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TECHNICAL ARTICLE

ModLayer: A MATLAB GUI Drawing Segmentation Tool for Visualizing and Classifying 3D Data

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Abstract
Characterizing a material's microstructure, especially as it relates to the manufacturing processes used to fabricate it, is of great interest to engineers and researchers. In recent years, state-of-the-art imaging techniques have been able to yield a plethora of high resolution 3D data that can be used to study materials at various length scales. This 3D data is usually organized as stacked serial sections of 2D images and almost always requires some combination of enhancement and segmentation (the process of separating an image into subsets), in order to extract meaningful information. To aid in this process, ModLayer was created as a MATLAB® executable. ModLayer is an interactive graphical user interface that seeks to remove the burden of import/export redundancies when interacting with 3D data in MATLAB during visualization, modification, or segmentation through manual drawing across image stacks. The utility of ModLayer is demonstrated here through three case studies; (1) classifying regions of damage with in-situ time lapse X-ray micro-computed tomography (μ-CT) of a glass fiber reinforced polypropylene (GFRP), (2) correcting multi-class segmentation errors in segmented X-ray μ-CT images of a GRFP composite, and (3) capturing features of interest within in-situ 3D X-ray μ-CT images during fatigue crack growth experiments of aluminum 7050. Overall, this tool is especially useful to engineers and researchers interested in correcting—within MATLAB—automated segmentation of noisy 3D images which can yield erroneous microstructural features in segmentation procedures.

Keywords Three-dimensional · Characterization · Image processing · Segmentation

Introduction

Modern characterization techniques are able to yield robust 3D images of materials and their microstructures, providing engineers and scientists powerful capabilities in understanding the behavior of materials [1, 2]. One requirement of most techniques is digital image processing, which is the process of either enhancing the images for visual observation, or segmenting and classifying features for measurement or statistical analysis [3]. Segmentation is a specific type of data processing and is defined as the separation of an image with intensity domain I into non-intersecting subsets. This can prove to be challenging, especially for 3D images [4]. In fact, selecting the appropriate segmentation technique in itself is usually a complex problem [5]. To combat the difficulties experienced in segmentation, which is typically considered the most critical step in image processing, a number of higher accuracy segmentation tools have been developed [6].

MATLAB is often used in these segmentation processes because of its user friendly matrix operation capabilities, as well as its robust image processing toolbox [7]. These capabilities are exemplified by MIPAR™, a MATLAB based software package used to align, pre-process, segment, visualize, and quantify 3D images [6]. MIPAR offers an automated segmentation module that allows the user to determine the optimum parameters for automated binary segmentation of 3D images, which can be conducted on different features within an image and stored as layers in multi-dimensional space (instead of a multi-class segmentation dataset). However, despite optimum segmentation parameters, certain imaging techniques - like X-ray micro-computed tomography (μ-CT) - contain stochastic fluctuations in image intensities which can still result in erroneous automated segmentation results. Even when coupled with trainable machine learning, automated multi-class segmentation

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procedures cannot always correctly segment every feature of interest and its exact edge [8]. Therefore, there remains a need to simultaneously view serial sections of 3D images, and apply manual modifications to multi-class 3D segmentation data. In MATLAB, this poses a challenge because there is no straightforward open-source method to visualize two sets of linked 3D images, and apply modifications through freehand drawing to multi-class datasets. To do so, the user would typically export their 3D data to external software with these capabilities [9], and re-import their 3D data back into MATLAB to continue their quantification analysis, as shown in Fig. 1.

To alleviate this issue, ModLayer, a user-friendly, open source, and easily implemented MATLAB graphical user interface (GUI), was created to allow the user to view and simultaneously scroll, zoom, and pan through linked sets of stacked images (typically the raw 3D image and its multi-class segmentation). Additionally, ModLayer allows the user to apply modifications to 3D images in order to classify features of interest, or correct segmentation results for cases of under- or over-detection, incorrect segmentation, and/or incorrectly touching edges of segmented features, through interactive freehand drawing.

This paper will first describe the general function and GUI, then provide three case studies to show the functionality of ModLayer by (1) classifying regions of damage with in-situ time lapse X-ray μ-CT of a glass fiber reinforced polypropylene (GFRP), (2) correcting multi-class segmentation errors in segmented X-ray μ-CT images of a GRFP composite, and (3) capturing features of interest within in-situ 3D X-ray μ-CT images during fatigue crack growth experiments of aluminum 7050. For the first case study, an explanation is provided outlining the importance of image classification for time lapse μ-CT, followed by an example using ModLayer to identify regions of damage found within time-resolved images. For the last two case studies, a brief background of the importance of image segmentation for the particular application is provided, an explanation of an automated segmentation procedure is given, and examples are provided in each case showing the use of ModLayer in correcting segmentation inaccuracies.

