

The Identification and Quantification of Pits, Cracks, and Corrosion from Container Material Image Surface Depth Measurements with Subsequent Container Classification

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Abstract

Hazardous materials or conditions may affect the integrity of their container. A sample is taken destructively from the interior surface of a container. Depth measurements on the sample are made using a Laser Confocal Microscope, LCM, to create an image of the surface height or depth over the sample area. The depth information is used to define void features of interest. The features of interest consist of pixels of the image that form contiguous areas with similar depths. A feature is characterized by various statistics. For each feature, the statistics include: number of pixels and the corresponding aggregate pixel area, maximum depth, average depth, volume below the surface, bounding box, major, minor axis and related eccentricity, the orientation of the major axis, the topological "holes" and other specific shape information, such as, exact absolute or relative locations of the forming pixels. The feature statistics may be summarized for all features in the image. The summary statistics of the image may be used to classify the image as interesting, in the sense of requiring further inspection, or uninteresting, in the sense that there are no unacceptable features present.

The container is then classified as acceptable or unacceptable.

Key Words: laser confocal microscope, pits, cracks, stress corrosion cracking (SCC), surface corrosion, container integrity, characterization

1. Introduction and Background

Containers have been used for various hazardous materials containing Plutonium (Pu) or Uranium (U) elements or compounds for many years, Figure 1a, thru today, Figure 1b, and will be used for the foreseeable future. For safety reasons containers must satisfy government requirements, [3]. For example, one of the current requirements is the container must hold its integrity for 50 years. One of the sources of container failure is container corrosion. Figure 2a shows Plutonium Oxide in a container. Such hazardous materials, if not stored properly, may cause container failure, see Figure 2b.

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(a) Early Historical Picture of the Main Gate Entry to Los Alamos National Laboratory (LANL).



(b) More Recent Picture of the Los Alamos National Laboratory

Figure 1: Historical and Modern Day Pictures of Los Alamos National Laboratory from LANL archives.



(a) Plutonium Oxide in a Container.



(b) Hazardous materials may be corrosive.

Figure 2: Containers Holding Hazardous Materials. Images from Los Alamos National Laboratory Actinide Research Quarterly, 3rd Quarter, 2004.

The study described here is to help determine if possible corrosion events exist in currently used in 3013 containers. 3013 is a specific type of container or container system. The system consists of nested containers, Figure 3a and Figure 3013 cutaway, [3]. The containers are named, from innermost to outermost, the convenience container, the inner container and the outer container.

The main possible corrosion events are: pitting, cracking and general surface corrosion. These categories may not be mutually exclusive. Pitting tends to be a single contiguous circular area on the surface and the main concern is the pit depth. There are pit growth models that depend upon the deepest depth of the pit, see [8]. Cracking is a very complex 3-dimensional feature in the material that may exhibit itself as linear like feature(s) on the surface, see [2], [18], [1], [10], [12], [17], [9], and [11]. General corrosion is a larger area



(a) DOE 3013 System of Three Containers for Nesting.



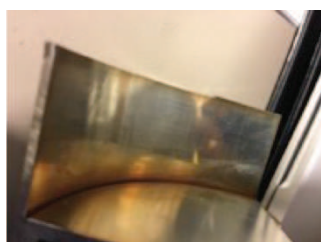
(b) Cutaway of a 3013 Nested Container System.

Figure 3: 3013 Container System. From innermost to outermost, the convenience container, the inner container and the outer container. Images from Los Alamos National Laboratory Actinide Research Quarterly, 3rd Quarter, 2004.

phenomenon that may deteriorate, at a relatively constant amount, a much larger area than a typical pit or typical crack. All of these types corrosion events are important and must be examined on the container(s) under investigation.

Initially this study focussed on possible corrosion pitting. After the pitting was satisfactorily quantified then the study focus changed to potential cracks. Eventually, further study will include estimating the general corrosion.

The inner surface of the inner container is the area of study. There is a weld around the circumference of the entire inner container to secure the “lid” according to the requirements, Figure 4a. The area near the weld is of primary concern as it has been subject to the affects of the welding process that may have introduced stresses and strains within the container wall. The container is destructively examined by cutting out container wall samples from this area. Figure 4b is an image showing how the wall surface changes from the weld on the top down to the original pre-weld container surface on the bottom. There are three zones labeled, 1 2, and 3, according to their proximity to the weld region. Various experiments have been run using a “teardrop” to simulate the stresses and strains near the weld region, 4c.



(a) 3013 Container Sectioned for Sample Preparation With Weld on Bottom Where the Flat Surface Meets the Curved Wall Surface.

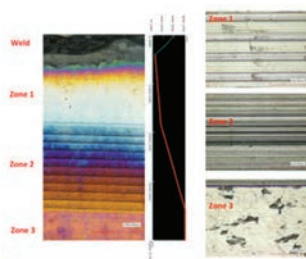


Figure 2-1. Representative optical images of the Inner Container Closure Weld Region with Zones 1-3 delineated.

(b) Container Zones With Weld on Top. From Top to Bottom: Weld, Zone 1, Zone 2, and Zone 3.



(c) Experimental “Teardrop” Used to Simulate the Stresses In the Container.

Figure 4: Container Weld Region (Images from Juan Duque) and Teardrop Sample Creating Stress (image Daniel Rios).

Only the surface of the inner wall region is studied here. The surface is interrogated with a Keyence, [7], laser confocal microscope (LCM). The microscope provides data of four types: height (or depth), intensity, optical, and laser optical. The optical and laser optical data are each comprised of three channels: red, green, and blue. There are a total of eight different data channels, one for height, one for intensity, three for optical, and three for laser optical. The eight data channels are plotted in Figure 5. The eight channels of data are provided in one LCM output file with Keyence, [7], extension “.vk4”. The “.vk4” file is a binary file and the specific format is discussed in [13] and [14]. The image used for Figure 5 is from a typical .vk4 file, *HCL_Pol_no_O2_Sec1_All_Y2_X8.vk4*. This is from a teardrop experiment using HCl acid with no polishing of the surface and under the condition of having oxygen present.

