Application of Deep Learning to Predict Shot Peening Coverage

Y.H.A Chua[1], Z.B. Wang[1], H.C. Ang[1], and A. Shukri[1]

1. Advanced Remanufacturing and Technology Centre, 3 Cleantech Loop, #01/01 CleanTech Two, Singapore 637143

Abstract
Coverage is one of the key process control variables for the shot peening process. Currently, the method to quantify coverage relies heavily on human visual judgement, which is highly subjective. This study explored the use of deep learning to predict coverage using images captured from peened SS316 and Ti-6Al-4V materials. It was found that all deep learning models developed with the SuaKIT software could achieve a high prediction accuracy of at least 93% based on fixed intensity and material testing. However, the models performed poorly when tested using crossed datasets with different materials and intensities. Combining the data from different datasets can improve the prediction accuracy to at least 93.5%.

Keywords: Shot Peening, Coverage, Deep Learning

Introduction

Shot peening is a cold work process that is widely used in many industries such as aerospace and automotive industries. It is a cost-effective process that improves the fatigue life and stress corrosion cracking of a treated metallic component. Shot peening is conducted by bombarding spherical shots onto a component, causing the surface to be plastically deformed. This results in a layer of residual compressive stress on the surface of the component, which acts as a resistance to prevent premature failure or cracks propagation during cyclic loadings. [1]

Coverage is one of the key process control parameters for the shot peening process, and it is described as the percentage of a peened area over the total surface area of the component. It is important to monitor coverage as premature failure such as crack propagation will potentially occur on areas which have not been sufficiently peened during operation. [1] Coverage is typically obtained through operators' visual assessment with the aid of either handheld magnifier, or a microscope of at least 10 to 30 times magnification. However, such method of quantifying coverage is highly subjective and relies heavily on skilled and experienced operators. There are other recommended indirect methods in the specifications [2] such as the use of fluorescent tracers, dye markers or the use of replicas to help aid the coverage analysis process. However, such indirect methods not only require experienced and skilled operators to use them in order to achieve the best results, but also, they only aid the operator to visually differentiate the shot peened indentations on a peened surface better. As such, this has opened up opportunities for development to find better methods to quantify coverage, with the hope of automating it in the future and bringing shot peening into the right direction towards autonomy in Industry 4.0.

There have been several studies in the literature that has looked into understanding and improving the current method of assessing coverage. Some literature looked more into understanding the concept of coverage through the use of simulation or theoretical models, while others tried to tackle the problem directly by using image segmentation or surface roughness (both 3D and 2D), with the aid of visual or scanning systems, to automate coverage assessments. There are also 2 studies that explored the use of machine learning or deep learning to aid in the image segmentation process to improve the overall performance of the model. Qiu Jiyuan et al [3] was able to achieve 98.45% accuracy during the UNet++ model training, and 100% accuracy in classifying the coverage of 18 random images using the model. Lubna Shahid et al [4] explored the use of artificial neural network to aid in the image segmentation process to help better identify coverage on specimens with presence of interference such as machining streaks which resulted in better accuracy of the image segmentation model. However, there are no studies conducted so far that looked into the performance of deep learning models, which are trained with images directly captured from peened specimens to predict coverage.

Therefore, this study will explore the performance of deep learning models trained with images of different coverage percentage ranges, taken from two different material types (SS316 and Ti-6Al-4V). The main aim of this study is not only to understand how well deep learning performs for coverage quantification, but also to study the challenges and limitations of applying deep learning in the use case of industry application.

Experimental Methodology

Flat rectangular SS316 and Ti-6Al-4V specimens of surface roughness of 0.5μm in Ra were prepared to ensure good visibility of peening indentations upon peening. Each specimen was then split into 3 different sections on the top and bottom of the specimen, to allow shot peening of different coverage percentages on each section.

Shot peening was conducted using a compressed air system, and cast steel shots of 0.58mm in diameter with hardness range of 45-52 HRC was used for the experiments. Each material type (SS316 and Ti-6Al-4V) was peened at 3 different intensities, with 10 different coverage ranges per intensity target as shown in Table 1. It should be noted that despite difficulties in visually differentiating coverage above 98% (or 100%), coverage range of 100-200% was also tested to study if the deep learning model could pick up the differences for such coverage range. Nozzle impingement angle of 80 degrees was used for intensities of 0.2mmA and 0.3mmA, while 30 degrees was used for intensity of 0.1mmA. The reason for the lower nozzle impingement angle for intensity of 0.1mmA was due to the limitations to achieve a low intensity value at 80 degrees impingement angle.