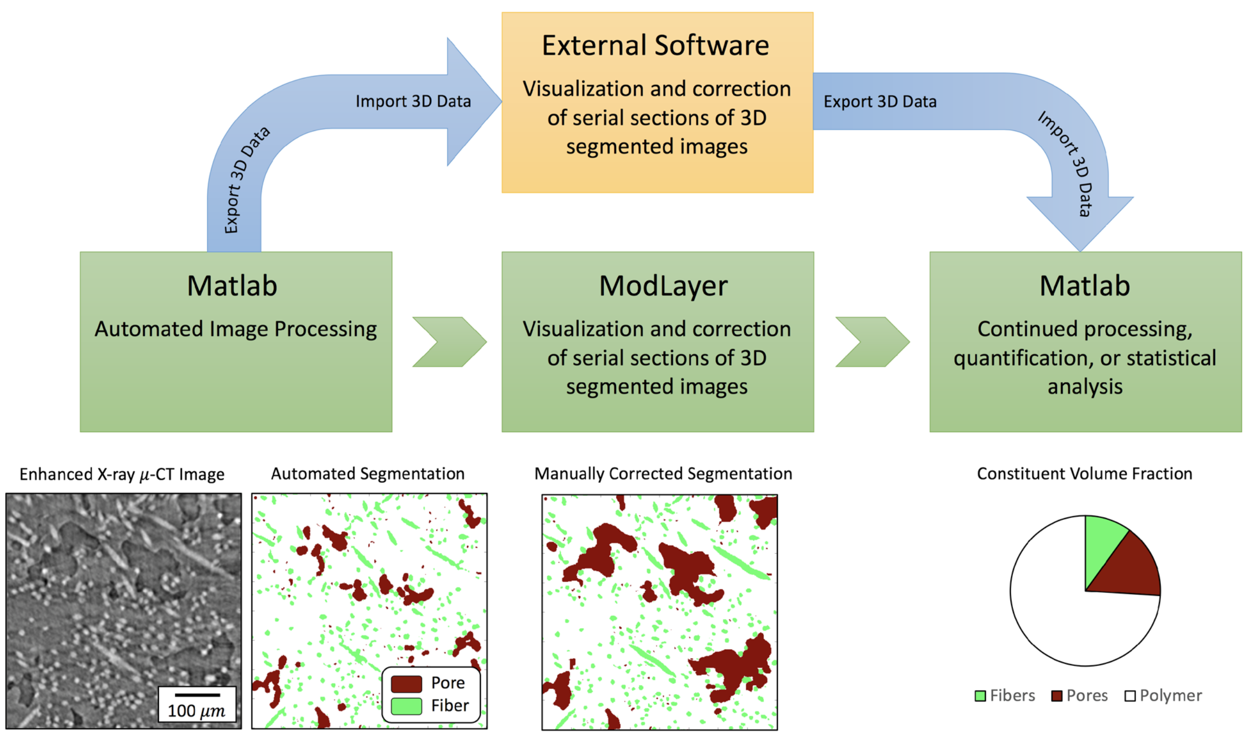

Fig. 1 A flowchart showing the post-processing of 3D images in MATLAB, which sometimes requires the user to export their data to an external software for visualization and manual correction of automated segmentation results that incorrectly captures certain features, whereas ModLayer allows for direct visualization and freehand drawing corrections of 3D stacked images within MATLAB (as shown by the sample images), providing a streamlined multi-class segmentation correction process that can yield accurate results for further quantification of segmented features

Methods

ModLayer, which is freely available for download at http://www.github.com/imadhanhan/ModLayer, is written as a GUI function in MATLAB that requires two inputs: the reference 3D image and the adjustable 3D image. The first input, the reference 3D image, is entered during the execution of the ModLayer function. The second input, the adjustable 3D image, is imported into ModLayer as a global variable. Therefore, the adjustable 3D image must be instantiated within the Workspace as a global variable called 'data_modify' prior to the execution of the function ModLayer. The use of the global variable (1) is a safety feature which ensures that in the event ModLayer is accidentally closed, manual modifications remain in the Workspace and are not lost, and (2) allows for real-time observations, within ModLayer, to bulk changes made to the adjustable 3D image in the MATLAB Workspace, such as feature dilation or erosion.