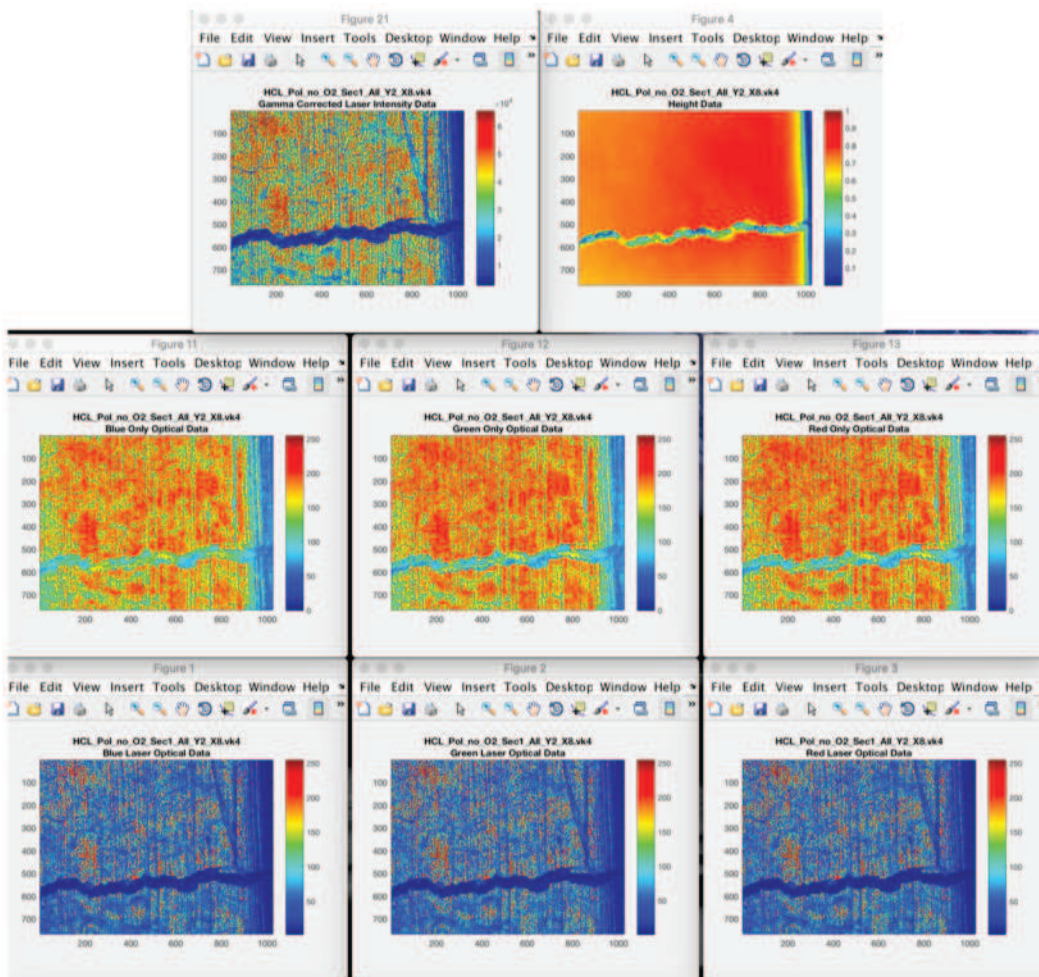


Figure 5: The Images Display the Types of Data In One Typical “.vk4” File, *HCL_Pol_no_O2_Sec1_All_Y2_X8.vk4*. Upper Left is the Intensity Data, Upper Right is the Height Data, Middle Left is the Blue Optical Data, Middle Middle is the Green Optical Data, Middle Right is the Red Optical Data, Lower Left is the Blue Laser Optical Data, ... Lower Middle is the Green Laser Optical Data, and Lower Right is the Red Laser Optical Data.

To properly handle the data channels requires some processing of the raw LCM data values. The main processing is to that of the height or depth measurement. The raw data has curvature that may affect the analysis. This curvature is estimated and removed from

further analysis.

The eight channels may be analyzed independently of one another or in synchrony with one another. The main synchronous use will be to determine the height/depth of feature created from the other channels.

We discuss within and between image classification. Some features, such as, general corrosion or long cracks, may span several contiguous images of a sample and hence may be best analyzed with knowledge of adjacent image(s). The main concern here will be the within image classification. The image analysis or within image classification consists of first determining features of interest in the area of the image. Then classification of the features as of concern or not of concern.

Once the features have been classified the images containing features may be classified. In one container there will be approximately 6,000 images available for analysis. The images will be ranked in order from those most likely requiring human follow up scrutiny to those least likely to require human follow scrutiny of the image.

Avenues for future, analysis and research paths are discussed. The conclusion of this study is the LCM data may be used to rank the images for further human scrutiny.

2. Handling Microscope Curvature.

The height/depth data may have curvature introduced by the sample removal process, the release of stress and strain after cutting, or the microscope stage horizontal alignment. This curvature is removed to allow for the feature depths to be more accurately obtained. The image on the left in Figure 6 is the height/depth data from a typical image treated with HCl. Y7 and X4 in the LCM file name indicate the position in a mosaic of 165 features, not further discussed here. The “raw” depth image on the left is normalized only by dividing by the maximum pixel value in the file. The curvature may be seen as the image tends to be “high” on the left and “low” on the right. The curvature is removed by fitting a very smooth non-parametric function to the unnormalized “raw” data and subtracting this smooth surface from the “raw” data. The resulting un-normalized height depth data is shown on the right of Figure 6. The very smooth non-parametric function has been implemented as a MATLAB subroutine called SMOOTHN, see [4], [5], and [6]. The subroutine has been modified to allow the user to supply a custom value of the smoothing parameter, see [15] and [16].

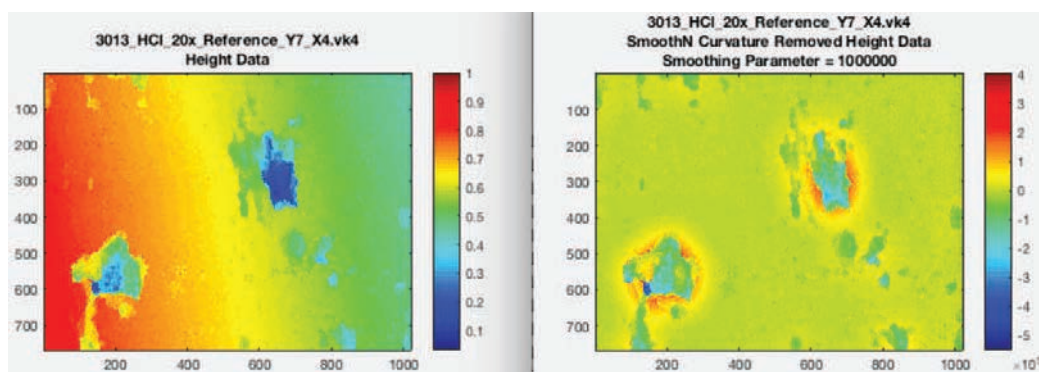


Figure 6: Raw Depth Data for Image Y7 X4 on the left (Normalized to Maximum Value of One). Curvature Removed From the Raw Data (Unnormalized in Microscope Output Values) on the Right. Each Axis Represents the Number of the Pixel in the Image(s).

3. Feature Creation

Features are determined for each of the data types: curvature removed height/depth, intensity, optical, and laser optical by thresholding the data and looking for contiguous patches in the image. Once these contiguous patches are found they are screened to verify that they have at least a minimum number of pixels and not more than a maximum number of pixels. Often in the analysis done here the minimum number is five pixels and the maximum number is some large number, such as 100,000 meant to exclude extraneous features such as edge of sample area or the weld area. In Figure 7 the top left image shows features, in yellow, created by height above a critical value and below another critical value. The critical values are user supplied to allow for pixels of interest to be included in features of interest and excluded from features of interest. That is setting them to zero would possibly include all pixels in one giant feature. Whereas setting them too large in magnitude would provide no features. An interim value that provides for features of interest is what is desired. In this analysis features less than 10 microns are often not interesting whereas those larger than 10 microns may be interesting. In Figure 7 the lower left image show features, in yellow, of the intensity value. A cutoff is supplied for thresholding intensity by providing a lower percentile for the threshold. Intensity pixels that have low intensity values make for features of concern that is, potential pits or potential cracks. The percentile is user supplied and a value of 1% may be a good starting value.