Table 1 Peening Parameters for Each Material Type

Coverage Ranges	10-29%, 30-39%, 40-49%, 50-59%, 60-69%, 70-79%, 80-89%, 90-97%, 98%, 100-200%
Intensity	**Peening Parameters (Impingement Angle, Standoff)**
0.100mmA	30 degrees, 150mm
0.200mmA	80 degrees, 150mm
0.300mmA	80 degrees, 150mm

In order to train the deep learning model with a larger variety of data, each coverage range consists of specimens peened with at least 5 different coverage percentages. For example, shot peening was conducted at 30%, 32%, 34%, 36% and 38% for coverage range of 30-39%. Such small intervals of coverage percentages were obtained through the development of a coverage curve as shown in Figure 1. Each point of the coverage curve was evaluated by 2 experienced operators during the development, and the average coverage percentages were used to plot the final curve. The exposure times to peen each coverage percentage were then taken through the formula of the coverage curve obtained. After peening at the calculated exposure times, the specimens were re-evaluated again, and regrouped accordingly into the respective coverage ranges (if necessary) to ensure all data taught during the deep learning model were as accurate as possible. It should be noted that exposure times for coverage percentages above 100% was taken as a multiple of full coverage (98%) instead of through calculation from the coverage curve. In this study, the development of coverage curves was conducted for each intensity and material type.

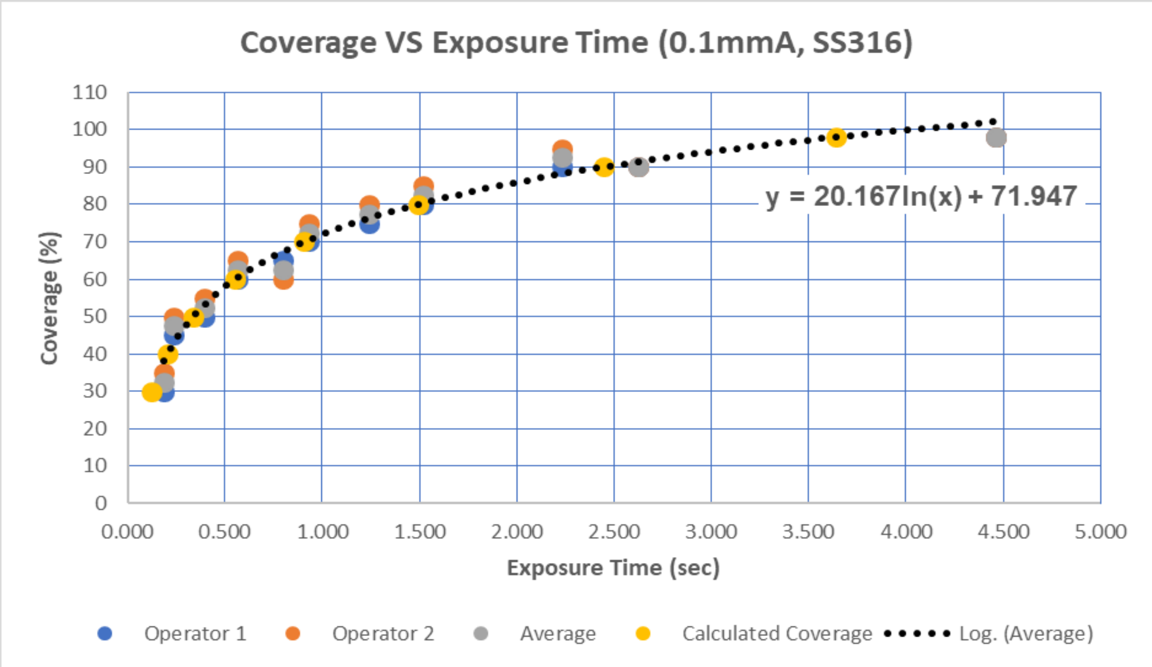

Figure 1 Coverage Development Curve for SS316, 0.1mmA

After all coverage percentages had been obtained from the shot peening process, a customized setup consisting of a telecentric lens with a field of view of 8mm by 7mm, a light source and a mono camera was used to capture images for the training of deep learning models. 30 images were captured and labelled for each coverage percentage in all 10 coverage ranges, resulting in a total of at least 1500 images (30 images x 5 coverage percentages x 10 coverage ranges) captured for each intensity per material type.