With both the reference 3D image and the adjustable 3D image (imported in the form of the global variable 'data_modify') visible in ModLayer, a Colormap that is best suited for viewing each of the data sets can be selected, as shown in Fig. 2a, b. The Colormap options include all the default MATLAB Colormaps, as well as an additional Colormap called 'jetwhite', which can make certain multi-class segmentation visualizations easier to observe. The images may also be linked in the XY and Z which couples the scrolling, panning, and zooming of the reference and adjustable images. The linked 3D images can be observed for time lapse activity, or multi-class segmentation, in each layer by either using the scroll bars next to the images, or by typing the desired layer number and pressing 'GO'.

If a region of interest or low accuracy segmentation is found, a manual modification to the adjustable 3D image can be conducted within ModLayer. Prior to applying a modification, a drop-down menu allows for the selection of freehand drawing on the left reference image (which is useful especially for under-detection corrections) or on the right adjustable image (which is useful especially for correcting over-detection or separating touching edges), as shown in Fig. 2c. The user can input any multi-class segmentation value they wish to impose on the adjustable 3D image, and press the modify button to make modifications. The user can then click and drag to freehand draw on the selected image, and when the click is released, the change is immediately applied to the selected layer of the adjustable 3D image which is also immediately saved to the MATLAB Workspace.

Visualizing and Classifying 3D Data Using ModLayer

Identifying Damage in 3D Time Lapse Images

The first case study to show the functionality of ModLayer was time lapse sequences of 3D X-ray μ-CT images

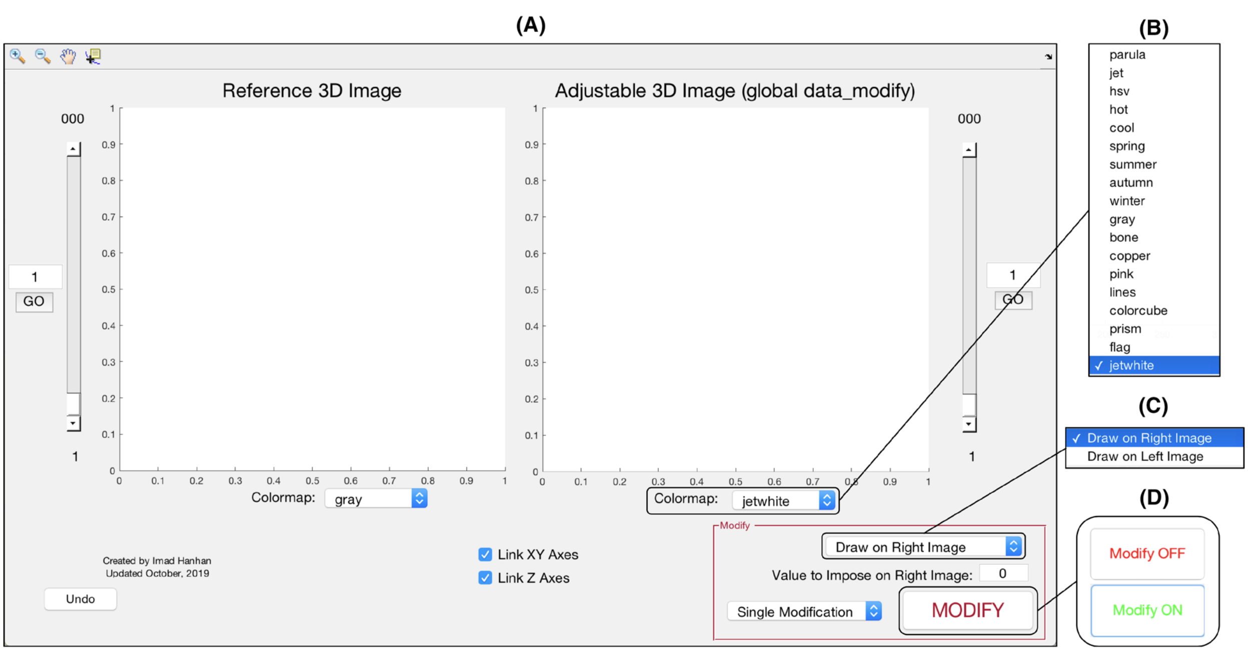

Fig. 2 The overall layout of ModLayer shown in **a**, with the Colormap options including the additional 'jetwhite' Colormap shown in **b**, as well as the image selection menu in **c** and the modify toggle button in **d**

of a GFRP composite under tensile load. Time lapse CT, in general, can be useful in understanding the evolution of certain materials or structures as damage accumulates under external loading conditions [10, 11]. Usually, the analysis of time lapse 3D images requires image processing and classification to segment locations of damage and identify types of damage within the 3D images [12–14].

