A QUANTITATIVE EVALUATION OF AFP STEERED COURSES THROUGH INSPECTION

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ABSTRACT

This article will discuss the use of a comprehensive methodology to inspect and track defects of steered Automated Fiber Placement (AFP) tows on a cylindrical surface. The high degree of automation in the AFP process makes the manufacturing method an excellent platform to produce variable stiffness composite structures. A key method in their production is the use of tow steering to create desired stiffness properties. However, with tow steering, there is an increased likelihood for the production of defects such as wrinkles and folds. A profilometry-based inspection method is utilized with a hand-crafted data processing technique to create accurate measures of tow displacement and tow deformation. This information is then used to create a quality metric which can be matched with processing parameters at the time of layup.

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1. INTRODUCTION

Automated Fiber Placement is a manufacturing process for the creation of large composite structures. Defect tracking in AFP production has largely been an exercise in qualitative observation. Particularly with respect to process parameter studies, the current state of the art does not incorporate any attempts at instantaneous defect measurement on a given course. To the authors' knowledge there exists no concrete quantitative measurement of defect quality derived directly from defect production. Attempts at automated inspection systems in the past, particularly those involving some machine learning approach, while reasonably effective and accurate, fail to produce the fidelity required for fine measurements. Therefore, a system capable of capturing instantaneous defect measurements for inclusion in process parameter studies is highly relevant.

In effect, the problem is three-fold. First, a data collection process capable of capturing relevant features in an AFP manufactured structure must be selected or developed. Relevant features are defined as any set of input vectors that are capable of encoding useful information about the quality of a layup, with certain sets of input vectors having a higher relevance than others[1]. Secondly, some method of processing the relevant feature set must be derived to extract defects. Lastly, it

[1] It is important to note that traditional imaging approaches have mixed success due to the low contrast nature of graphite composites. Therefore standard RGB images may not have a feature set relevant to defect identification.

must be ensured that this method for defect identification can map the input to both defect type and defect characteristics. Simply being left with a region in which a defect exists is not pertinent to this exercise. What is required is a solution with finer detail that can precisely characterize a given defect.

The following document outlines the author's approach to this problem. A comprehensive approach to gathering the quality conditions of a layup will be demonstrated with respect to defect detection on steered tows across a cylinder. Analysis and extraction of course geometry features will also be demonstrated.

1.1 Purpose

Steering of AFP tows on ruled surfaces presents tremendous opportunities for structural performance and stiffness tailoring at fractions of the weights currently achieved with standard design paradigms [1]–[3]. Unfortunately, steering in the context of AFP will trend towards inducing a number of major defects, notably wrinkles and folds [4]–[7]. While defect production is a phenomenon that is generally known in fiber steering, exacting correlation between processing parameters, steering radius, surface geometry, and defect production are not well developed.

To address these questions, a series of experiments were run at the University of South Carolina at the McNair Center for Aerospace Innovation. Steered paths were created across a 1219.2mm diameter cylinder in a design of experiment (DOE) intended to explore a complete solution space for processing parameters. Finding the effect of these design and manufacturing features on part quality requires that defects are tracked precisely and then encoded into useable knowledge to make statements on the layup quality and parameter relationships to layup quality. It is the author's intention to show that the inspection and data processing solution contained in this document are suitable to answer this question.

1.2 Literature Review

AFP inspection is an open research topic that has been explored extensively in several previous works by the authors [8]–[10]. Traditional manual inspection used currently in industry is a considerable drain on time, with some estimates of inspection accounting for more than 30% of machine operation [11]–[13]. Manual inspection is also principally a qualitative exercise, with somewhat arbitrary judgements about layup quality being rendered without precise measurement. It is in many ways a "gut" determination if a given part is acceptable.

