AUTOMATED FIBER PLACEMENT DEFECTS: AUTOMATED INSPECTION AND CHARACTERIZATION

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ABSTRACT

Automated Fiber Placement (AFP) is an additive composite manufacturing technique, and a pressing challenge facing this technology is defect detection and repair. Manual defect inspection is time consuming, which led to the motivation to develop a rapid automatic method of inspection. This paper suggests a new automated inspection system based on convolutional neural networks and image segmentation tasks. This creates a pixel by pixel classification of the defects of the whole part scan. This process will allow for greater defect information extraction and faster processing times over previous systems, motivating rapid part inspection and analysis. Fine shape, height, and boundary detail can be generated through our system as opposed to a more coarse resolution demonstrated in other techniques. These scans are analyzed for defects, and then each defect is stored for export, or correlated to machine parameters or part design. The network is further improved through novel optimization techniques. New training instances can also be created with every new part scan by including the machine operator as a post inspection check on the accuracy of the system. Having a continuously adapting inspection system will increase accuracy for automated inspections, cutting down on false readings.

1. INTRODUCTION

1.1 Purpose

AFP manufacturing has allowed for a big leap in the large scale industrial manufacturing of composite parts. Its consistency and ease of use offer a distinct advantage over traditional layup methods. However, the automation allowed by AFP also can generate problems that may otherwise be avoided with a human influence. AFP layup can create defects across each individual ply. In a traditional aerospace industrial setting, human inspectors asses the defects and their significance during the manufacturing of the part. This allocation of manpower and resources represents a clear area for automation. In addition to the cost and time penalties of using human inspectors, this method is also subject to losses with the fatigue that is often associated with a process's reliance on humans. Additionally, the training time required to teach an inspector to recognize defects, and the experience to understand defect significance is a further drain on resources. Thus, automation of inspection has the potential to yield faster and cheaper inspections with the ability to improve upon the common errors of human inspectors. With this change, among others, AFP parts can be brought fully into the Internet of Things (IoT) and have predictive analysis capabilities through the configuration of a digital twin. Defect information can be attached to the part as a digital footprint of the manufacturing process, informing maintenance and wear schedules. Moreover, defect information can reveal certain adjustments that need to be made to particular machines.

1.2 Proposed Solution

When devising an automated inspection system for AFP, one needs a data acquisition system and algorithms to process that data. In both of these areas, we intend to present a unique approach to the automated inspection processes. The inspection software generally falls into two categories: handcrafted or machine learning. Handcrafted solutions work on a limited range of data artifacts and are rigid structures that cannot be adapted to account for error or defects outside of set tolerances. Because of their limited use, this will be the extent of our reference to them. Machine learning approaches offer several distinct advantages, and in recent years have begun to achieve the levels of performance necessary to be used on an industrial scale.

Machine learning is a set of processes and their respective algorithms that automatically create relationships between sets of data. These algorithms can be extended for use on classification tasks, clustering, and even image and signal processing. Algorithms such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) [1] have allowed greater generalization of tasks. Particularly in industry supervised learning processes are utilized to develop accurate and high generalization systems. These systems are trained on a set of input data and are then expected to produce a desired output when shown a similar data sample. The great advantage of machine learning systems is that they can take highly dynamic and non-linear data sets spread among a large number of features and find relations between inputs and desired outputs. A traditional approach to object detection is the “Sliding Window Techniques” by which small portions of an image are evaluated for the objects in question and then the window is moved to another portion of the image and the process continues. This precipitates a fine balance between the resolution of analysis and the run time of the inspection. Our system does away with the sliding window approach in favor of a pixel-by-pixel classification scheme. The additional detail can then be used for a number of processes including the creation of defect models for finite element analysis or precise logs of defects for use in maintenance record. The focus of this paper is to develop a new inspection process through a unique machine learning approach.