To show how ModLayer can be used to identify locations of activity in time lapse 3D images, the microstructure of a discontinuous GFRP (30% by weight glass fiber) was imaged using synchrotron X-ray μ-CT [8]. The 3D images were examined for signs of damage, which appear as dark pixels at the loaded state (4% strain) which were not present at the unloaded state. To visualize and locate these regions of damage, the 3D X-ray μ-CT images were normalized so that $0 \leq I \leq 1$, and were inputted into ModLayer so the unloaded state was the reference (Fig. 3a) and the loaded state was the adjustable image (Fig. 3b). The 3D images were simultaneously inspected by scrolling, zooming, and panning through the linked stacked images and examined for regions of damage activity. When regions of damage activity were found in the image at the loaded state, like those circled in Fig. 3b, ModLayer was used to draw directly on the image and impose a segmentation value of -1 (a value outside of the range of $0 \leq I \leq 1$) in order to classify regions of damage within the microstructure, as shown in Fig. 3c. This shows that ModLayer can be used to examine and investigate linked time lapse 3D images directly in MATLAB without the need to open multiple windows or export to external software, while also providing the capability to classify locations of damage activity through freehand drawing for further quantification in MATLAB.

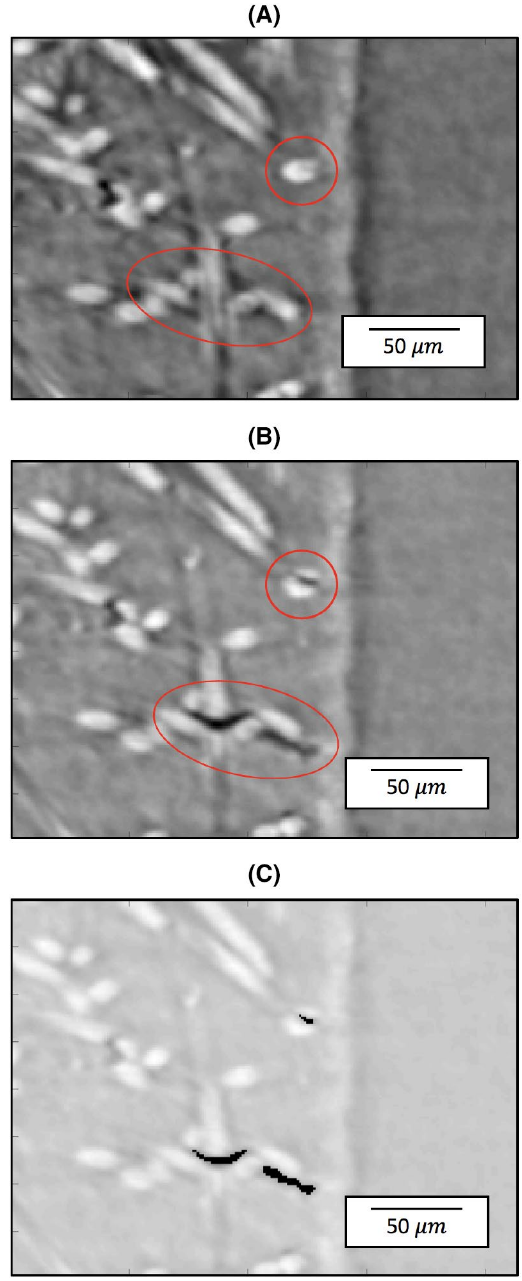

Fig. 3 Using ModLayer to visualize and investigate time lapse X-ray μ-CT images of a GFRP composite simultaneously at **a** the unloaded state and **b** the loaded state by scrolling, zooming, and panning through the linked time-resolved images. ModLayer was then used to mark the locations of damage by drawing around the regions of interest circled in **b**, in order to impose a segmentation value of -1 to produce the classified image shown in **c** for damage quantification

Correcting Feature Segmentation in Tomography Images of a Composite Material's Microstructure

The second case study to show the functionality of ModLayer was to correct segmentation errors in X-ray μ-CT images of a fiber composite. In discontinuous fiber reinforced polymers, the full characterization of the microstructure, including the fiber volume fraction, porosity volume fraction, fiber length, and fiber orientation distributions, is important to not only qualify composite materials for use, but also predict their mechanical behavior [15–19]. Because the characterization of these microstructural features is sensitive to segmentation errors, researchers have worked to develop tools and techniques to conduct these characterizations with the highest possible fidelity and to minimize segmentation errors of microstructural features that could impact characterization or predictive capabilities [20–22]. However, despite these efforts, sometimes it can be very difficult—especially for characterizing porosity—to achieve high fidelity segmentation of every feature [8]. To show how ModLayer can be used to correct these occurrences, X-ray μ-CT images of a discontinuous GFRP (30% by weight) were analyzed [8].