Novel hardware approaches to the imaging or data collection of a composite part has been the subject of significant research. Thermography has become a leading technique for the inspection of composite parts. Thermographic inspection tracks the flow of heat through a part after thermal excitation. When defects are present, apparent material properties will differ from the reference background, thus affecting heat transmission through the part at the affected area [14]–[17]. Thermography has also been directly explored in AFP inspection, yielding some novel solutions to online AFP inspection [18], [19].

Once data has been collected, it must have relevant features extracted and then processed to determine damaged areas automatically. This is quickly becoming the realm of machine learning (ML); and with this development semantic meaning can be assigned to given feature sets in data.

This is apparent in the world of computer vision. Remarkable advances have been made following the introduction of the deep convolutional neural network in the AlexNet algorithm [20]. ML and particularly deep neural networks appear to be the future stalwarts of data analysis and processing. It should be noted that the strength of deep networks lies in the many layers of processing units, allowing for features to be automatically extracted and transformed from a raw input vector.

1.3 Proposed Solution

The creation of our system relies on a bedrock of several previous explorations into the area. Previously, an ML-based inspection method was developed for the automated identification of defects on an AFP manufactured structure [9]. The principle of precise defect characterization was first forwarded in this paper and resulted in an algorithm capable of determining both the class and the exact shape of a defect. Later additions to the system included a comprehensive user interface for creating user-defined defects and correcting defects misplaced by the automated system [8]. For data collection, the Ingersoll Machine Tools (IMT) Advanced Composite Structures Inspection System (ACSIS) [Figure 1] was utilized to scan a part and capture precise data about the height profile of the part. ACSIS data collection is a profilometry system utilizing 4 Keyence LJ-7080 blue-light profilometers.

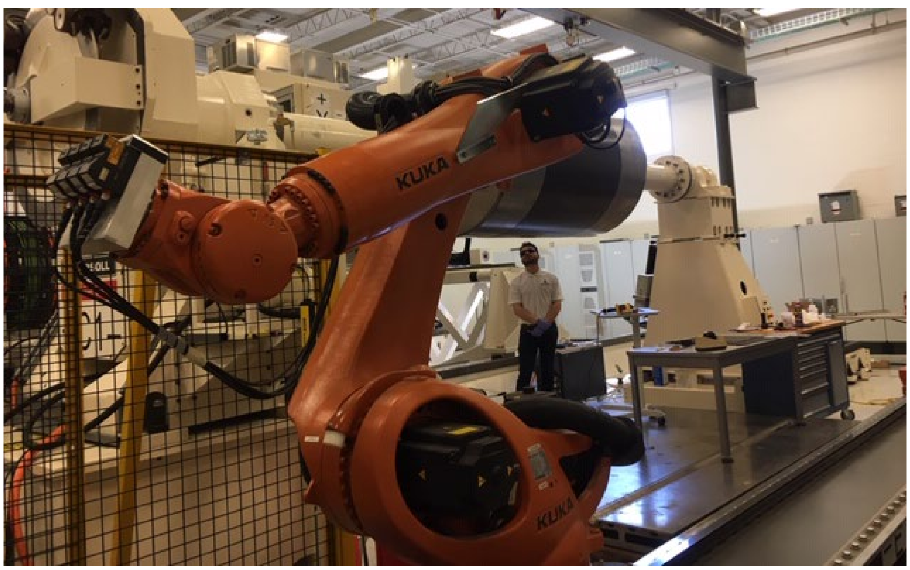

Figure 1: ACSIS AFP Inspection System

Profilometry has the capability to rapidly produce height profiles of a part, which ACSIS then maps to pixel values to create a grey scale image to be processed. Coupled with the nature of the defects relevant to the steering study, this offers a unique opportunity for analysis. ML is becoming the preferred tool on the principle that features can automatically be pulled from raw data. However, if features are readily available, then it may often be more convenient to use a hand-crafted approach to data processing. In the case of profilometry scans, height profile is a potential mechanism to highlight defects.

