV machine vision system includes a high-resolution, high-magnification camera with a built-in laser projector. Model-directed software captures and analyzes detailed images of an in-process composite layup.

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.

Because this machine vision system is completely independent of the AFP head (or other automated fabrication equipment), the AFP can continue to add material even when the inspection system detects a nonconformance or foreign objects and debris (FOD). Operators may remotely conduct a detailed examination of analyzed inspection images (Figure 3) while layup continues. If entry into the work cell is warranted, the system's laser projector pinpoints the area of interest, minimizing AFP downtime while near real-time corrective measures are taken.

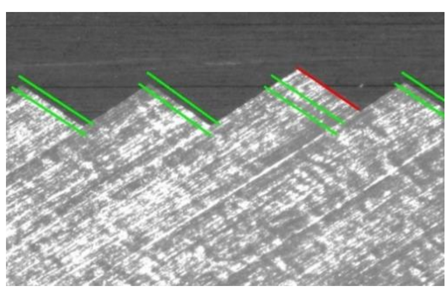

Figure 3. Analysis enabled by transform. Out-of-tolerance tow placement identified.

Low-Code AI/ML

AI-enabled algorithm development uses the type of AI known as machine learning (ML), which is the ability of a computer to use data to improve performance of a particular task without being explicitly programmed to do so [6]. With exposure to a set of tagged images, an ML model trains a classifier to correctly categorize images with similar characteristics. A “tagged image” is one that is identified as either being flaw free or containing particular flaw(s). Timely creation of the hundreds or thousands of tagged images needed to train a classifier is one of the procedures of this research study, as discussed below.

Building ML-based algorithms for in-process inspection involves classifier development that requires innovative application of a novel convolutional neural network (CNN) architecture to create real-time detection and classification of inspected features. The CNN architecture entails innovative manipulation of data called “semantic segmentation,” which classifies layered imaging data by segmenting image pixels into classes [7].

Low-code ML is needed to allow composites engineers to perform AI/ML-enabled inspection engineering without the assistance of data scientists. This “democratized” ML requires the creation of a software abstraction layer called a workflow and orchestration engine, which automates model evaluation and selection, model deployment, verification and monitoring. The workflow and orchestration layer hides the complexity of building an AI/ML model from the user, instead guiding the user through the various steps of completing an AI/ML project without coding.

An example of a low-code ML user interface is shown in Figure 4. The graphical interface with drag-and-drop functionality enables users with basic engineering computer skills to develop application-specific ML models.