1.3 Literature Review

One of the particularly interesting applications of machine learning is in the inspection stage of production, whether as a classification tool, or as a tool for defect detection. [2] Demonstrates how convolutional neural networks (CNN) similar to the network outlined in [3] can be utilized for the sorting of natural stone in an attempt to reduce dependency of the human inspectors traditionally used in the classification process. Images of the granite are presented to the algorithm, which then classifies them. CNNs are particularly adept for this task, as the convolutions in the system allow for what is in effect a data compression process. [4] Notes how SVM has been used for analysis of images for defects among certain fabric patterns to a high degree of accuracy. [5] Notes how statistical features extracted from images can be used to improve on the accuracy of a defect detection and pattern recognition system. Metrics such as the central moment of an image patch were used. These computer vision tasks can include further refinement. [6] Expands on the CNN architecture extending all layers to contain convolutions, thus generating classifications on a pixel by pixel basis, allowing for refined detection over traditional CNN architecture. Finding relations in data is a strength of SVM and other statistical classification systems. SVM attempts to merge data into various categories by looking for a hyperplane that is able to separate the data with a minimized error. [7] Describes how SVM can be utilized to identify key data points that contribute to process states in a significant way. [8] Show how a supervised learning based ranking system can be used to organize and identify state characteristics. [9] Examines how Bayesian Networks can be utilized to find indications of failure modes in structures. Features such as loading conditions, time, and position information were attributed to a model in order to determine critical points of failure. The complex computational subject of optimization is a unique niche for machine learning to make an impact in. [10] shows how a combination of linear regression and SVM can be used to optimize Automated Fiber Placement (AFP) machine parameters for the manufacturing of AFP parts. Data generated from process monitoring was used for analysis and learning features were utilized to update the planning process. The process monitoring was accomplished through a visual inspection system using an infrared camera mounted directly on the AFP machine head.

Machine learning represents an alternative to those manufacturing tasks that are too complex for traditional handcrafted solutions. It gives operators the ability to monitor, inspect, and identify every stage of the manufacturing process. This creates tools that can separate every stage of manufacturing from expert knowledge, localizing both information and allowing non-experts to be informed on a decision making process. Moreover, reviewing the previous work in AFP defect inspection we can find several techniques being used. Non-destructive composite structure evaluation techniques include thermography, radiography, ultrasonic testing, and laser imaging methods among others [11]. In, [12] they use a digital imaging system and compare the images captured to the CAD models to locate the differences in the structure. They use this technique to find traits like: wrinkles, bridging, shear and foreign objects. [13] Describe an AFP inspection system utilizing both a camera system equipped with laser projection, in addition to an array of profilometers. An image recognition software is used for the digital imagery to determine ply boundaries and a handcrafted algorithm is used for the raw data of profilometer to determine gaps, overlaps, and foreign objects. In, [14] the mentioned system is further elaborated and a user interface is also described, through which an operator can check for the measured features and locate them.

After reviewing the previous work we can notice that there’s still no comprehensive technique for detection of the various AFP defects counting up to 15 distinct defects. Hence this study offers a novel approach, where the combination of profilometry and machine learning is used for comprehensive defect detection.

2. EXPERIMENTAL PROCESS

2.1 Data Acquisition

As mentioned in the literature review, there is a number of interesting approaches for defect detection in AFP parts. In this study, the Automated Composite Structure Inspection System (ACSIS) is used. This system utilizes Profilometry and was developed by Ingersoll Machine Tools for the National Center for Manufacturing and Machining (NCDMM) [15], Figure 1. The system is comprised of 4 KEYENCE LJ-V7080 profilometers, a KUKA robotic arm and a corresponding controlling unit. The Profilometers scan the surface of the part and measure the height profile. The system then processes the readings and produces high quality grayscale images, (**Error! Reference source not found.**Figure 2) mapping the surface topography of the part with high accuracy. It should be noted that our analysis with ACSIS was pre-cure. The greater detail presented from a pre-cure part represents a greater degree of validity when performing feature extraction. After curing the height information that the sensors rely on will change, since some defects would be covered and hence won't be detected through profilometery.

Variations in the uniformity of the part surface are identified by differences in the grayscale of the images. A white patch indicates an area of higher elevation on the surface while a black patch indicates a drop. Each defect will lead to a unique variation in this grayscale. The scans are carried out after each ply is laid up by AFP, and the images from each scan are logged. The scan trajectory generation is carried out using an extension in CATIA which is developed by Ingersoll Machine Tools. The trajectories are set to follow fiber direction in order to obtain consistent images from every ply. The images hence obtained are passed on to the detection software for processing and classification of defects, which will be elaborated in the following section.

Our material was strictly limited to thermoset pre-impregnated carbon tows. AFP is also capable of manufacturing parts with dry fiber and thermoplastics. The profilometer has a limited range of materials that will result in quality data, thus a change in material may greatly affect the outcome of both our profilometery and machine learning algorithms.