Coupling this with the UI developed for previous inspection systems, the mechanism for potential error in a simple hand crafted solution become apparent. Simple marking of the course boundary allows for recreation of the course geometry, and from it a centerline description of the course can be determined.

2. CONCEPTUAL OUTLINE

The analysis algorithm is subdivided into several parts: (1) the extraction of defects from the height profile, (2) determining the centerline of each course, and (3) the iteration of a measurement line over the length of the course to determine the percentage of course width at a given instance is occupied by defects. Figure 2 shows the dataflow to from inspection to quality measurement.

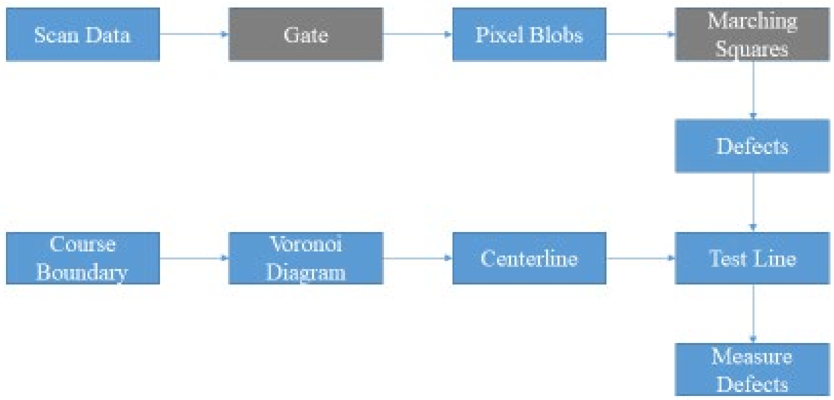

Figure 2: Quality Measurement Algorithm

2.1 Height to Defect

As mentioned, the ready abundance of height data draws us towards a relatively simple method for defect identification. By applying simple gates to the height profiles and shading in pixels, out of plane deformations and tow displacement can be determined. The lower gate represents the tow displacement and the upper gate the out-of-plane tow deformation. The resulting pixel blobs can be extracted using the marching squares algorithm [21], resulting in a bounding polygon around each collection of pixels. From this, small polygons generated from artifacts in the image were filtered out, resulting in a precise bounding polygon being placed around defects of interest. In the case that a significant deformation may cast a shadow that could trigger a false positive for a displacement. This is easily accounted for with a quick adjustment through the UI. The resulting defects map for the courses steered using different process parameters is shown in Figure 3 where tow displacements are represented in green and out-of-plane deformations in orange.

2.2 Reconstruction of Course Geometry

Before quality measures can be gathered, the defect data must first be placed in context to the course that the defects are on. In order to better represent the course geometry, a centerline is determined such that a general “direction” to the course can be used for further evaluation. First the Voronoi Diagram [22] is generated with the course boundaries as seed points [Figure 4]. From this, a set of Voronoi edges is constructed. The set is then filtered such that only edges within the course boundary remain. What is left is a series of unsorted edges lying within the course. Figure 5 gives an example of these unsorted edges. Note that while a general centerline description can easily be seen, there are several edge artifacts that require more processing to remove.