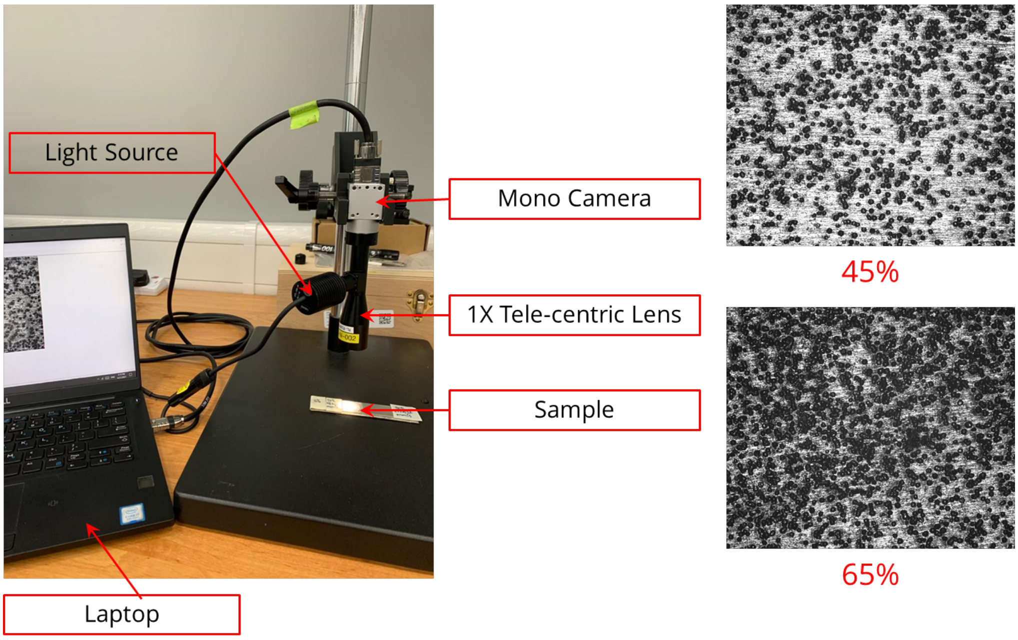

Figure 2 Customized Image Capturing Setup (left) and Sample Captured Images (right)

With all images captured and labelled according to coverage range, intensity and material type, a commercial deep learning vision software called SuaKIT [4] was used for the development and training of the deep learning models. Deep learning models were created for each intensity per material type through iterative sorting, validation and testing of image datasets. In general, images in a single dataset for each intensity and material of at least 1500 images were split into the following during the deep learning model development:

- **Training images** (60% of total image data collected): Images used to train the deep learning models

- **Validation images** (20% of total image data collected): Images used to test the performance of the models during the training phase
- **Testing images** (20% of total image data collected): Images used to test the performance of the models after the final model has been developed

In addition to studying the models' accuracy through the testing phase during the model development, the deep learning models were deployed into a separate software which was developed separately to simulate the actual performance of the models during an industrial deployment (Figure 3). This was done by capturing an additional set of 10 images from each coverage range from the peened specimens, followed by using the deployed model in the software to evaluate the overall model's accuracy. The output model accuracy from this simulated deployment test would then give an indication of the actual accuracy one would expect when the deep learning models are used in a production setting.