The optical image features, in yellow, are in the upper right of Figure 7. The thresholding is more complex as we have three values or channels for the optical data, red green, and blue. For the purposes here we have found that dark values are those of interest to comprise the features. To decide which pixels to use or exclude in the feature formation step the user supplies first a percentile for the optical data, as in the intensity data, and then the vertices of a polytope in the RGB space to determine “dark” or pixels of interest to form the features. The user may also supply a “buffer” to include pixels that are close to the supplied polytope. The percentiles are first used for each channel to determine the channel cutoff value. Next the polytope is scaled according to these cutoff values. And final for each pixel in the image it is determined whether or not the RGB values for the pixel lie either within or within the buffer distance to the polytope. The selected pixels are then used to form the features. The laser optical data features, in yellow, are in the lower right side of Figure 7. The creation of these features is handled in a similar way as is the optical data. Similar to the height/depth data and the intensity data, the features are required to have a minimum number of pixels and to not exceed a maximum number of pixels.

Potential general corrosion is evident in Figure 7. Notice the change in density of the smaller features, especially in the two lower figures. Three of the images have identified two very large pit-like features. These features may be interrogated for further information, such as, maximum depth.

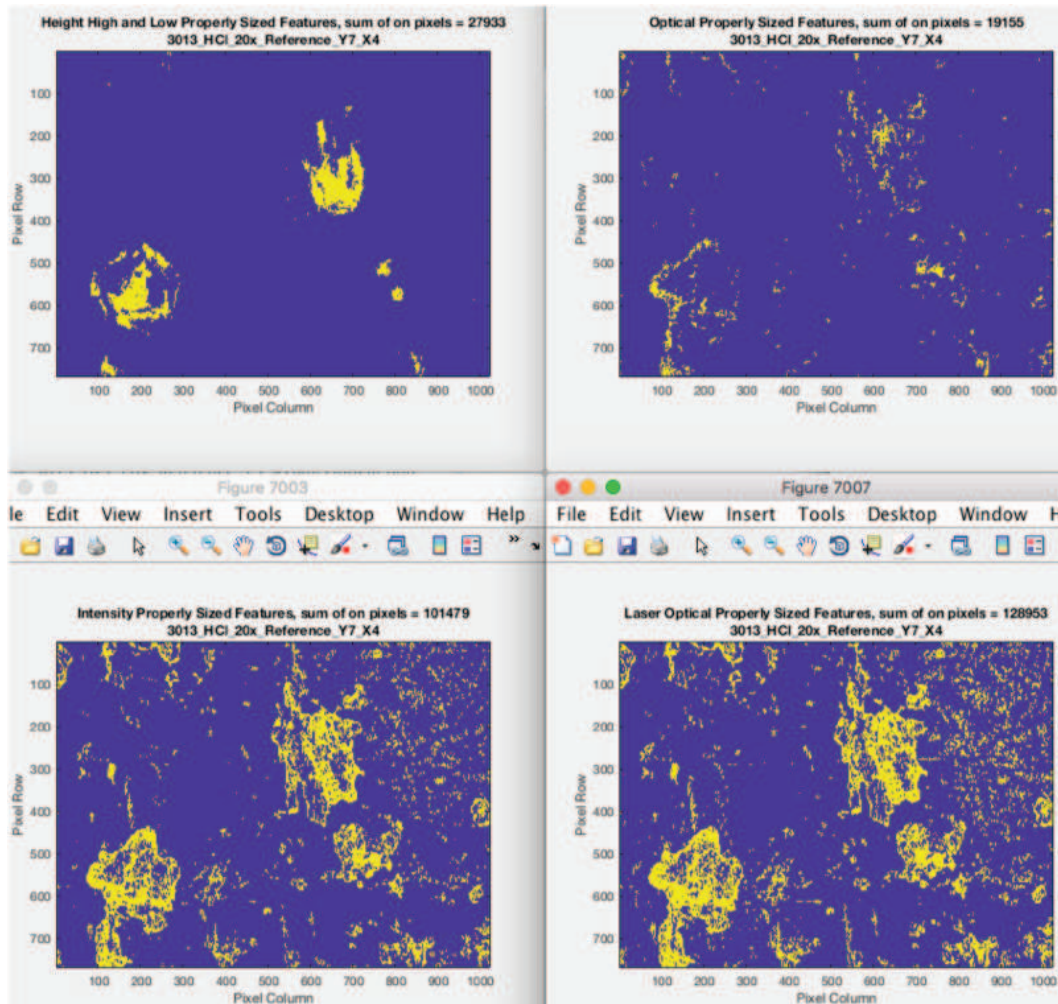


Figure 7: All Features Created from the Four Types of Data. Height in upper left, Intensity in lower left, Optical in upper right, and Laser Optical in lower right.

To visualize the polytopes and how they are used with the RGB channels see Figure 8. On the left is the polytope used for the laser optical feature formation and on the right is the polytope used for the optical feature formation. Each of these use four vertices for the polytope as listed above the figures. Each vertex consists of three values of RGB. The values are: $[0,0,0]$, $[75,0,0]$, $[0,75,0]$, and $[0,0,75]$. The polytope formed in 3-dimensions is the same as a cube sliced in half at four of its vertices forming a right angled tetrahedron in 3-dimensions. The points in the scatterplot each represent the RGB values for one pixel in the image. If the pixel falls within the buffer units of the wedge polytope or within the polytope then the pixel is colored red. If the pixel RGM values are at least the buffer number of units from the polytope then the pixel is colored black. The red pixels are used to define the features by contiguity.

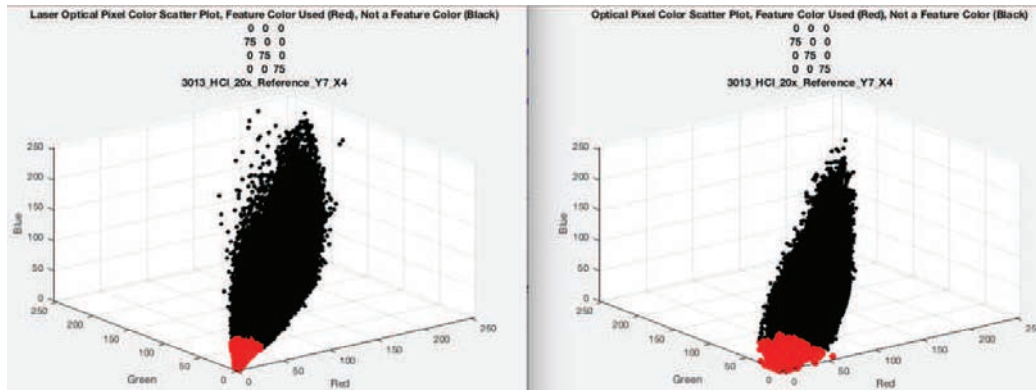


Figure 8: Scatter Plot of all Pixel Values in an Example Image. Red Indicates the Point Falls within the Polytope Defined by Vertices $[0,0,0]$, $[75,0,0]$, $[0,75,0]$, and $[0,0,75]$ and Black Otherwise. Left Image is For Laser Optical Data and Right Image is for Optical Data.

