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Automatic Nondestructive Detection of Damages in Thermal Barrier Coatings Using Image Processing and Machine Learning

Andrew Sprague[1], Pouya Tavousi[2], Sina Shahbazmohamadi[2], Zahra Shahbazi[1*]

[1.] Department of Mechanical Engineering, Manhattan College, Bronx, NY, United States.
[2.] Department of Biomedical Engineering, University of Connecticut, Storrs, CT, United States
[*] Corresponding Author: Zahra Shahbazi

Introduction

Thermal barrier coatings (TBCs) are multilayer coatings meant to insulate gas turbine engine metal component and allow it to operate at elevated temperatures. Typically, a TBC is made from four layers: a ceramic topcoat, a thermally grown oxide (TGO), an aluminum-containing bond coat, and a superalloy substrate. Figure 1 shows a representative image of TBC layers. After certain hours of service time the ceramic topcoat eventually spalls off which can result in the exposure of substrate to melting temperatures. The delamination of the topcoat is attributed to several reasons: i) The growth and linkage of cracks within topcoat ii) the growth in undulations within bond coat and TGO exceeding strains of thermal expansion coefficient mismatch and iii) growth of the TGO thickness. [1] In order to fully understand the failure mechanism of TBC systems and predict their life, one needs to study the evolution of cracks and the TGO interfacial surface geometry as a function of hour of operation. 3D Xray Microscopy (XRM) allows us to obtain such information non-destructively at various intervals of heat treatment corresponding to engines' operation. However, lack of quantitative information does not allow us to develop or confirm constitutive relationships or failure mechanisms. Therefore, it is critical to assign materials to voxels in XRM images. This process is known as segmentation. Segmentation of TBCs, however, is not trivial. The top coat Zirconia-based composition significantly attenuates the Xray photons. Higher energy X-rays are usually used along with aggressive filtering to avoid beam hardening effects. However, even at high energies, the contrast between the top coat material and cracks and voids changes from slice to slice. Also, detection of rough aluminum-based interfacial layer, TGO, proves to be difficult and discerning that from cracks and voids close to the interface is very difficult. Previous efforts of segmenting TBCs systems have all been manual which is both time consuming and labor intensive. [1]

This work aims to automate the detection of cracks in the topcoat and the TGO interfacial geometry of a heat-treated TBC sample using image processing and machine learning. To achieve this, TBC image data was first solicited from [1], where a cyclically heat-treated APS 7 wt.% Yttria-stabilized-zirconia TBC was imaged using 3D XCT [1]. In total, 1,007 2D X-ray micrographs were taken, serving as this work's TBC image dataset. In an attempt to identify cracks from this data, the 3D visualization software, Dragonfly was used [4].

Methods

To automate the detection of cracks, a training dataset was first made. To do this, a manual segmentation approach was taken, and three tools were used within an image processing software "Dragonfly". The first was the smart grid tool, which decomposed the TBC images and assigned regions within them. Once created, the regions were filled using the ROI painter tool and, depending on their location, were classified as one of the four layers or the surrounding. After being segmented, the thresholding tool created an intensity domain of dataset values inside the topcoat. Once applied, those voxels within this domain were segmented as cracks. Following this approach, 20 total TBC micrographs were segmented. An example of one of these slices is shown in Figure 1.

Once made, the training dataset was used to teach a machine learning architecture, U-Net, to automatically segment cracks in the topcoat. Chosen for its ability to segment images, it was trained with an initial filter count of 128, a depth level of 5, a batch size of 32 pixels, and a patch size of 64 pixels. To obtain the most accurate results from this architecture, two parameters were varied between each training session: learning rate and epoch number. For the present work, learning rates of 1, 0.75, 0.5, 0.25, 0.1, and 0, and epoch numbers of 100, 200, and 300 were used.

Once trained on each learning rate and epoch number, the pairing with the largest categorical accuracy was identified and then retrained on a new, modified training dataset. Using the same manual segmentation approach, this training dataset's "topcoat" class was segmented with less labeled data than that of the preceding. For this, 20 total TBC micrographs were segmented. Again, categorical accuracy was used to evaluate this model's performance from the retraining, showing the percentage of predicted classes that match the actual ones.

Results

From the training sessions on the initial dataset, categorical accuracies were exported. These are shown in Table 1, which indicate how well the U-Net architectures labeled data to match those generated manually. From these results, there are three features to notice:

1. For the most part, the training parameters affected the machine learning architecture's accuracy. This is seen by the different accuracies between training sessions, except for the U-Net architecture trained with a learning rate of 0.25 for 100 and 200 epochs.
2. Small categorical accuracies were recorded for the U-Net architectures trained with a learning rate of 0. This result was expected because, by using a learning rate of 0, the architecture does not change under the estimated error.
3. The U-Net architecture trained with a learning rate of 1 for 200 epochs has the best overall accuracy, and so it was retrained on the modified training dataset. A TBC slice segmented with this architecture is shown in Figure 2.

Shown in Table 2 are the results from the retraining. Comparing this value to that of the same architecture in Table 1, one will notice its value is slightly less. This difference outlines that, for detecting cracks, the labeled dataset's size affects the architecture's accuracy.

Conclusion

In this work, it was shown that detecting cracks in TBCs and interfacial TGO geometry can be automated using image processing and machine learning. In doing so, costs, variability, and segmentation time can be reduced. Due to the trade-off between time and accuracy, the U-Net architecture was trained on labeled data of different sizes and for training parameters of varying values. In this way, the training parameters and labeled dataset's size were shown to affect the machine learning architecture's accuracy. From these findings, a machine learning-based approach is a likely alternative to detecting cracks in TBCs.