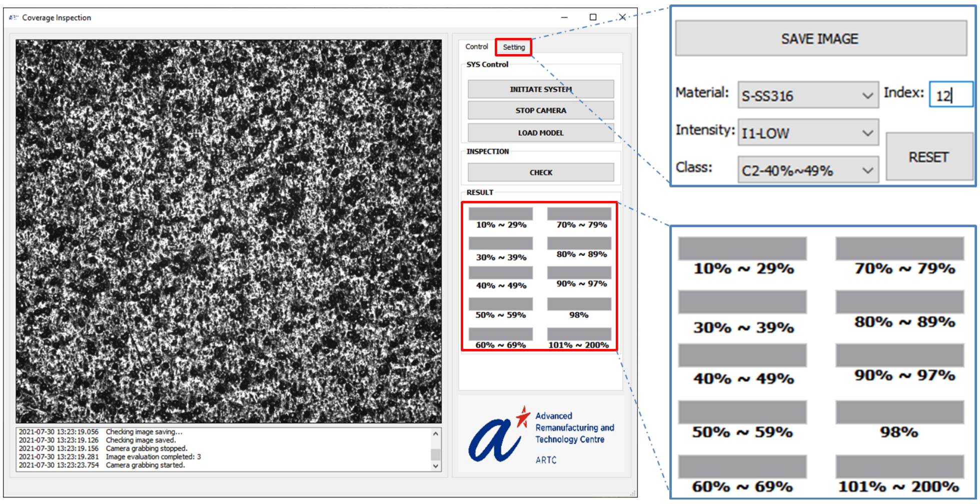

Figure 3 Inspection Software Developed for Simulation of Industrial Deployment

The deep learning models were also cross-tested against a separate dataset to study how robust the models were to identify coverage against another intensity value or material type. In this cross-testing study, the following was tested:

- **Cross Materials Study**: Ti-6Al-4V model trained with 0.200mmA images tested with SS316 images peened at 0.200mmA
- **Cross Intensities Study**: Both Ti-6Al-4V models trained with 0.200mmA and 0.300mmA images tested with Ti-6Al-4V images peened at 0.100mmA

Experimental Results

With the models developed, the performance of the models was evaluated during the model testing phase and the simulated deployment test. Model accuracy was the key metric used to evaluate the overall performance of the models, and this is defined as the percentage of correct coverage predictions over the total number of predictions made. In order to classify as a correct prediction, the model has to output the correct coverage range (i.e. 30-39%) upon evaluating an image data. Table 2 shows the summarized results from the models tested for a fixed dataset (same intensity and material).

Table 2 Summary of Model Prediction for a Fixed Dataset

Dataset	Model Accuracy	
	Model Testing Process (Out of Min. 300 Images)	Simulated Deployment Test (Out of 100 Images)
Ti-6Al-4V: 0.100mmA	100%	93%
Ti-6Al-4V: 0.200mmA	99.5%	95%
Ti-6Al-4V: 0.300mmA	99.7%	100%

SS316: 0.100mmA	100%	94%
SS316: 0.200mmA	100%	94%
SS316: 0.300mmA	100%	94%

It was observed that the developed models could achieve at least 99.5% and 93% model accuracy during the model testing phase and the simulated deployment test respectively. A deep dive on the false predictions showed that all models were mis-predicting images in the neighboring coverage range of the actual coverage range (i.e. 30-39% range was predicted instead of actual being in the 40-49% range). As such, the overall performance of the model showed very promising results for deep learning technologies for shot peening application.

In addition, several models were tested across different datasets to study how they performed against a dataset that the model was unfamiliar with, and it was observed that the models did not perform well for both cross material and cross intensity study. The cross-materials study, where the Ti-6Al-4V: 0.200mmA model was tested with 350 images from the SS316: 0.200mmA dataset, only achieved 16% accuracy, whereas the cross-intensities study, where both Ti-6Al-4V: 0.200mmA model and Ti-6Al-4V: 0.300mmA models were tested with at least 350 images from Ti-6Al-4V: 0.100mmA dataset, only achieved 23.4% and 30.2% respectively. The main possible reason for the poor model performances was due to the visual differences in images for different materials and intensities. Since the models were trained mainly on a single type of dataset, the model could not recognize images that looked vastly different from a different dataset, causing significant number of false detections. Figure 4 shows the differences between materials and intensities for 40% coverage. It was observed that not only the textures and light reflectivity were different between SS316 and Ti-6Al-6V, the size of peening indentations was also different between peening intensities.