4. Feature Analysis

A group of neighboring pixels determines a possible feature, [16]. Statistics are computed for each of the possible surface features from each of the data types. The possible features are uniquely labeled and related statistics include:

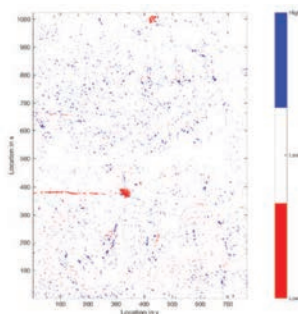
1. Data type origin (type of data used to define feature, ie. height)
2. Pixel locations (row and column locations of the pixels in the image)
3. Number of pixels or area in square microns (area of the feature, number or square microns)
4. Orientation (angle of the major axis of the feature, defined in MATLAB)
5. Eccentricity (defined in MATLAB)
6. Centroid (defined in MATLAB)
7. Bounding box (defined in MATLAB)
8. Euler number (defined in MATLAB)
9. Convex Area (defined in MATLAB)
10. Equivalent Diameter (defined in MATLAB)
11. Solidity (defined in MATLAB)
12. Extent (defined in MATLAB)
13. Perimeter (defined in MATLAB)
14. Number of pixels (defined in MATLAB)
15. Pixel length in nano-meters (length of square side of a pixel)
16. Below and above surface areas (area above the smooth level of the height surface)
17. Maximum depth or height (the deepest or highest pixel in a height feature)

18. Below and above surface variability - roughness (the standard deviation of the height of the pixels in a feature)
19. Below and above surface volume (sum of depth & height times pixel area)
20. Below and above surface average depth or height (the average of the below or above height of the pixels in a feature)

The feature statistics are next used to determine features of interest for further investigation. A set of criteria are created to classify the features. In this study we created five different sets of criteria. For pit-like criteria we used maximum pit depth. For crack-like criteria we used eccentricity values near one. The three additional criteria are basically used to find features in the non-depth/height data that may be indicators of potential cracks. These rely on eccentricity, extent, and solidity. The various statistics use cutoff values and categorize the features as “red” if they are of great concern, “yellow” if they may be of concern, and as “green” if there is no concern about the feature being corrosion that may eventually cause container wall compromise.

4.1 Example Image 1

A summary image showing the results of this analysis in an image chosen for illustrative purposes is provided in Figure 9a. In this image the blue features are features above the surface and the red features are those below the surface. Typically, we ignore the features above the surface as they represent noise, debris, or other uninteresting features. The features below the surface are those of most interest. In this image three of the features cause particular attention. Two are pit-like and one is crack-like. In this case we are most interested in the maximum depth of the pit-like features. and we would be interested to find if the crack-like feature is part of a crack network or just some surface type blemish. Blemishes may be machining marks, scratches, polishing marks, or debris. The lower center type feature has been enlarged and is provided in Figure 9b. The enlargement shows the feature has “holes” and is generally circular. The feature Euler number is related to the number of holes and the feature roughness reflects the non-constant behavior of the feature values. Although not further used here, these statistics may become useful for eventual feature and image ranking.



(a) Example Image With Pit-Like (at locations [330,390] and [450,1010]) and Crack-Like (from [0,380] to [280,370]) Features Below the Surface (red) and Small Noisy Features Above the Surface (Blue) and Below the Surface (Red).



(b) Zoom of Pit-Like Feature at location [330,390] in Figure 9a.

Figure 9: Example Image With Potential Pit and Potential Crack Type Features and Zoom.

4.2 Example Image 2: “Crack1_20X.vk4”

The example image “Crack1_20X.vk4” is from an experiment intentionally designed to create cracks. This example contains “obvious” crack features. Various graphics have been created to “see” the features in an image. These graphics are detailed below.

The height data may have features both above and below the surface of the sample. These features are displayed in Figure 10. The features above the surface are in blue and those below the surface are in orange. It is clear from inspecting this image that the crack features occur mostly above the surface. This may be due to debris forming around the top edge of a crack.

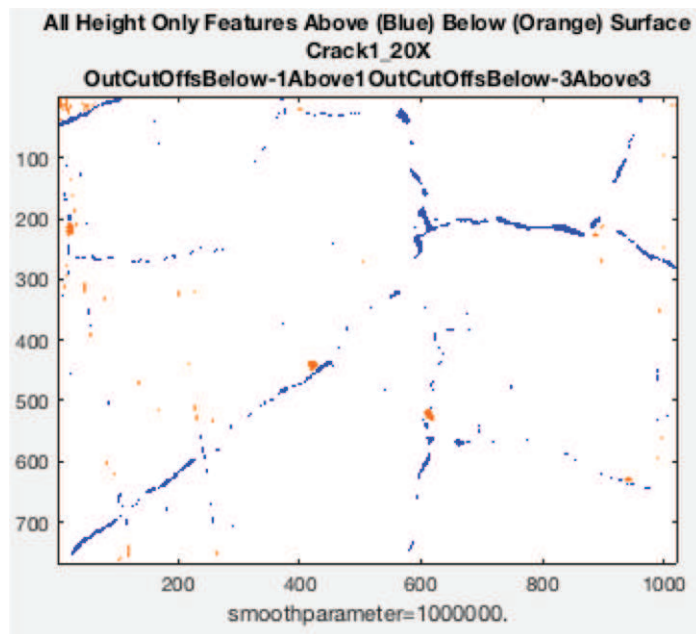


Figure 10: All (Green, Yellow, or Red) Features for Height Data. Features Above the Surface in Blue and Features Below the Surface In Orange.

The features created from the intensity data are portrayed in Figure 11. There are only a few very small green features in the image and a small yellow feature. Most of the features are flagged as red and visually form a weblike crack network. The parameters listed on the bottom of the image list the values used to determine green, yellow and red features. To be labeled as a red feature the feature must have eccentricity greater than 0.95, solidity less than 0.1, or extent less than 0.05 and the feature must contain at least 5 pixels. To be labeled as a yellow feature the feature must not be labeled red, must have eccentricity greater than 0.9, solidity less than 0.2, or extent less than 0., and the feature must contain at least 5 pixels. To be labeled as a green feature the feature must not be classified as either red or yellow.

The features created from the optical data are portrayed in Figure 12. There are a few small green and yellow features in the image. Most of the features are flagged as red and visually form a weblike crack network. The parameters listed on the bottom of the image list the values used to determine green, yellow and red features. These parameters are the same as those used in the intensity feature classification listed above for 11.

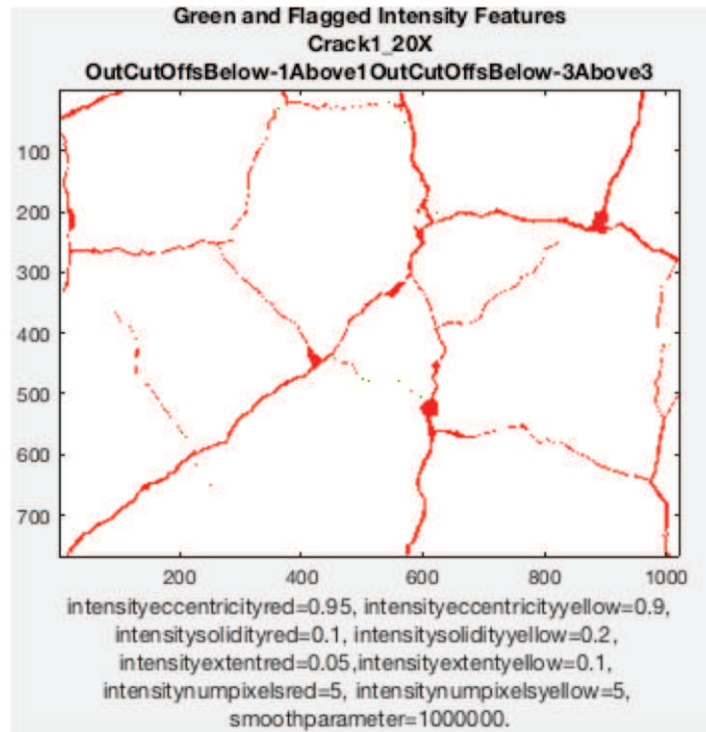


Figure 11: Green, Yellow, or Red Features for Intensity Data.