Figure 1: ACSIS in operation

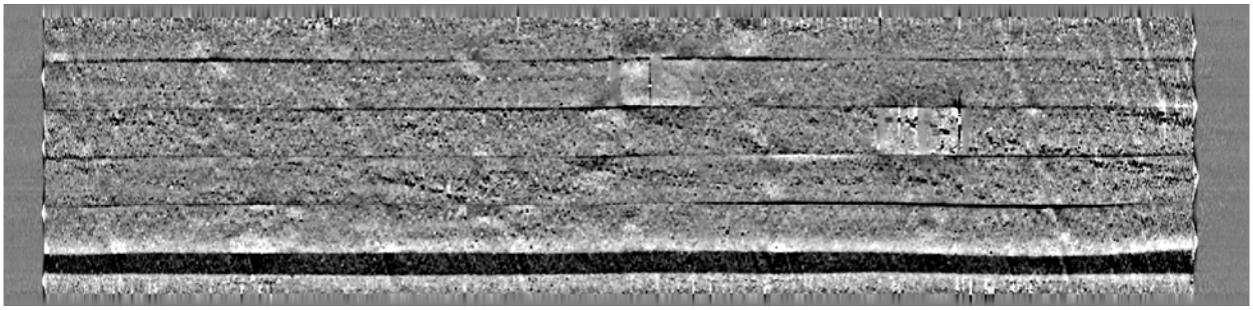

Figure 2: A grayscale image of AFP part from profilometer scan

2.2 Detection System

2.2.1 Machine Learning Approach

As mentioned previously, the traditional sliding window approach to image analysis has several significant drawbacks. They are ideal for image identification and location, but are fundamentally lacking for greater detail. Our algorithm applies the concept of fully convolutional neural networks to the scan images for an image segmentation task. In image segmentation training is carried out for each pixel where multiple features can be extracted and output into separate layers. Given this fact, image segmentation requires a sufficiently large training set to insure accurate detection of defects. This allows for our system not just to classify, but to simultaneously locate, classify, and make predictions as to size and shape of the defect.

Convolutional networks typically are constructed of a number of convolutional layers extracting image features resting under several dense layers containing hidden neurons. A fully convolutional network, Figure 3, extends the convolutional layers throughout the network, generating a “machine learning filter”, rather than a traditional classification network.

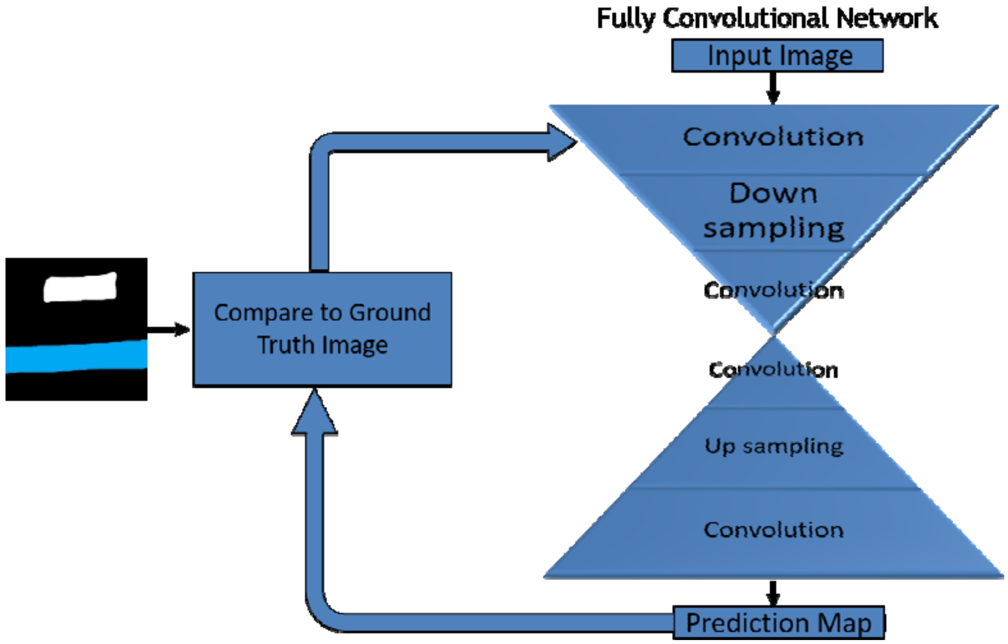

Figure 3: Fully Convolutional Network Training Structure

This network takes an image as an input, and outputs a classification for each pixel in the image. Because this classification takes place on a pixel-by-pixel basis, the network can reveal exact detail as to how the classes in question are constituting an image. Once this process is completed, a simple pixel search of the image can reveal some of the detailed information discussed. This flexible system is trainable and adaptable in just the same way as sliding window.