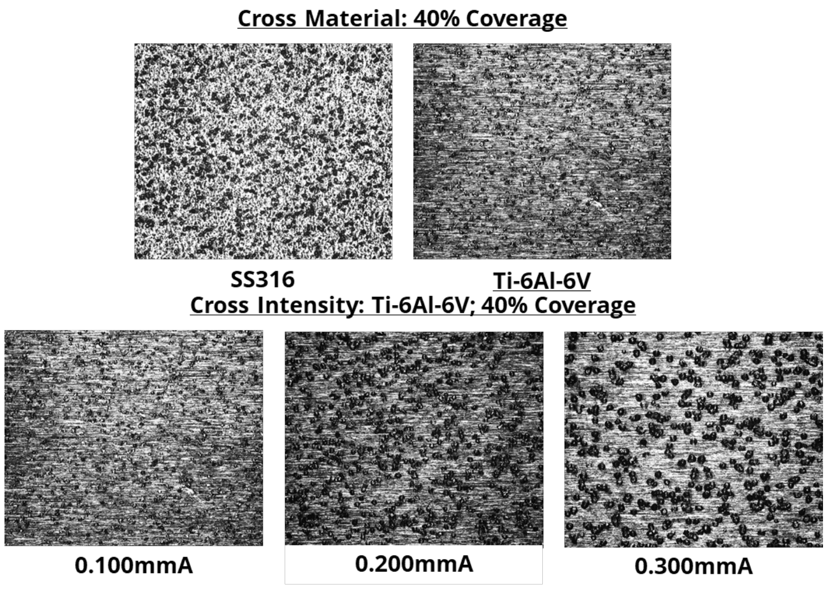

Figure 4 Images Captured for Different Materials and Intensities for 40% Coverage

Additional models were then built to study the performance of combined datasets, and this was done by combining both datasets for Ti-6Al-4V: 0.200mmA and SS316: 0.200mmA to form a combined materials model, as well as combining all datasets from Ti-6Al-4V (Ti-6Al-4V: 0.100mmA + Ti-6Al-4V: 0.200mmA + Ti-6Al-4V: 0.300mmA) to form a combined intensities model. It was observed that the models' accuracy significantly improved due to the model's ability to better recognize different images from different datasets. Table 3 shows the summarized results from the cross-materials and cross-intensities study. Similar to the fixed dataset study, the false predictions from the models were mainly mis-predicting images in the neighboring coverage range of the actual coverage range.

Table 3 Summarized Results for Cross Materials and Cross Intensities Study

Dataset	Model Accuracy	
Cross Materials (Ti-6Al-4V: 0.200mmA VS SS316: 0.200mmA)	16%	
Cross Intensities (Ti-6Al-4V: 0.200mmA VS Ti-6Al-4V: 0.100mmA)	23.4%	
Cross Intensities (Ti-6Al-4V: 0.300mmA VS Ti-6Al-4V: 0.100mmA)	30.2%	
Combined Materials (Ti-6Al-4V: 0.100mmA + SS316: 0.200mmA)	100% (Model Testing Process)	93.5 % (Simulated Deployment Test)
Combined Intensities (Ti-6Al-4V: 0.100mmA + Ti-6Al-4V: 0.200mmA + Ti-6Al-4V: 0.300mmA)	99.3% (Model Testing Process)	97.3% (Simulated Deployment Test)

Conclusions

This study shows the overall abilities and limitations of using deep learning inspection algorithm for coverage prediction. The deep learning models showed that they could perform well with high model accuracy of 93% and higher, but are limited to the type of data or images that the models were trained with. It is possible to improve the models' accuracy through introducing a larger dataset, but that would require re-training with new images.

In terms of application to industry, applying deep learning inspection algorithm can be particularly useful for production sites with 1 or 2 components, as the database could be easily built based on such limited component types. However, this could be challenging for factories or production sites that manufacture multiple types of components as all images or data type has to be collected and trained in the model for such robust applications.

There could be work-arounds towards implementing a quicker way of updating the deep learning models with additional data, such as ongoing research on online, transfer and continuous learning for quick teaching of the deep learning models. However, it would be most ideal to further study on how to teach a model to properly recognize images like how humans do in recognizing peening coverage templates and applying them on any material types and intensity values.

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