The features created from the laser optical data are portrayed in Figure 13. There are very few small green and yellow features in the image. Most of the features are flagged as red and visually form a weblike crack network. The parameters listed on the bottom of the image list the values used to determine green, yellow and red features. These parameters are the same as those used in the intensity and optical feature classification listed above for 11.

In the images in Figures 10, 11, 12, and 13 it is seen that the crack network features are different for the different types of data used to create the features. The intensity data seems to pick out most of the web network. However, the intensity data seems to miss the small crack connecting the two pit-like features in Figure 11 that is more visible in the optical data features of Figure 12. This small connecting crack is centered near the point [450,500]. In this example, the parameters set to determine green, yellow, and red features are the same for the intensity, optical and laser optical data. For other examples these parameters may be different for the different types of data.

Figure 14 displays a set of 9 arbitrary feature classifications for the data of Example 2. Each row has a classification for the image in column 1 and for the five different feature classification methods in columns 2 thru 6. The image is classified as "Red" because there is at least one red feature in the entire image (including features not displayed in Figure 14). For the 9 arbitrarily chosen features none of them are pit-like so they are all listed as "Green" in column 2. In column 3, for the crack-like classification method there is one "Yellow" and one "Red" classified feature. Columns 4 thru 5 are identical to one another because in this Example 2 the same criteria were applied for each classification method. Two are classified as "Yellow" features and seven are classified as "Red" features. As mentioned earlier, the user may specify different parameters for the last 3 classification methods and this may result in a different classification color for any one feature.

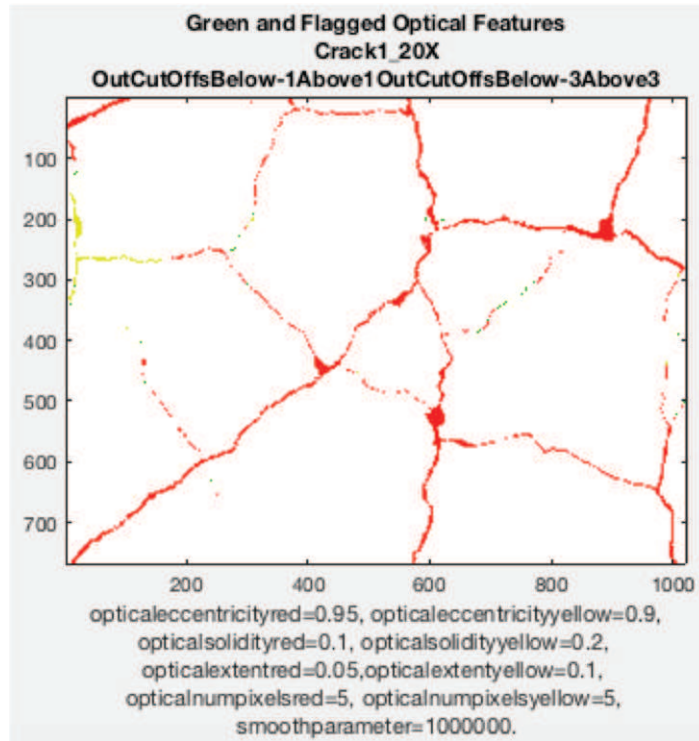


Figure 12: Green, Yellow, or Red Features for Optical Data.

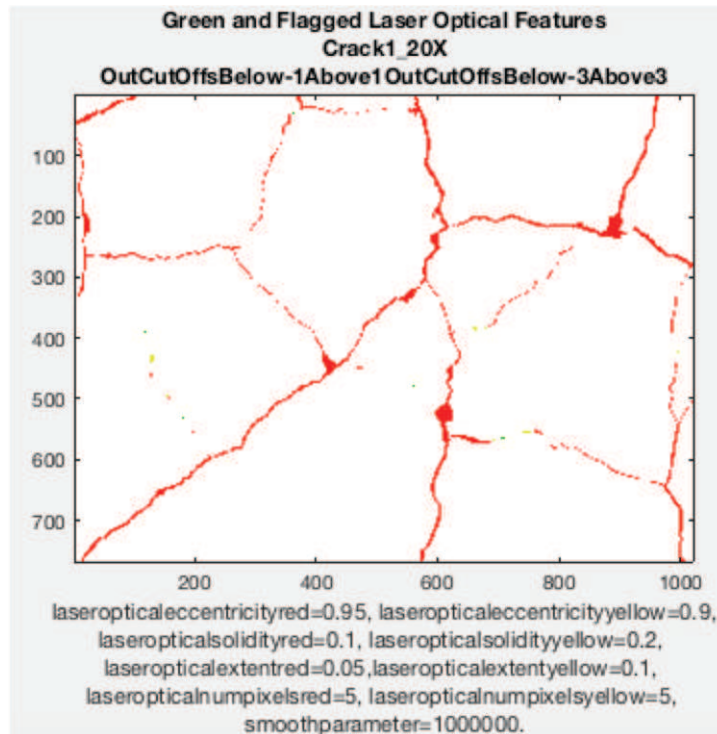


Figure 13: Green, Yellow, or Red Features for Laser Optical Data.

ImageColor	PitIndicator	CrackIndicator	IntensityIndicator	OpticalIndicator	LaserOpticalIndicator
"Red"	'Green'	'Green'	'Red'	'Red'	'Red'
"Red"	'Green'	'Red'	'Red'	'Red'	'Red'
"Red"	'Green'	'Green'	'Red'	'Red'	'Red'
"Red"	'Green'	'Green'	'Red'	'Red'	'Red'
"Red"	'Green'	'Yellow'	'Yellow'	'Yellow'	'Yellow'
"Red"	'Green'	'Green'	'Red'	'Red'	'Red'
"Red"	'Green'	'Green'	'Red'	'Red'	'Red'
"Red"	'Green'	'Green'	'Red'	'Red'	'Red'
"Red"	'Green'	'Green'	'Red'	'Red'	'Red'
"Red"	'Green'	'Green'	'Yellow'	'Yellow'	'Yellow'

Figure 14: Feature Classification for Image “Crack1_20X.vk4”. Columns are for Image Overall Color, Pit Indicator Color, Crack Indicator Color, Intensity Indicator Color and Optical Indicator Color, and Laser Optical Indicator Color. Rows are for Individual (unlabeled here) images.

Figure 15 is a montage of the images in Figures 10, 11, 12, and 13. This figure makes it easier for a visual comparison of the features determined by the different types of data: height/depth, intensity, optical, and laser optical.