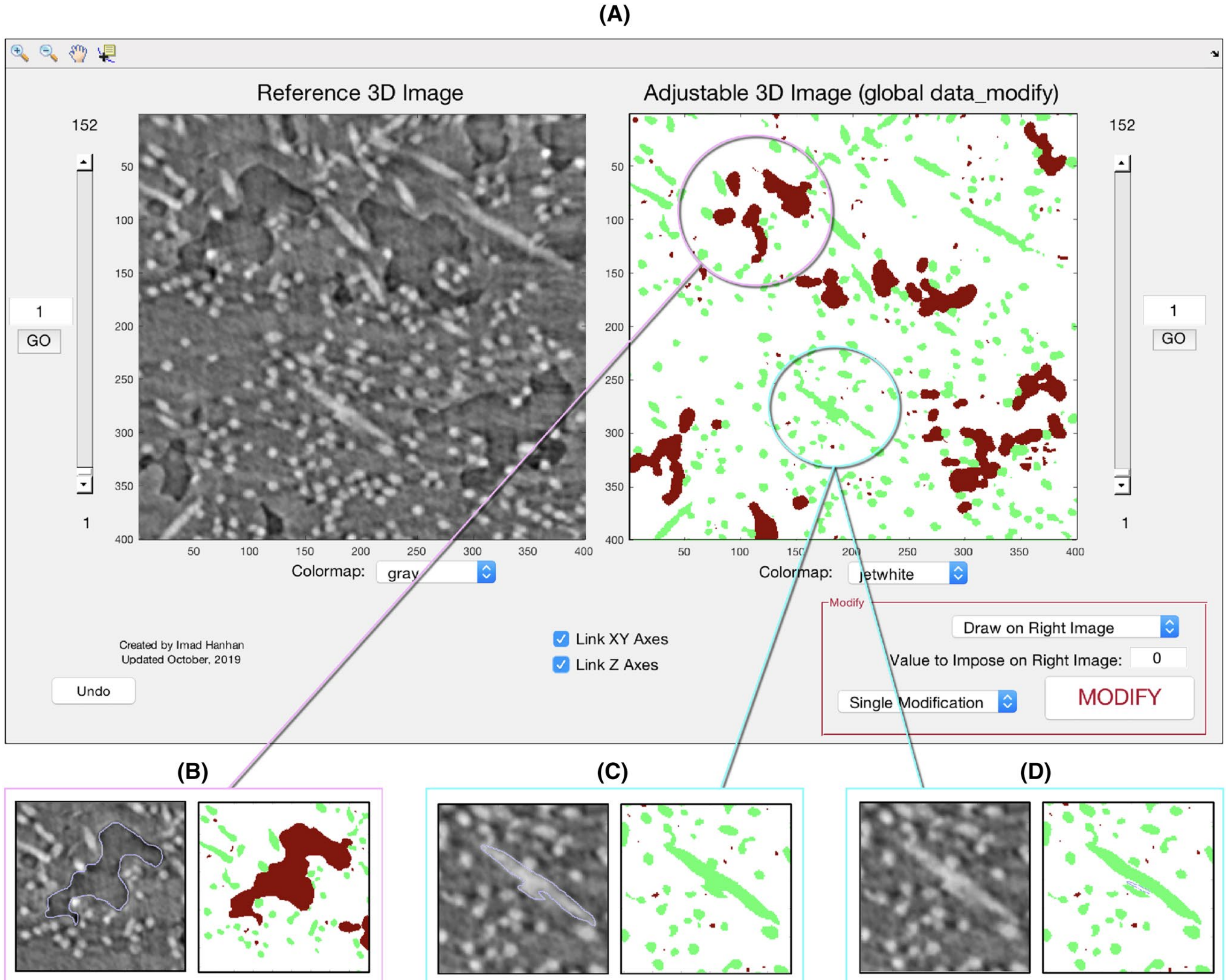

Fig. 4 **a** Using ModLayer to improve automated segmentation conducted on X-ray μ-CT images (with axes shown in pixels and where 1 pixel = 1.3 μm) of a glass fiber reinforced polymer, where **b** shows an example of drawing directly on the μ-CT image to correct the segmentation of a pore, **c** shows drawing directly on the μ-CT image to correct under-segmented fibers, and **d** shows drawing directly on the segmented image to separate touching segmented fibers

The serial sections of the reference 3D image, as shown in Fig. 4a, show high intensity pixels (white) at the locations of fibers, and low intensity pixels (black) at the locations of small pores and at the edges of large pores. An automated segmentation procedure was conducted in MATLAB to segment the image into values of 0 for the matrix, 1 for the fibers, and 2 for the pores. The procedure was as follows:

1. normalization so that $0 \leq I \leq 1$,
2. segmentation of fibers by $I > 0.65$,
3. segmentation of large pores by
   (a) selection of pixels with $I < 0.33$,
   (b) dilation using a spherical structural element with radius 4,
   (c) adjustment to fill 3D holes,
   (d) erosion using a spherical structural element with radius 5,
   (e) removal of features with a volume smaller than 10,000 pixels, and
4. segmentation of small pores by $I < 0.25$.