2.2.2 Image Processing

We took the fully convolutional network for semantic image segmentation concept and applied it to AFP defect detection. The network was trained on 800x800 pixel scan images across 15 defect categories shown in Figure 4. A color coding was chosen to distinguish between defect and the training sets were developed according to that. A distinct RGB value was allocated to each defect as shown in

Table 1.

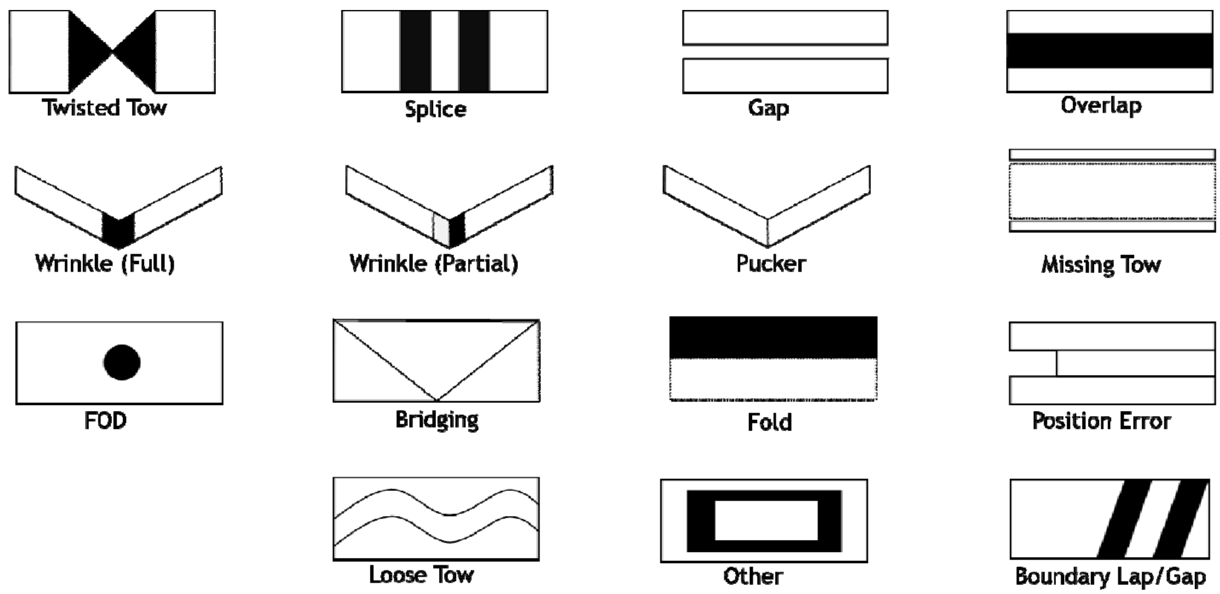

Figure 4: Representation of 15 identified AFP defects

Table 1: RGB values of the 15 defects

Defect	Defect ID	R	G	B	Color
No Defect	0	0	0	0	black
Twist	1	255	255	255	white
Splice	2	236	28	36	red
Missing Tow	3	0	168	243	blue
Gap	4	14	209	69	green
Overlap	5	255	157	0	orange
Bridging	6	140	255	251	light blue
Wrinkle	7	4	0	255	Dark blue
Pucker	8	13	255	0	light green
FOD	9	255	0	255	purple
Boundary Coverage	10	221	162	234	light purple
Angle Deviation	11	253	115	118	light red
Wandering Tow	12	255	255	0	yellow
Shredders	13	142	137	143	dark grey
Loose Tow	14	128	96	0	brown
Position Error	15	204	153	0	light brown
Fold	16	247	249	165	light yellow

We certainly could increase the size and complexity of the network, however the run time considerations and hardware requirements for an industrial setting influence our decision to have a large network that could be operated on limited hardware. For our setup, we used a single

Nvidia Titan Xp GPU to train and operate the network. The imagery from our profilometers was labeled as shown in Figure 5. The labeling was the most time intensive part of the process, as it had to be done manually and for hundreds of images. The labeled images were then used to train a fully convolutional version of the state of the art ResNet neural network architecture outlined in [16]. A ResNet architecture has scored a 3.6% top five error rate for the ILSVRC image recognition competition. ResNet attempts to build a deep network while reducing the number of trainable parameters [17]. The result is an architecture that generates many layers for feature extraction, but that can reduce the chance of overfitting and make the network easier to train, as shown in Figure 6. The network relies on the use of functions that add the output of previous layers to the input of a later layer, allowing certain parameters to “skip” over lower layers.