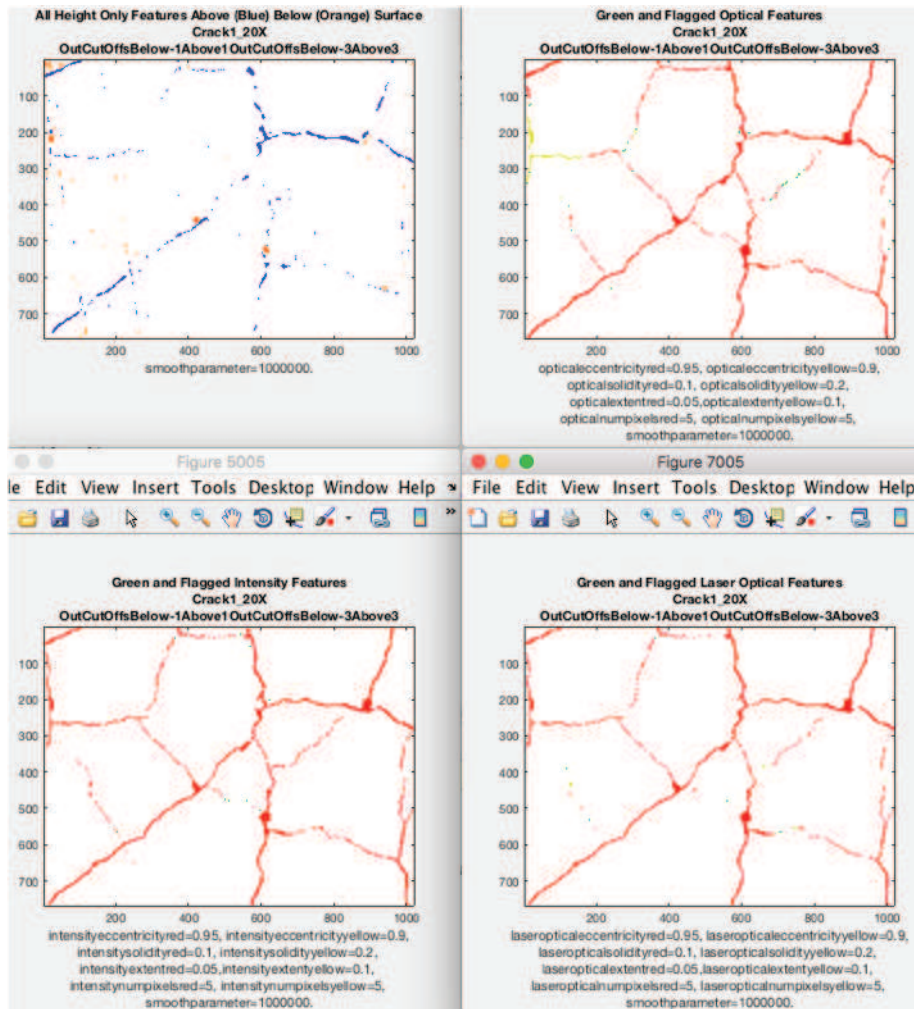


Figure 15: Feature Comparison Image “Crack1_20X.vk4”. Height in upper left, Intensity in lower left, Optical in upper right, and Laser Optical in lower right.

Figure 16 is a montage using height to portray a feature as being completely above the surface (orange), completely below the surface (green), or sometimes above and sometimes

below the surface (black). The height/depth data image in the upper left is the same as that in figureheightall. The other three images have mostly black features indicating most features from the intensity, optical, and laser optical data types yield features that are both above and below the surface.

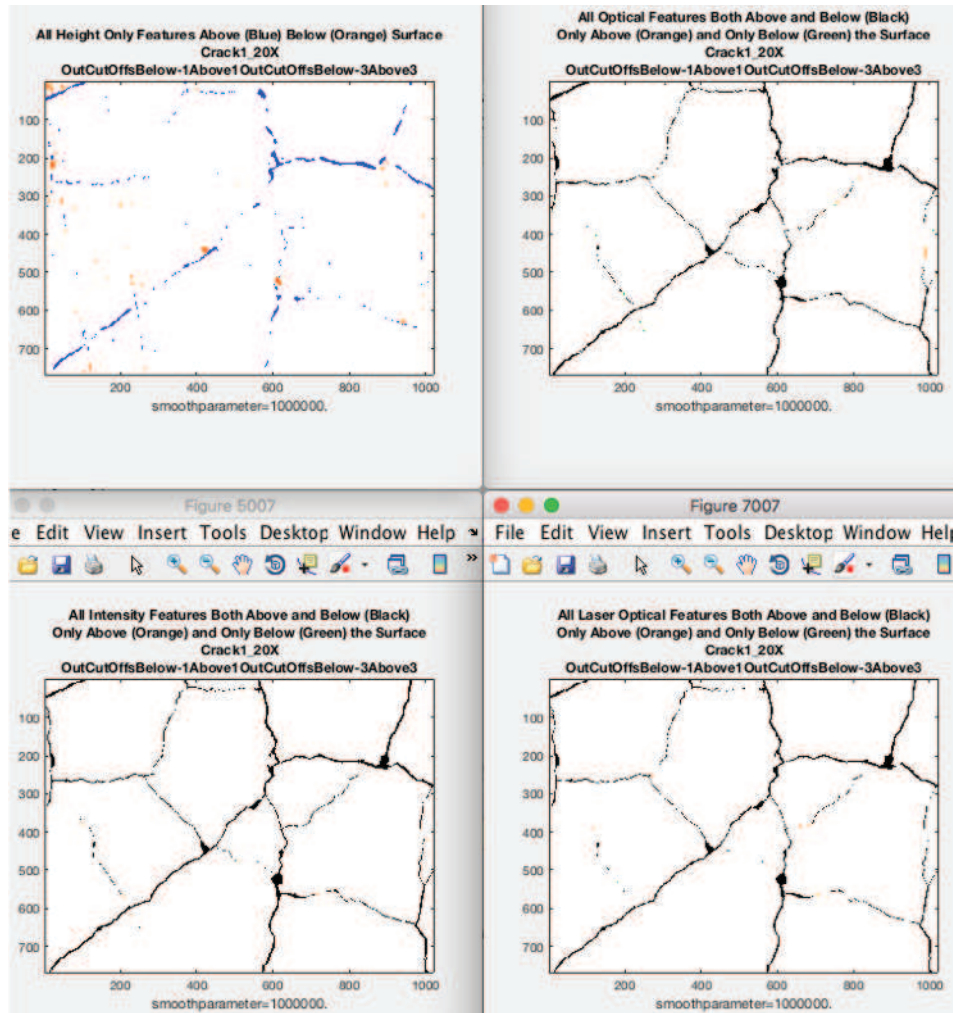


Figure 16: Height Comparison Image “Crack1_20X.vk4”. Height in upper left, Intensity in lower left, Optical in upper right, and Laser Optical in lower right.

Once all of the features in an image are classified, then it is possible to classify the entire image as green, yellow, or red..