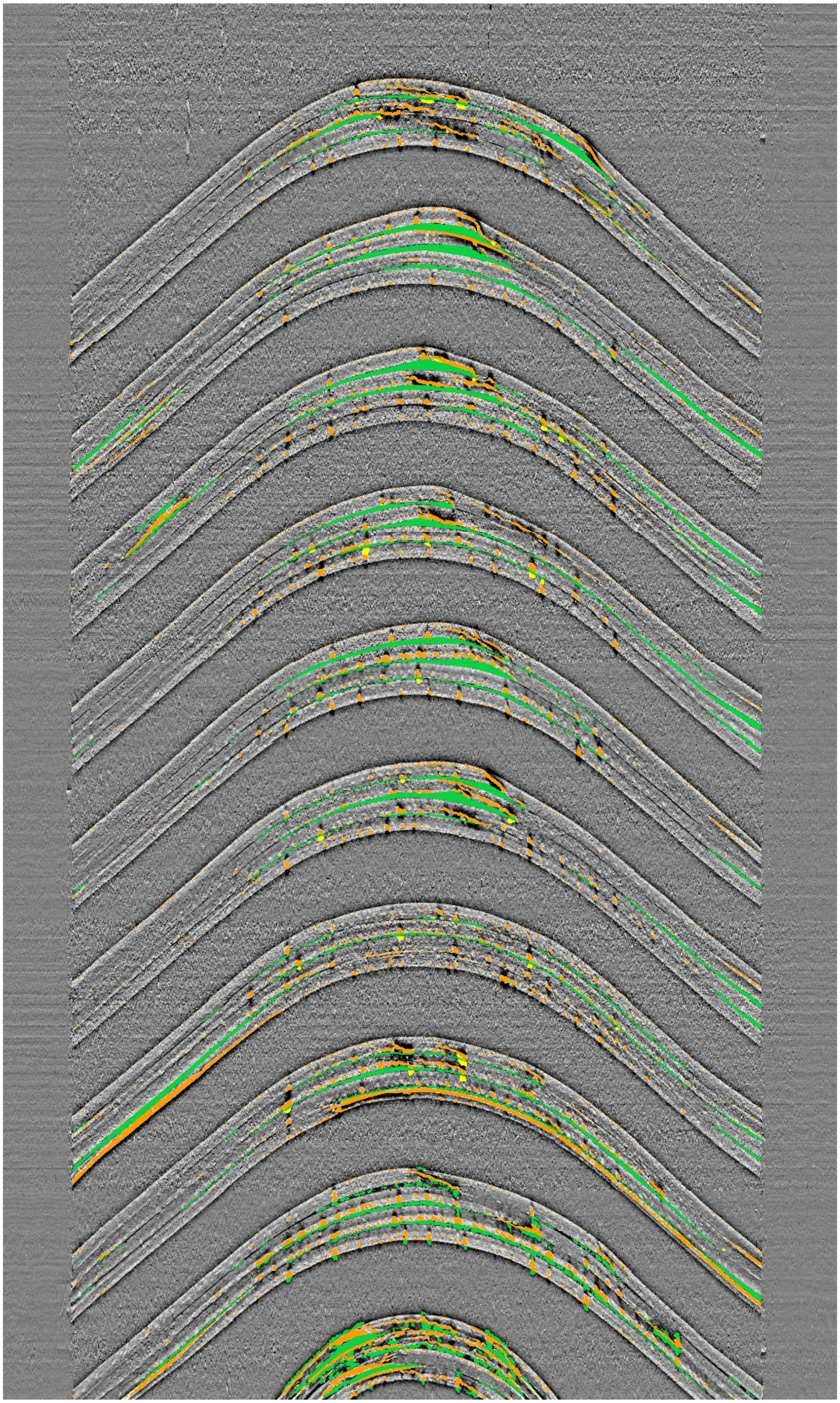

Figure 3: Defects Identified on Steered Courses

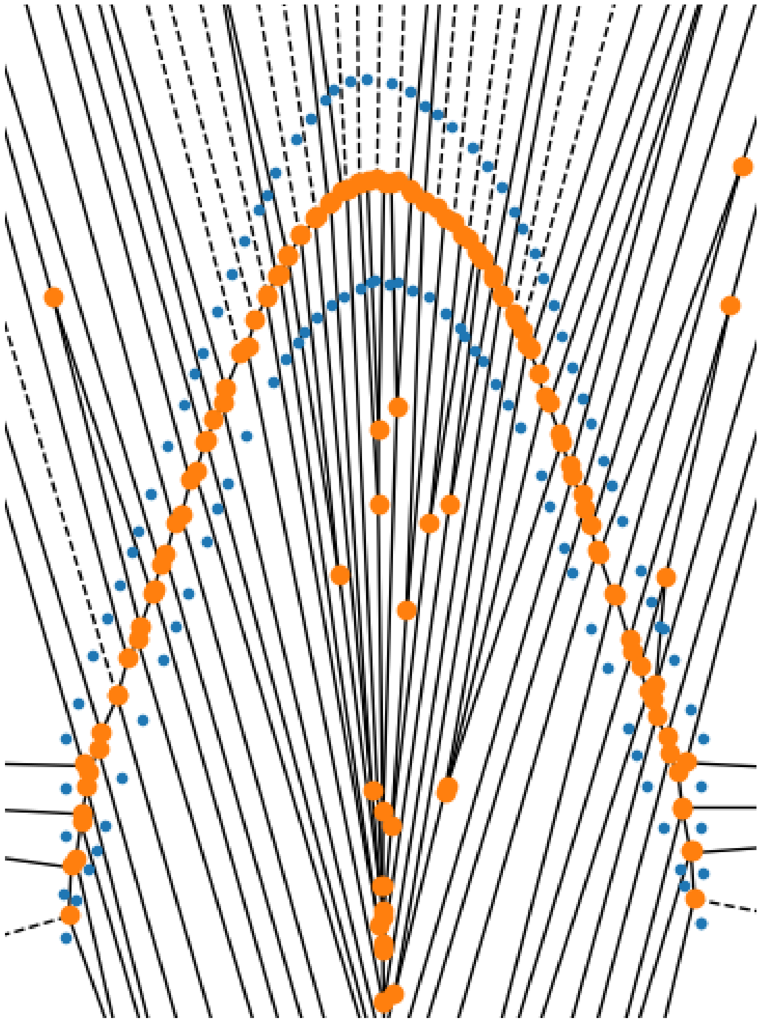

Figure 4: Voronoi Diagram Generated from Course Boundary

These edge artifacts can be removed through a number of potential methods. The authors can speculate about a number of transformational or clustering approaches using the vertices of the edges could result in good results. However, if we create a graph reflecting the connectivity of each of the edges, then a number of fast graph theoretic approaches can be deployed.

Principally, if the assumption is made that these edge artifacts do not bridge across the interior of our pseudo-centerline, then by extension the centerline approximation is the shortest path from the leftmost to the rightmost edge vertex. This is easily and quickly accomplished using Dijkstra's Algorithm [23] and assuming that all of the edges in the graph have equal weight. Therefore, so long as the number of edges is low enough such that the process of mapping back and forth between graph space and coordinate space is computationally reasonable, then the general centerline [Figure 5b] can be extracted.

If one wishes to improve this description of the centerline, then a simple smoothing procedure by approximating the extracted centerline by a piecewise linear function [Figure 6a] achieves a nice result and is an important step for preprocessing when iterating a line normal to the center for final defect measurement.