The result of this automated procedure is shown in Fig. 4a with the adjustable 3D image shown on the right, where it can be seen that small pores were detected well but large pores were generally under-detected.

ModLayer was then used to visualize the results of the segmentation analysis in each layer of the 3D images, and apply corrections to cases of low accuracy segmentation of porosity by drawing on the left reference image in Fig. 4b (to capture the full pore) and imposing a value of 2 for the drawn region in the multi-class segmented image. Additionally, regions with fibers that were under-detected were corrected by drawing on the left reference image in Fig. 4c and imposing a value of 1 for the drawn region in the multi-class segmented image. Lastly, regions with touching fiber edges were separated by drawing on the right segmented image in Fig. 4d and imposing a value of 0 between detected fibers in the multi-class segmented image. This shows that ModLayer can be used to visualize and improve the multi-class segmentation accuracy of the microstructural features of a composite material imaged through X-ray μ-CT, as was seen in Fig. 4b–d, especially for large pores which can be very difficult to capture through standard segmentation algorithms.

Correcting Feature Segmentation of In-Situ AA7050 Fatigue Crack Growth Tomography Images

To show another example of the functionality of ModLayer, segmented X-ray μ-CT images of an aluminum alloy acquired in-situ were improved to increase the accuracy of segmentation. Certain aluminum alloys, like AA7050, are known to have fatigue properties which can be severely impacted by intermetallic particles and voids [23]. Therefore, it is of interest to study the fatigue crack growth behavior within this alloy as the crack interacts with particles and voids [24]. Carter et al. noted that the noise levels and reconstruction artifacts in the X-ray μ-CT images posed many challenges in image segmentation, which is necessary in understanding the behavior of the crack in 3D. A sample of the tomography images acquired after 5651 cycles of fatigue loading on the specimen [24] is shown in Fig. 5a, where the notch tip can be seen in the upper left corner. The particles are seen as high intensity white pixels, and the crack plane/voids are seen as dark gray pixels.

An automated segmentation procedure was conducted in MATLAB as follows:

1. normalization so that $0 \le I \le 1$,
2. segmentation of particles by $I > 0.7$,
3. segmentation of the notch by
   (a) selection pixels with $0.44 < I < 0.57$,
   (b) slice-by-slice 2D erosion with a disk structural element of radius 4,
   (c) adjustment to fill holes,
   (d) removal of features with a volume smaller than 10,000 pixels,
   (e) dilation with a disk structural element of radius 40, and
4. segmentation of the crack plane by $I < 0.49$.

It can be seen in the segmentation result (Fig. 5b) that the notch was slightly under detected, and the sharp gradient