5. Image Analysis

Using the feature classifications derived as described above, images may be classified to determine how images should be prioritized for further human investigation. As an example of image classification, we use 252 images from the FY09 DE02 container. Figure 17 displays the 252 images in one figure. The images are in 14 rows and 18 columns. In this figure the surface is represented in black, the green features in green and the flagged features (yellow and red features) in orange. The information in these 252 images is extremely condensed and much lost in order to display them all in one montage. The montage reveals a likely relatively corrosion free area in the upper middle that is mostly black and green. There are also many areas that are simply green possibly indicating there may be general

corrosion present but no pit-like or crack-like features. The areas with orange indicate potential pit-like and crack-like features.

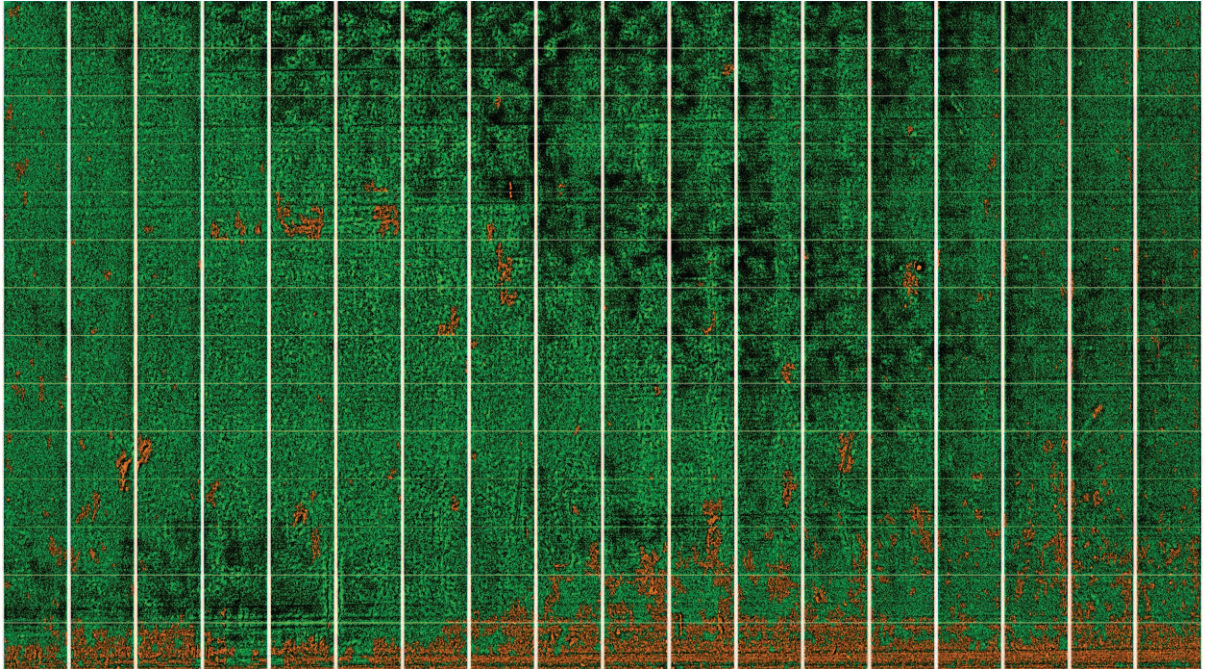
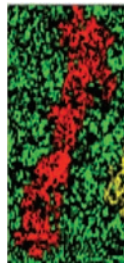


Figure 17: 252 Images (in White Bordered Rectangles) With Features of Interest in Orange, 14 Rows and 18 Columns.

As an example of the information loss consider the image from row 6 from the bottom and column 2 from the left. This image is flagged as red using the two feature classification methods of pit-like and crack-like for the height/depth data. However, a zoom into this individual image yields the following two features displayed in Figures 18a and 18b. One is a red crack-like feature and one is a red pit-like feature. As a consequence of the existence of either these two features in the image the entire image is classified as red and it is flagged for further human investigation. This entire methodology has been automated in MATLAB.



(a) Feature 1, arbitrary scaling for display.



(b) Feature 2, arbitrary scaling for display.

Figure 18: Features Extracted from One Image (Column 2 from the Left and Row 9 from the Top) of the Montage Figure 17 for Easier Viewing.

Using only these two classification measures, pit-like and crack-like, we see the feature classification results in Figure 19. Column 1 has the overall image color for pit-like features only (column heading is "pitcolor"), column 2 has the overall image color for crack-like features only (column heading is "eccentricitycolor"), and column 3 has the image name. We see from this table that, for example, image Y1X2 would be labeled red, Y1X3 would

be labeled yellow, and Y1X6 would be labeled green. Y1X2 red because the "eccentricity-color" or crack-like feature is red. Y1X3 yellow because the "pitcolor" or pit-like feature is yellow (and the crack-like feature green). Y1X6 is labeled green because both the pit-like and crack-like features are each labeled green. This figure contains a summary of only a selection (41 images) of the 252 images.

pitcolor	eccentricitycolor	imagename	yellow	yellow	Y13X17
yellow	red	Y1X2	red	yellow	Y13X18
yellow	green	Y1X3	red	red	Y13X19
green	yellow	Y1X4	yellow	yellow	Y14X2
green	yellow	Y1X5	red	red	Y14X3
green	green	Y1X6	yellow	yellow	Y14X4
yellow	yellow	Y1X7	red	red	Y14X5
yellow	green	Y1X8	yellow	red	Y14X6
yellow	yellow	Y1X9	yellow	red	Y14X7
green	green	Y1X10	red	green	Y14X8
green	green	Y1X11	yellow	red	Y14X9
green	green	Y1X12	red	red	Y14X10
yellow	green	Y1X13	red	red	Y14X11
green	yellow	Y1X14	red	red	Y14X12
green	green	Y1X15	red	red	Y14X13
yellow	green	Y1X16	yellow	green	Y14X14
yellow	red	Y1X17	red	green	Y14X15
yellow	green	Y1X18	yellow	green	Y14X16
yellow	red	Y1X19	red	red	Y14X17
yellow	yellow	Y2X2	red	yellow	Y14X18
yellow	green	Y2X3	red	yellow	Y14X19

(a) Example Images Y1X2 thru Y2X3.

(b) Example Images Y13X17 thru Y14X19.

Figure 19: Classification of Images by Pit Color and Crack Color for Select Images. The Column "pitcolor" Contains the Color of the Most Extreme Pit-Like Feature Found in the Image. The Column "crackcolor" Contains the Color of the Most Extreme Crack-Like Feature Found in the Image. The Column "imagename" Identifies the Analyzed Image Unique Identifier. The Omitted Column Headings of Figure 19b are the same as the Column Headings in Figure 19a.

Figure 20 contains histograms detailing the number of features that are pit-like and crack-like in the 252 images. The histograms are on different scales in both the horizontal and vertical axes. There are many green features, fewer yellow features, and still fewer red features in the 252 images. Displaying them on different scales allows for better within histogram information. The first row contains the histograms for pit-like features. The horizontal axis represents the maximum depth of the pit-like features. This allows for an easy way to see how many features of various maximum depths exist for each of the feature classification types. The second row contains the histograms for crack-like features. The horizontal axis represents the eccentricity of the crack-like features. This allows for an easy way to see how many features of various eccentricities exist for each of the feature classification types.