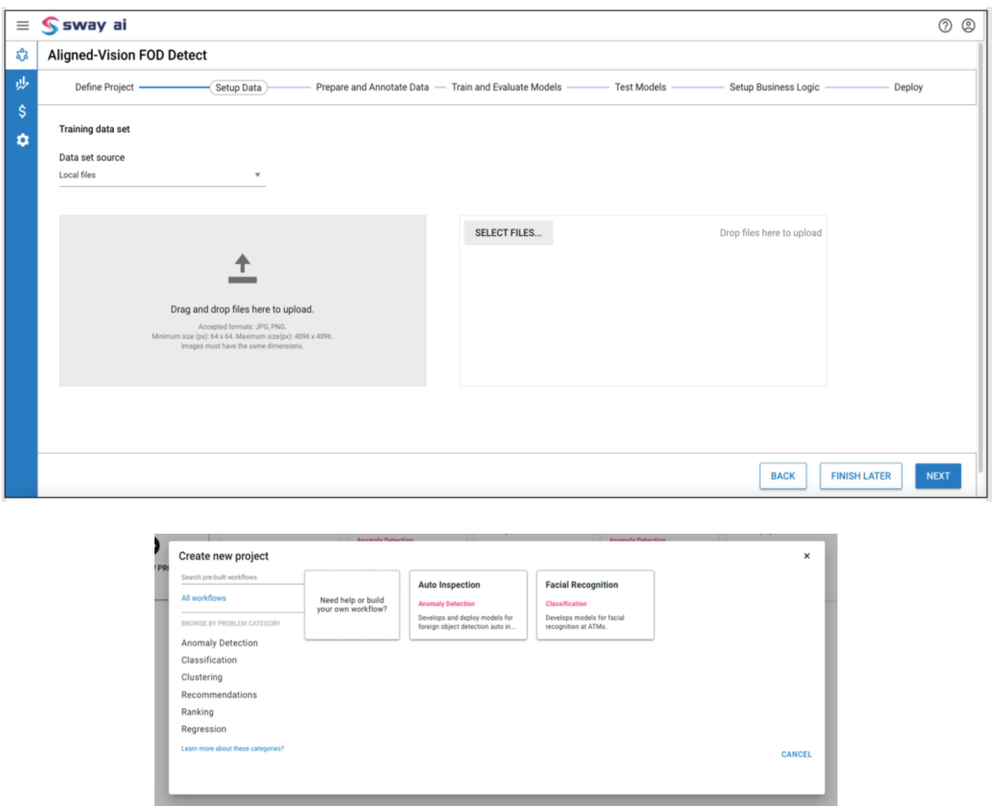

Figure 4. Low-code ML interface allows non-specialists to create ML models for inspection applications.

Current Status and Findings of the Study

The research is ongoing at this writing. Researchers have achieved objective (1), the identification of a production composite component, and are currently performing tasks associated with objectives (2) and (3), the creation of an image database and AI/ML-generated analysis algorithm.

The research team identified and secured the cooperation of a prominent U.S. manufacturer of advanced composite components. The company currently uses laser projection in its operations, which can easily be switched out for a machine vision/laser projection unit to capture inspection images. Its production components are well suited to the study, featuring large size and complex geometries. This composites manufacturer has identified a component and production work cell on which to conduct the study. The component is a glass fiber-reinforced polymer (GFRP) radome with a geometry similar to the hull of a rounded kayak, approximately 1.8m long, 1.2m at its widest point, and 0.8m at its deepest point. The radome is hand laid up from 116 ply patterns and is up to 28 plies thick. Characteristics of this part and process that make it a suitable subject for the study include its complex geometry and multiple attributes requiring inspection (ply edge locations, fiber orientation, absence of FOD). The first attribute for which the team is creating an image database is presence or absence of FOD.

The company has begun working with the research team to create needed artifacts for image generation. The laboratory at Aligned Vision’s facility has received GFRP panels and three packaging materials commonly found in the production area. To generate a large quantity of images, the artifacts have been mounted on a rotate tilt system which, in conjunction with the machine vision system, is capturing and automatically tagging images from various points of view (Figure 5).

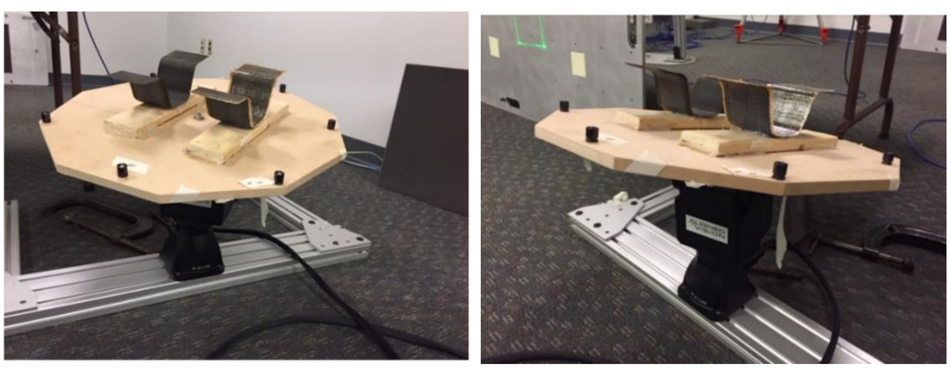

Figure 5. Rotate-tilt system for capture of hundreds or thousands of tagged images.

Using the tagged images as a database, Sway AI ML scientists are developing and training the ML tool. They are evaluating several ML models to determine which responds most accurately and efficiently to the image classification task. At this writing the Sway AI team has achieved excellent results using the laboratory-generated tagged image database. The ML model is correctly recognizing contaminants as small as 3 mm (Figure 6), including FOD consisting of white paper being detected on the white GFRP test panel. The ML user interface (Figure 7) depicts how

ML scientists are currently able to test the ML model, and how straightforward such testing should be for non-specialists.