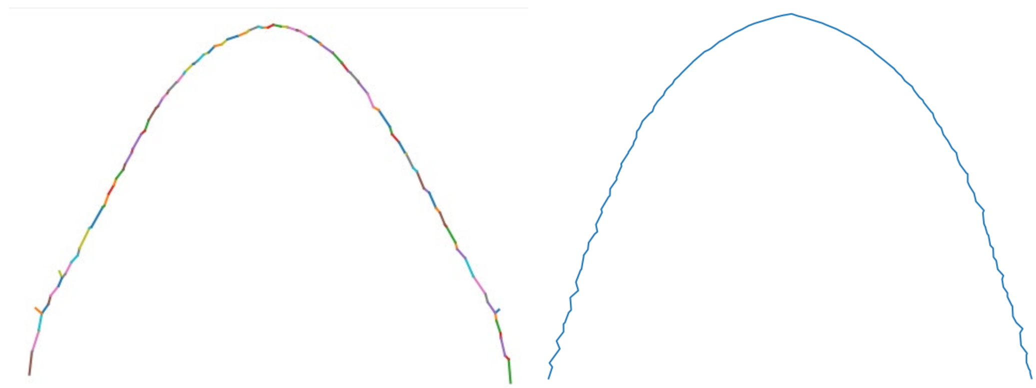

Figure 5: a. Set of Voronoi Edges in Course Boundary. b. Extracted Centerline

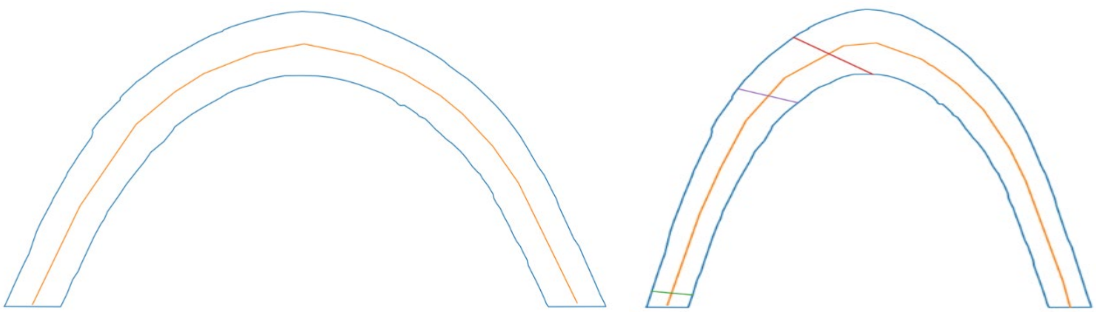

Figure 6: a. Piecewise Linear Function Fit to Centerline. b. Intersection Lines Normal to Course Center

2.3 Measuring Layup Quality

Thus far, the discussion of the analysis present in this document has centered on the identification of defects and the creation of corresponding geometry markers that enable locating the defects in context of the course. To link these two portions of our analysis together for the creation of a quality metric, a definition of the instantaneous effect of defects on the course must be created. To do this, the centerline extracted in the previous sections is used as a reference through which a line normal to the course can be created [Figure 6b]. This normal line is then iterated over the length of the course, where the length of that line intersecting with defects is determined. The length of the intersection is normalized against the width of the course at that section, resulting in the percentage of the course at a point that contains defects. Building this description over the course, and entire profile of manufacturing defect production across the entire course can be constructed. For each of the classes, a profile can respectively be built. In the case of the steered tow defects in this experiment, out of plane deformation, tow displacement, and total defects can be measured. However, this system is applicable to any set of defects that one might wish to identify.

3. RESULTS

In the case of a course generated in the steering experiments, a defect profile can be produced according to the methods outlined in the previous section. This defect profile [Figure 9] shows defect production as a function of the length of the course. One can note that as expected, the number of defects increases as the course moved from the linear regime to the steered section.