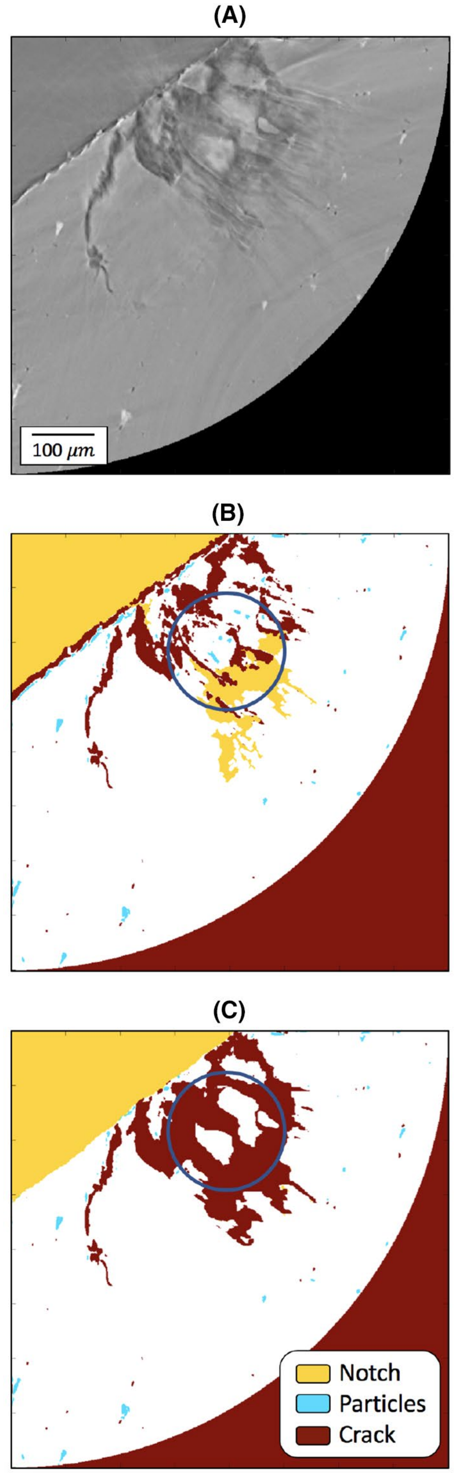

Fig. 5 ModLayer was used to improve the automated segmentation conducted on **a** in-situ X-ray μ-CT images of an aluminum alloy undergoing fatigue crack growth, where **b** shows an example of the result of automated segmentation, and **c** shows the segmented image after corrections were conducted in ModLayer by drawing directly on the μ-CT image or on the multi-class segmentation, with locations of correcting over-detection of particles circled in **b** and **c**

near the edge of the notch caused some erroneous segmentation of particles as well as the crack plane. Additionally, it can be seen in Fig. 5b that a portion of the crack plane had slightly higher intensity values and was therefore incorrectly segmented as part of the notch. Lastly, regions near the edge of the crack plane circled in Fig. 5b, c, had locations of particle over-detection. Therefore, ModLayer was used to draw on either the X-ray μ-CT image or the multi-class segmented image to correct the notch segmentation, increase the accuracy of the crack plane segmentation, and remove areas of erroneous crack and particle detection by imposing a value of 0 on the segmented image. The final multi-class segmentation after corrections conducted in ModLayer can be seen in Fig. 5c, and shows that ModLayer can be used to increase the accuracy of the automated segmentation shown in Fig. 5b for a more accurate analysis of the interaction of the crack plane with its neighboring microstructural features.

Conclusion

A tool was created within MATLAB that provides the capability of viewing successive slices of a reference 3D image and an adjustable 3D image. The tool, ModLayer, was created to also manually modify the adjustable 3D image—through an interactive freehand drawing GUI—in order to classify features that are either of interest, or correct the classification of features too difficult to segment automatically. ModLayer allows the user to select Colormaps that best display the images, while allowing the user to scroll, zoom, and pan through linked serial sections of the reference and adjustable 3D images. By clicking 'Modify', the user can draw directly on either of the two images to classify features or correct segmentation errors in the form of under- or over-detection, incorrect segmentation, and/or incorrectly touching edges of segmented features. This tool is especially useful in correcting the multi-class segmentation of features that may arise from noise or erroneous artifacts in imaging techniques which are often too difficult to capture through standard automatic segmentation procedures. The utility of ModLayer was shown through its ability to classify regions of damage in time lapse 3D X-ray μ-CT images of a fiber reinforced polymer matrix composite, correct automated segmentation of porosity features, and separate touching segmented fiber regions. Additionally, it was shown to be useful in correcting automated segmentation errors of the notch, the particles, and the crack plane in a fatigue cracked AA7050 specimen captured through in-situ X-ray μ-CT. ModLayer is distributed as an open source MATLAB function freely available for download at http://www.github.com/imadhanhan/ModLayer.

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Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