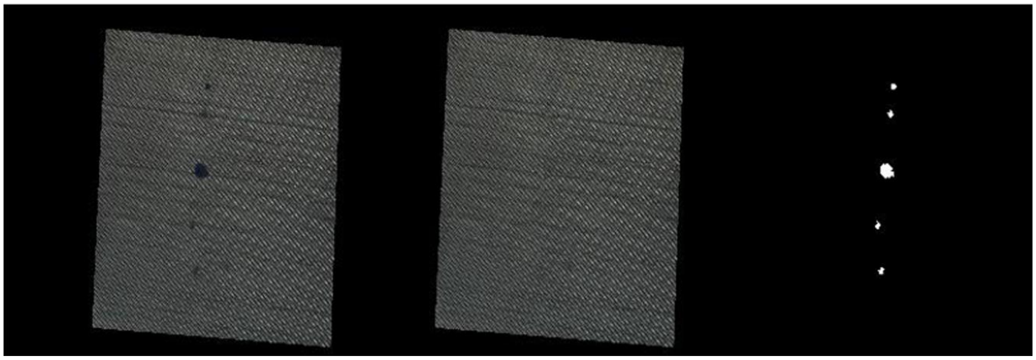

Figure 6. Example of anomaly detection. Left is the input image; center is the reconstructed image; and right shows the detected anomalies.

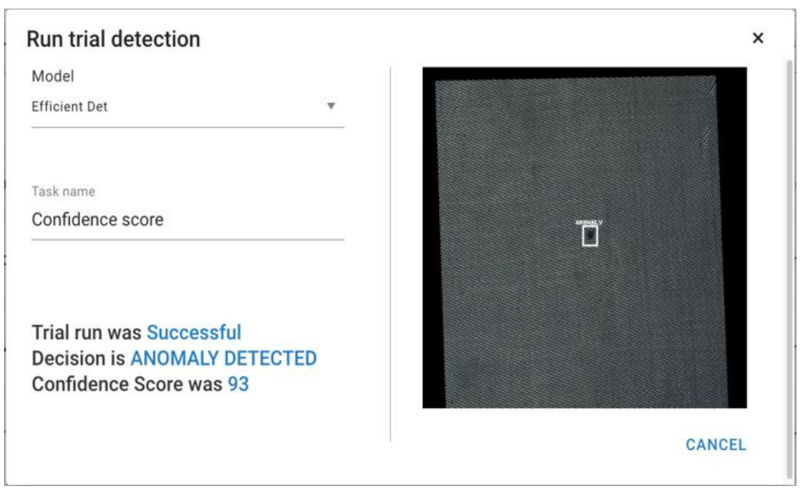

Figure 7. Low-code ML user interface is designed to enable non-specialists to test inspection models simply. The software hides the complexity of AI/ML coding and guides the user through model evaluation and selection, deployment, verification and monitoring.

For the ML tool to be deployed in a production setting, ML team members are addressing in-field computational requirements and robustness. They are also investigating the transferability of image analysis capabilities to other production lines and composite components. Machine learning and other AI technologies also feature the ability to continue learning and improving the capabilities of the system to which they are applied. Once the ML-enabled automatic inspection system is deployed in the selected production work cell, it will capture and tag more images, creating a database on which the selected ML tool will refine the analysis algorithms.

Up to this point in the research study, the application of machine learning has been conducted by ML specialists at Sway AI. The company's low-code ML user interface and supporting software (screenshots displayed in Figures 4 and 7 above) are designed for composites engineers to refine algorithms without data scientist intervention. The final procedure in the research study is to have engineers at the composites fabricator use the low-code ML tool for inspection engineering of additional components being fabricated at the same facility.

Integration of Composites Inspection and Other Quality Systems

As this and other studies help advance automatic inspection of composite WIPs toward feasible commercial application in automotive manufacturing facilities, another critical requirement for widespread adoption is the ability of the system to be integrated into the facility's quality program.

Manufacturers in the automotive industry are typically at the forefront of applying digital technologies to their manufacturing floors. This industry is appropriately characterized as an early adopter of manufacturing automation, including computer numeric control (CNC) machining, robotics, and mature supervisory control and data acquisition (SCADA) systems, as well as automatic inspection technology. To orchestrate manufacturing operations in this digital environment, most automotive manufacturers have already implemented MOM systems, including manufacturing execution system (MES), advanced planning and scheduling (APS), enterprise manufacturing intelligence (EMI), and QMS software. [8] As in-process automatic inspection of advanced composite components is introduced to an automotive manufacturing plant, it is capable of operating as a standalone system. Manufacturers then have several options to integrate the system into their existing MOM systems.