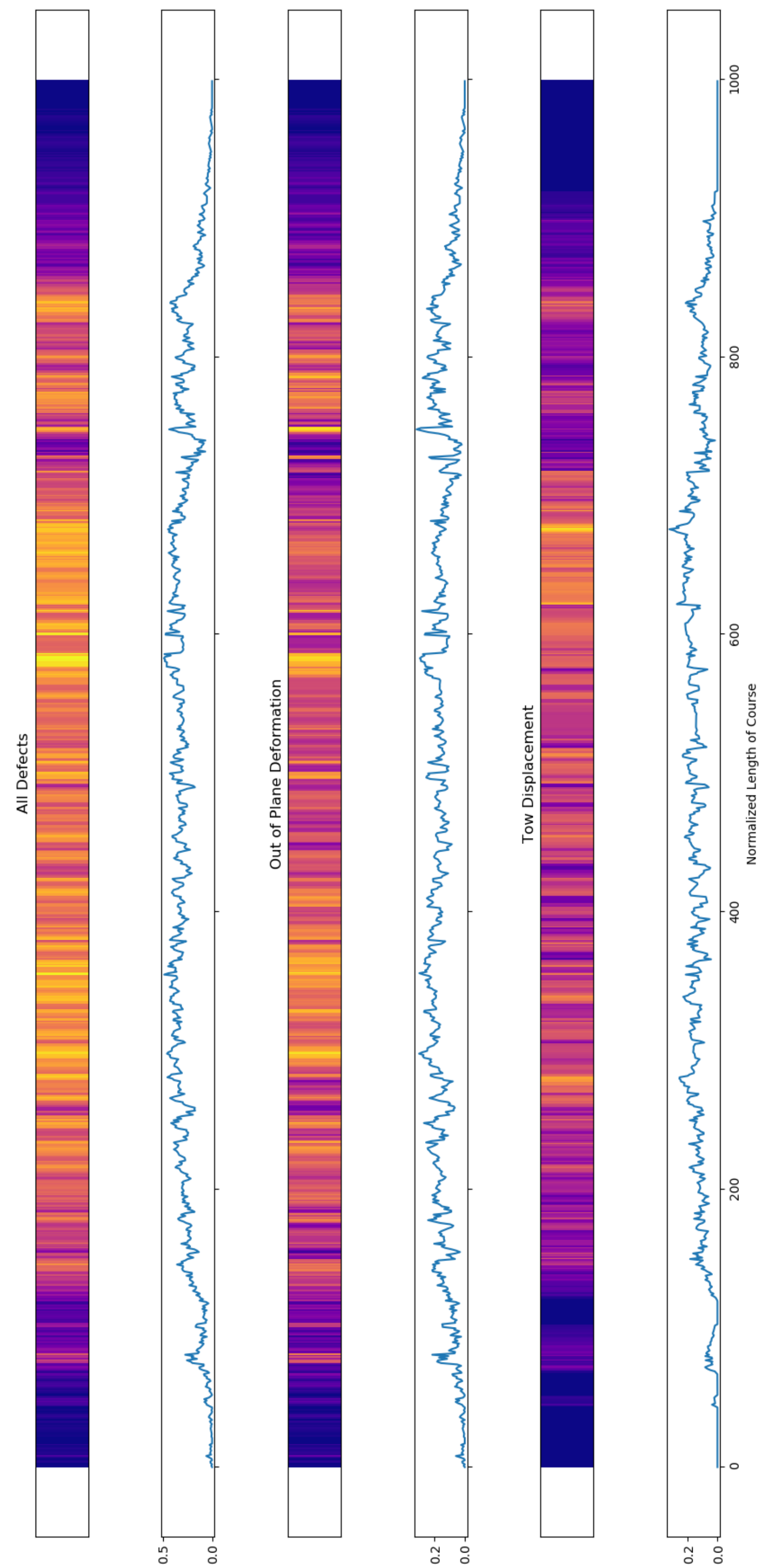

Figure 9: Defect Production Across a Steered Course

4. CONCLUSION & FUTURE WORKS

The method for quality assessment outlined in this document represents a novel method for understanding the production of defects instantaneously across a course under steering. Profilometry scans provided a manner by which defects could be identified such that the precise boundary of the defects could be characterized through the gating of height profiles for the identification of tow displacement and out-of-plane deformation. A process based on principles of computational geometry was developed to extract the centerline of a course from inspection data using the Voronoi Diagram and graph theoretic relationships between Voronoi elements. Using this information a measurement of the amount of a course width that was occupied by defects could be made. An instantaneous measurement of defect production was then created.

The quality measurements of the steered courses was done while keeping detailed process parameter information. Processing parameters for AFP manufacturing such as heating temperature, compaction pressure, and feed rate are poorly understood in the context of layup quality. It is the author's intent to use this new quality assessment tool to correlate process parameters along with design variables such as steering radius; therefore enabling a qualitative statement about the rank, optimality, and effect of processing parameters on layup quality.

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