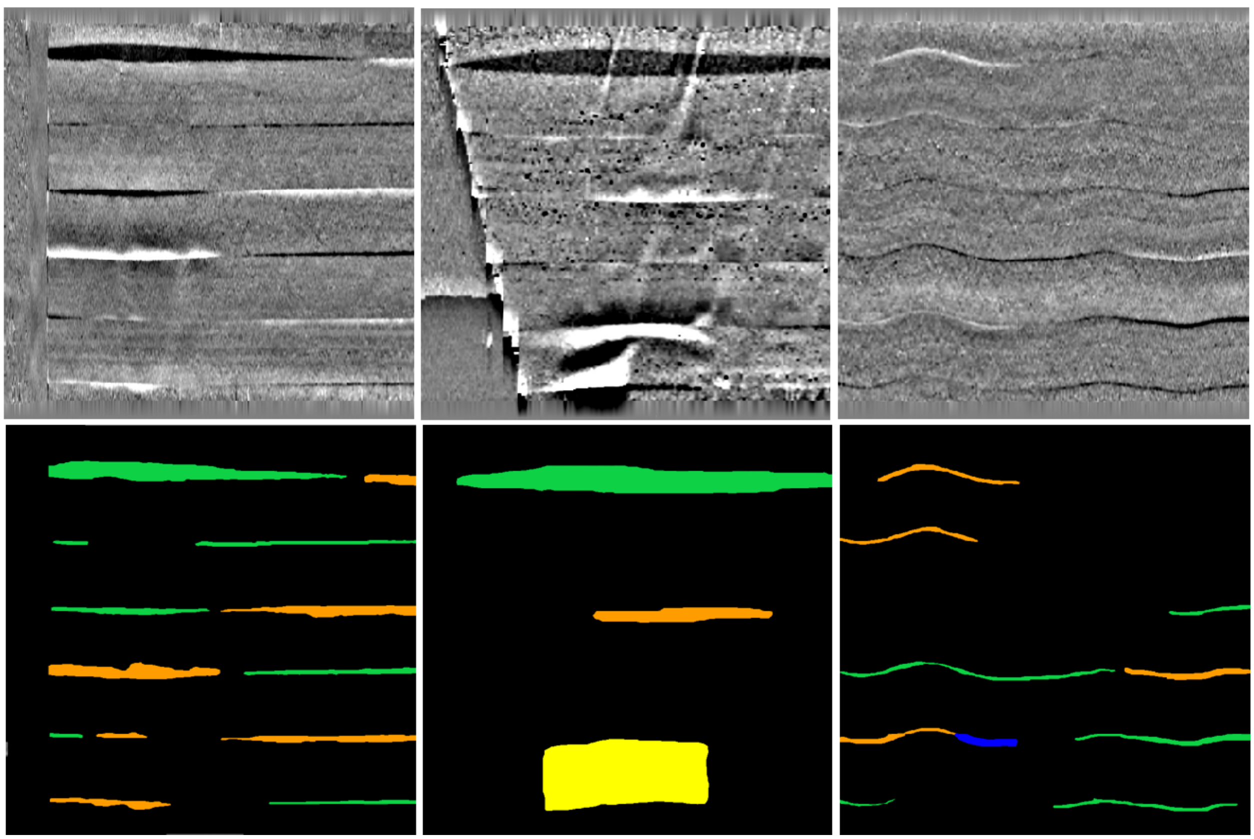

Figure 5: Labeling of three distinct scan images

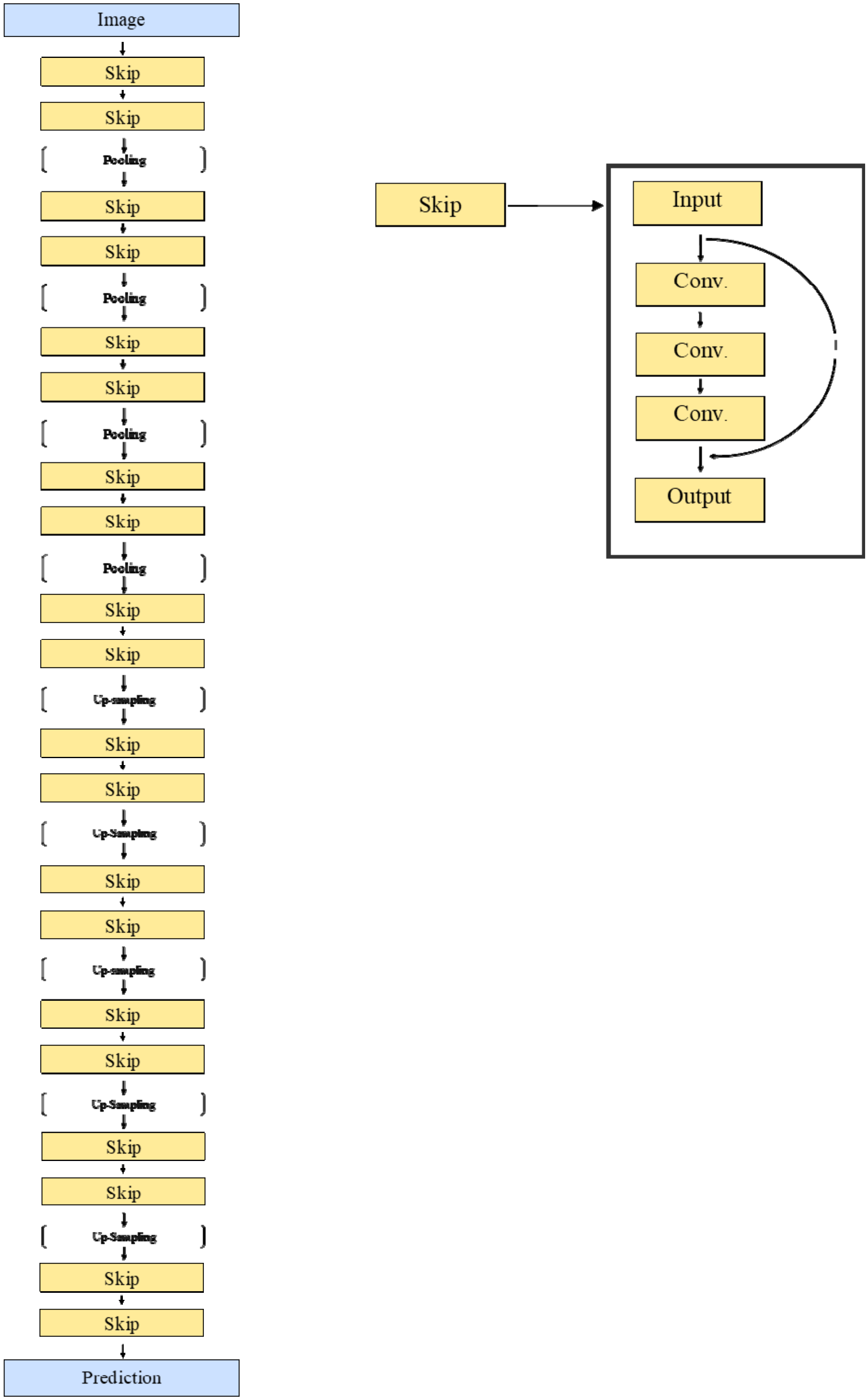

Figure 6: The structure of the network

2.2.3 Optimizing the network hyperparameters

One of the most subjective portions of the neural network architecture, the hyperparameter selection, was optimized using a genetic algorithm (GA). The GA tuned the activation function, the kernel size, and the filter size for each block of the network by running iterations of varying combinations of those values. Each instance of the network was trained on a dataset of 200 images and then a validation set of 10 images was used to determine the fitness of each iteration and the accuracy of the predictions of each iteration. Almost 120 combinations were tested and then the hyperparameter values from the iteration yielding the highest accuracy was chosen for our network. Alterations to this method could also be used including a hill climbing algorithm or simulated annealing.