References

1. Landis EN, Keane DT (2010) X-ray microtomography. Mater Charact 61(12):1305–1316. https://doi.org/10.1016/j.matchar.2010.09.012
2. Burnett TL, McDonald SA, Gholinia A, Geurts R, Janus M, Slater T, Haigh SJ, Ornek C, Almuaili F, Engelberg DL, Thompson GE, Withers PJ (2014) Correlative tomography. Sci Rep 4:1–6. https://doi.org/10.1038/srep04711
3. Russ JC, Neal FB (2016) The image processing handbook. CRC Press, Boca Raton. https://doi.org/10.1201/b18983
4. Shi J, Malik J (2000) Normalized cuts and image segmentation part of the electrical and computer engineering commons recommended citation normalized cuts and image segmentation normalized cuts and image segmentation. IEEE Trans Pattern Anal Mach Intell 22(8):888–905. https://doi.org/10.1109/34.868688
5. Vaithiyanathan V, Rajappa U (2013) A review on clustering techniques in image segmentation. Int J Appl Eng Res 8(20 SPEC. ISSUE):2685–2688
6. Sosa JM, Huber DE, Welk B, Fraser HL (2014) Development and application of MIPAR: a novel software package for two- and three-dimensional microstructural characterization. Integr Mater Manuf Innov 3(1):1–18. https://doi.org/10.1186/2193-9772-3-10
7. Solomon C, Breckon T (2011) Fundamentals of digital image processing: a practical approach with examples in Matlab. Wiley, Hoboken
8. Hanhan I, Agyei R, Xiao X, Sangid MD (2019) Comparing non-destructive 3D X-ray computed tomography with destructive optical microscopy for microstructural characterization of fiber reinforced composites. Compos Sci Technol 184:107843. https://doi.org/10.1016/j.compscitech.2019.107843
9. Abràmoff MD, Magalhães PJ, Ram SJ (2004) Image processing with ImageJ. Biophotonics Int 11(7):36–42
10. Maire E, Withers PJ (2014) Quantitative X-ray tomography. Int Mater Rev 59(1):1–43. https://doi.org/10.1179/1743280413y.0000000023
11. Wang Y, Mikkelsen LP, Pyka G, Withers PJ (2018) Time-lapse helical X-ray computed tomography (CT) study of tensile fatigue damage formation in composites for wind turbine blades. Materials. https://doi.org/10.3390/ma11112340
12. Scott AE, Mavrogordato M, Wright P, Sinclair I, Spearing SM (2011) In situ fibre fracture measurement in carbon-epoxy laminates using high resolution computed tomography. Compos Sci Technol 71(12):1471–1477. https://doi.org/10.1016/j.compscitech.2011.06.004
13. Patterson BM, Cordes NL, Henderson K, Williams JJ, Stannard T, Singh SS, Ovejero AR, Xiao X, Robinson M, Chawla

N (2015) In situ X-ray synchrotron tomographic imaging during the compression of hyper-elastic polymeric materials. J Mater Sci 51(1):171–187. https://doi.org/10.1007/s10853-015-9355-8
14. Rolland H, Saintier N, Robert G (2016) Damage mechanisms in short glass fibre reinforced thermoplastic during in situ microtomography tensile tests. Compos Part B Eng 90:365–377. https://doi.org/10.1016/j.compositesb.2015.12.021
15. McGee SH, McCullough RL (1984) Characterization of fiber orientation in short-fiber composites. J Appl Phys 55(5):1394–1403. https://doi.org/10.1063/1.333230
16. Mlekusch B (1999) Thermoelastic properties of short-fibre-reinforced thermoplastics. Compos Sci Technol 59(6):911–923. https://doi.org/10.1016/S0266-3538(98)00133-X
17. Avérous L, Quantin JC, Lafon D, Crespy A (1995) Determination of 3D fiber orientations in reinforced thermoplastics, using scanning electron microscopy. Acta Stereol 14(1):69–74. https://popups.uliege.be:443/0351-580x/index.php?id=705
18. Bay RS, Tucker CL (1992) Stereological measurement and error estimates for three-dimensional fiber orientation. Polym Eng Sci 32(4):240–253. https://doi.org/10.1002/pen.760320404
19. Sharma BN, Kijewski SA, Fifield LS, Shin Y, Tucker CL, Sangid MD (2018) Reliability in the characterization of fiber length distributions of injection molded long carbon fiber composites. Polym Compos 39(12):4594–4604. https://doi.org/10.1002/pc.24571
20. Sharma BN, Naragani D, Nguyen BN, Tucker CL, Sangid MD (2017) Uncertainty quantification of fiber orientation distribution measurements for long-fiber-reinforced thermoplastic composites. J Compos Mater. https://doi.org/10.1177/0021998317733533
21. Agyei RF, Sangid MD (2018) A supervised iterative approach to 3D microstructure reconstruction from acquired tomographic data of heterogeneous fibrous systems. Compos Struct 206(August):234–246. https://doi.org/10.1016/j.compstruct.2018.08.029
22. Emerson MJ, Dahl VA, Conradsen K, Mikkelsen LP, Dahl AB (2018) Statistical validation of individual fibre segmentation from tomograms and microscopy. Compos Sci Technol 160(January):208–215. https://doi.org/10.1016/j.compscitech.2018.03.027
23. Bowles CQ, Schijve J (1973) The role of inclusions in fatigue crack initiation in an aluminum alloy. Int J Fract 9(2):171–179. https://doi.org/10.1007/BF00041859
24. Carter ST, Rotella J, Agyei RF, Xiao X, Sangid MD (2018) Measuring fatigue crack deflections via cracking of constituent particles in AA7050 via in situ x-ray synchrotron-based micro-tomography. Int J Fatigue 116(May):490–504. https://doi.org/10.1016/j.ijfatigue.2018.07.005