Standalone Operation

In-process automatic inspection of composite components may be introduced to the automotive manufacturing floor as a "digital point solution" or standalone technology. In this configuration (Figure 8), the system imports needed data from CAD and composites-specific CAM files (such as Fibersim or CPD). In the case of the large-FOV automatic inspection system

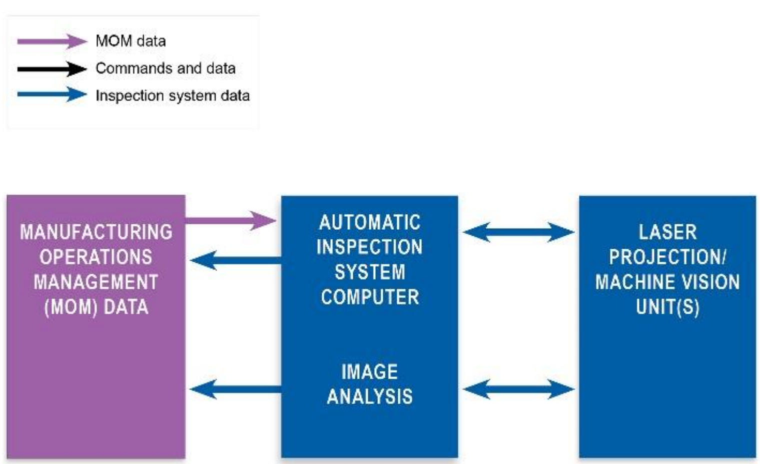

Figure 8. As a digital point solution, an automatic inspection system imports design and control data from the manufacturing operations management (MOM) system and exports as-built data back to the MOM system.

discussed here, these files direct the system to aim the laser projector/machine vision unit and capture the desired images. The system's control computer then performs image analysis and provides verification that an analyzed feature meets spec; or it sends an alert regarding a nonconformance and provides a CAD-directed laser projection to direct operators to the nonconformance location. Specifically, the inspection system's software includes an "image to part" function that calculates where to aim the laser projector based on the image analysis data, as well as a "part to image" function that accurately projects model-based tolerance bands and other quality data.

MOM Integration

Using a software development kit or other integration process, automatic inspection can be integrated into a manufacturing operations management (MOM) system (Figure 9), 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 manufacturer's ability to respond to real-time 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 nonconformance event is detected by an automatic inspection system, a machine operational parameter related to that nonconformance 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 indicate a dropped tow, which can be corrected in real time on the AFP.

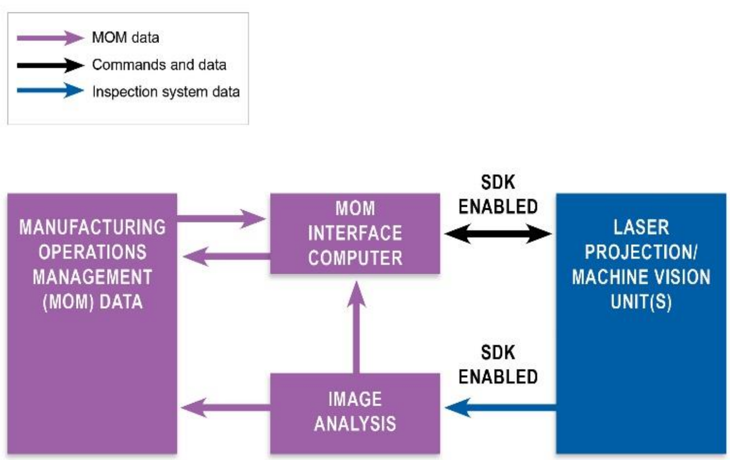

Figure 9. Integrated into a manufacturing operations management (MOM) system, automatic inspection becomes one of the critical functions within a quality ecosystem.

Summary and Next Steps

The high strength-to-weight ratio of advanced composites has made them an appealing material choice, especially as automotive manufacturers seek new ways to make their vehicles lighter and more energy-efficient. Obstacles to widespread use of advanced composites in the automotive sector include relatively high material costs and slow cycle times. Because a large portion of cycle time is consumed by inspection and other quality tasks – estimates range from 30 to 65 percent of cycle time, depending on the component being fabricated [9] – the development of rapid automatic inspection is essential to making advanced composites more technologically and economically feasible for high-volume automotive applications.

The ongoing study reported here promises to accelerate inspection engineering for advanced composite components. Being able to apply the automatic inspection system to new and modified production components in a timely manner and to integrate that system into a manufacturer's existing digital manufacturing system represent critical steps toward more extensive use of advanced composites in automotive components.

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