3. RESULTS

As an initial trial for our system we trained across 4 defects only using a training set of 200 images. This was done to validate the viability of the system and check its capability of picking up defects. Figure 7 shows an example of a processed image, where we see that the part contains two missing twos and that the system is able to locate the defects and give the right classification of the defects. However, since the training set was small, the network tended to overfit and misclassified some of the defects. This is due to the limited number of occurrences of some defects in the training set. For example, in Figure 8, we can see a good localization of the defects however the classification wasn't accurate, where a gap was being classified as a twist. Using another set of training images containing a large concentration of gaps in comparison of other defects, allows for better identification of that defect. Figure 9 clearly shows that the processed image closely resembles the ground truth where gaps were picked up almost perfectly, but it was still lacking in the detection of wrinkles and splices. This phenomenon can be remedied by using a large enough training set containing a sufficient number of instances of each defect. Extending the detection into segmentation across all 15 defects will need a drastic increase in the training data up to thousands of images. The larger this set is, the more accurate this classification is.

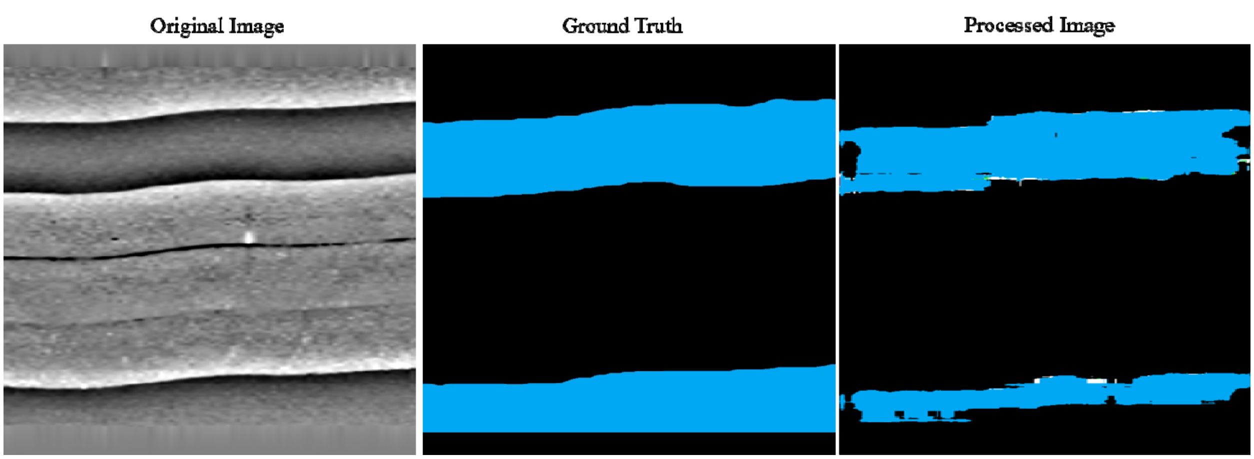

Figure 7: A processed scan showing two missing tows

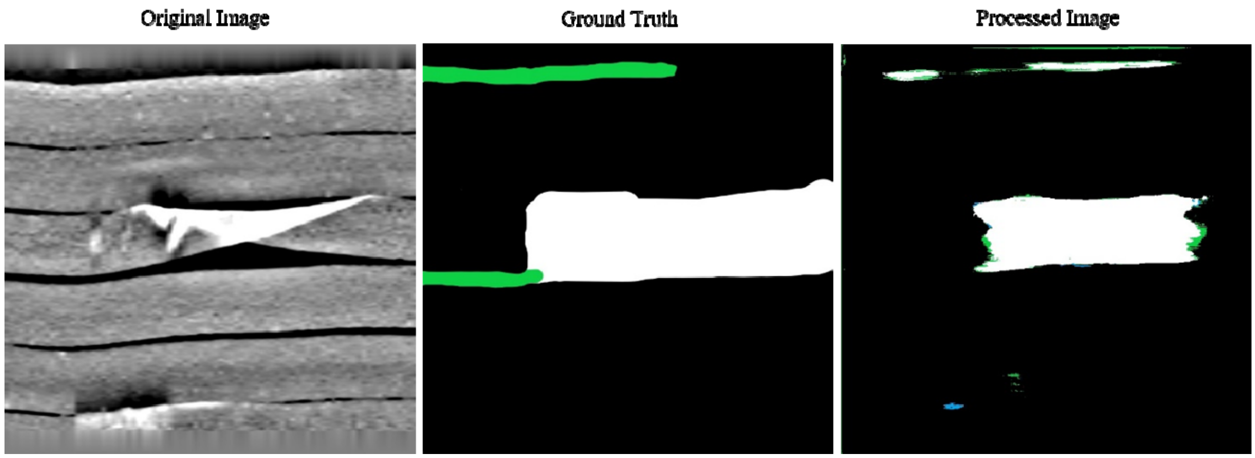

Figure 8: A processed scan showing a twist and gaps

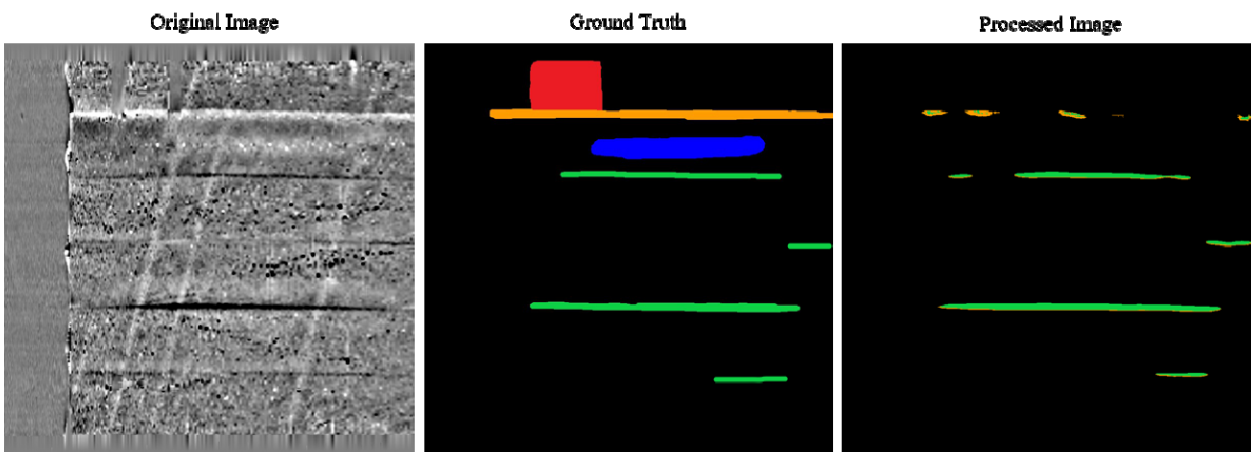

Figure 9: A processed scan showing gaps, overlaps, wrinkle and splice

4. CONCLUSION

This paper demonstrates a new approach towards AFP defect inspection. ACSIS is used to perform scans on the manufactured parts by means of profilometery. The scans result in grayscale images demonstrating the variations in the topography of the part's surface. These images are then processed by a detection system we developed. The system uses machine learning and is based on fully convolutional neural networks, where classification tasks are performed on a pixel by pixel basis. We demonstrated how this approach can lead to an accurate determination of the defect's nature and dimensions. A large enough training set will allow the inspections better identify all 15 AFP defects.