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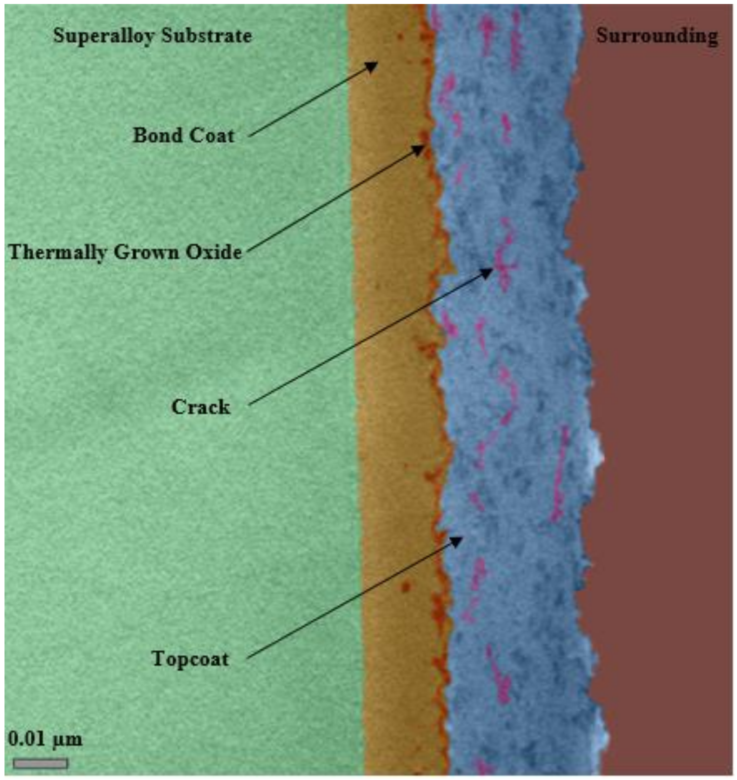

Figure 1. TBC slice segmented using a manual segmentation approach and the smart grid, ROI painter, and thresholding tools in Dragonfly for the initial training dataset. Shown in the segmentation are the superalloy substrate (green), the aluminum-containing bond coat (yellow), the thermally grown oxide (orange), the ceramic topcoat (blue), the cracks (light pink), and the surrounding (pink). This segmentation, and the 19 other slices like it, are considered the accepted ground truth for this work.

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Architecture: U-Net **(Original Training Data)**			
Epoch Number	100	200	300
Learning Rate	**Categorical Accuracies**		
0	0.10137	0.19323	0.18869
0.1	0.92801	0.98801	0.92691
0.25	0.98716	0.98716	0.98907
0.5	0.98841	0.98957	0.98962
0.75	0.98826	0.98935	0.87176
1	0.98770	0.98976	0.98973

Table 1. Categorical accuracies measured on the initial training data for the U-Net architecture using varying learning rates and epoch numbers.

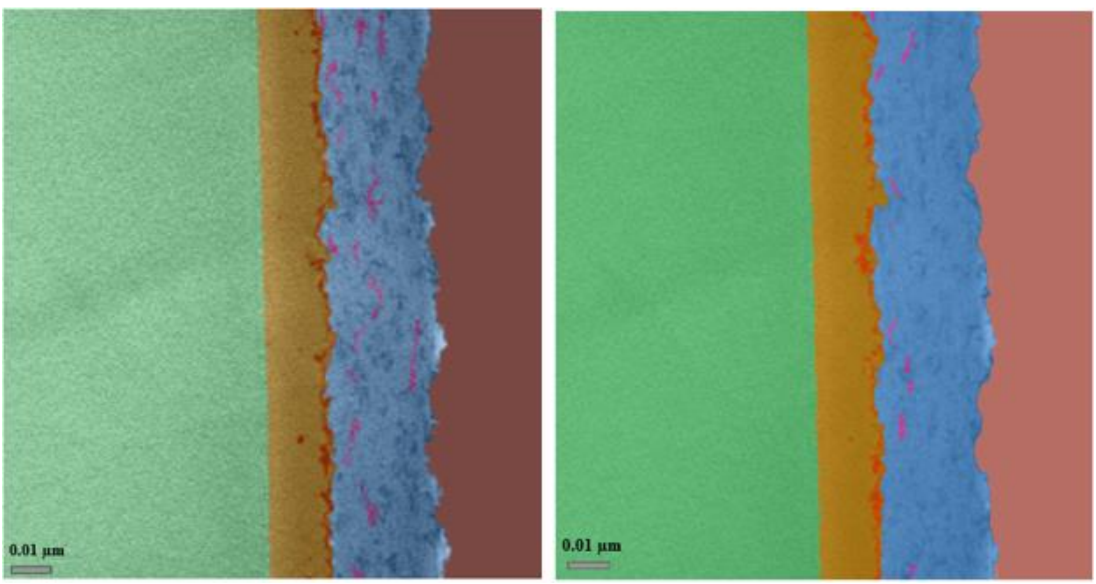

Figure 2. TBC slice segmented using the U-Net architecture trained with a learning rate of 1 for 200 epochs (right), and the Figure 1 TBC slice, which is a part of the dataset it was trained on (left). From a comparison of the two images, it can be seen that the "best" U-Net architecture of all others trained was able to segment and detect cracks in a TBC slice that it had not seen during training. However, although this architecture did detect cracks, it did not segment many, which partly led to the new training dataset being labeled with fewer data in its "topcoat" class.

Architecture: U-Net **(Modified Training Dataset – Smaller "topcoat" Class)**

Epoch Number	200
Learning Rate	**Categorical Accuracy**
1	0.98830

Table 2. Categorical accuracy measured on the modified training dataset for the “best” U-Net architecture of all those trained.

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