Our upcoming goal is to extend the capabilities of our machine learning algorithms and sensors further. Future focus will include the following areas: advanced pre-training with Generative Adversarial Networks (GANs), the incorporation of multiple sensors for data fusion, and developing a GUI to allow operator integration for network updates. GANs are a unique tool by which two networks attempt to gain an advantage over each other. One network is tasked to produce false data, while the other is tasked with determining which sample are from the real dataset and which were generated by the rival network. Performing this process with our scan images and then transferring the weights from the generative and discriminatory network into our defect detection network would allow a learning of low level features across our dataset without requiring the tedious production of ground truth images. This could also be a creative strategy to deal with material changes or retraining.

Strategies for material changes are also a subject of debate. As mentioned, the GAN could be a useful tool for such an issue. Stopping the learning of our bottom layers, and just retraining to top of the network could also prove to be a valid solution. However, the potential introduction of additional sensors almost guarantees that some manner of retraining will be necessary to ensure acceptable accuracy of the system.

Future work will also include adding an array of sensors that will contribute to an increase in accuracy. The tendency is towards incorporating an infrared camera and an eddy current sensor with the profilometer. This will allow the surface to be under analysis by multiple methods reinforcing the confidence in defects the profilometer finds with ease, and adding an additional check for those defects that up until this point we have a hard time discerning. We would also like to push toward a comprehensive system that has a full graphical interface, and can be operated without specific knowledge of the mechanics within the system. By doing this, we not only improve ease of use, but allow for the possibility of having the operator check the system for correct classification, and then have the computer vision network retrain itself based on these inputs.

5. ACKNOWLEDGMENTS

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