Potential Pit and Potential Crack Features by Classification Type Green, Yellow or Red

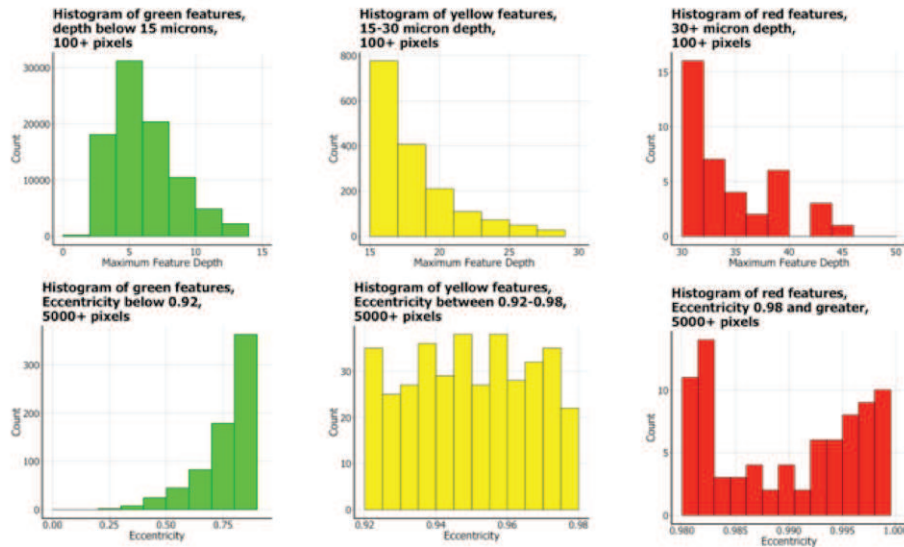


Figure 20: Potential Pit (Row 1) and Potential Crack (Row 2) Features by Classification Type of Green, Yellow, or Red. Histograms are on Different Vertical Scales.

6. Analysis Examples

Using the analysis methodology above it is possible to analyze images. We are currently working on selecting appropriate parameters to identify pit-like and crack-like features of interest while excluding those that are not of interest. To this end we analyzed two images that were identified by the subject matter expert to contain possible crack-like features of interest.

6.1 RGB Features in Image “FY09 DE02 Y13 X12”

There is a potential suspect crack in the image “FY09 DE02 Y13 X12” of Figure 21. The potential suspect crack spans from approximately (795,620) to approximately (790,360). It is hard to see and appears as a dark line in the optical image.

Using the analysis methodology detailed above we get the features displayed in Figure 22. Again we see that the different data types pick up different aspects of the surface as portrayed by the different features created.

Using the analysis methodology detailed above we get the features displayed in Figure 22. Using these features we classify them, as described previously above, to yield the classified features in Figure 23. The height/depth data did not pick up the suspect crack in the sense of finding linear features where the potential crack is located. The other three types of data, intensity, optical, and laser optical all not only picked up the crack-like features with high eccentricity but also classified them as red features.

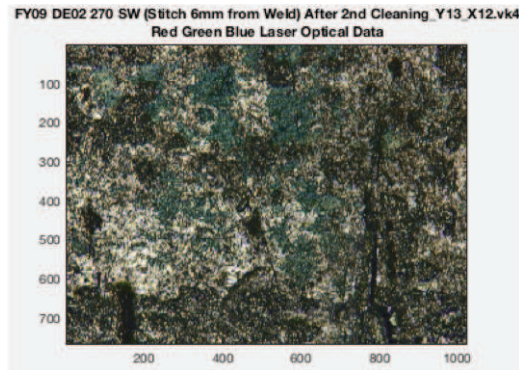


Figure 21: Optical image of “FY09 DE02 Y13 X12”. Potential suspect crack approximately from the point (795,620) to (790,360).

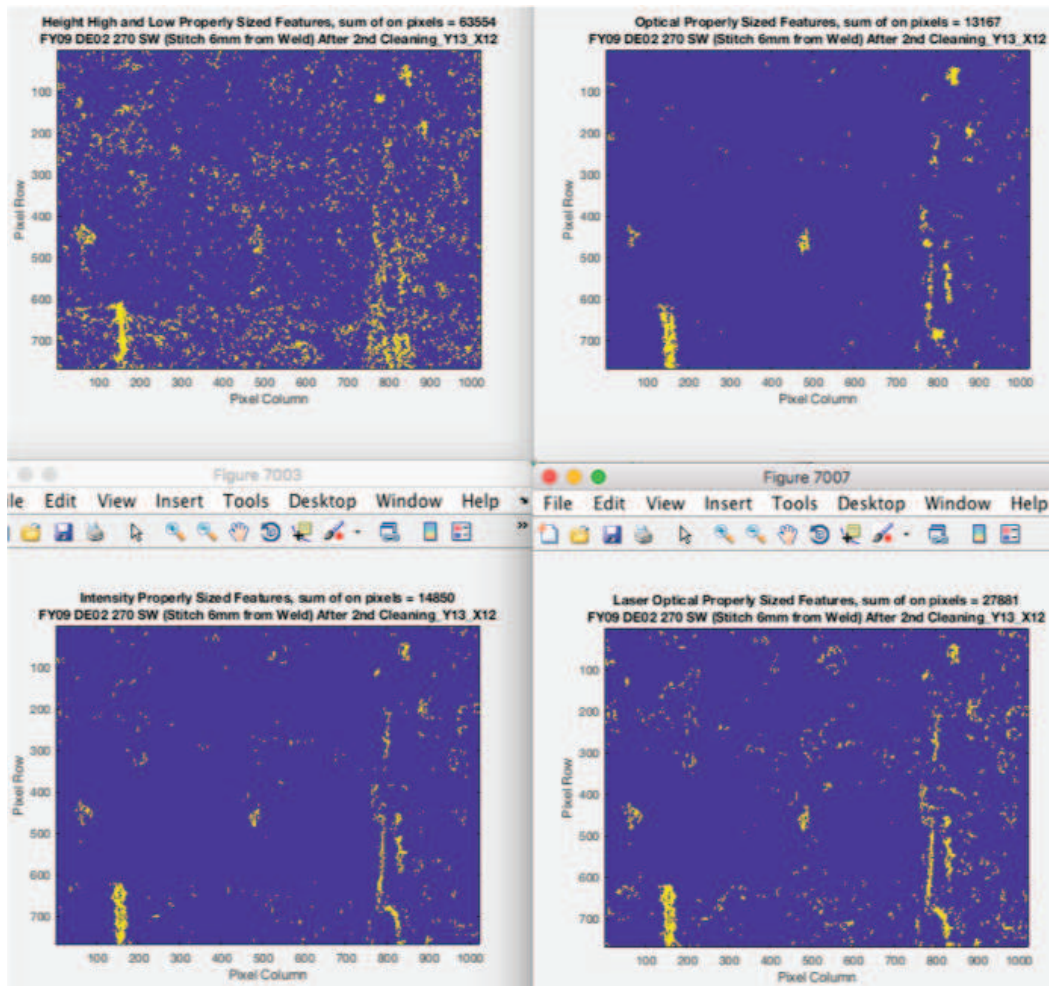


Figure 22: Possible Features Created in Image “FY09 DE02 Y13 X12”. Height in upper left, Intensity in lower left, Optical in upper right, and Laser Optical in lower right.

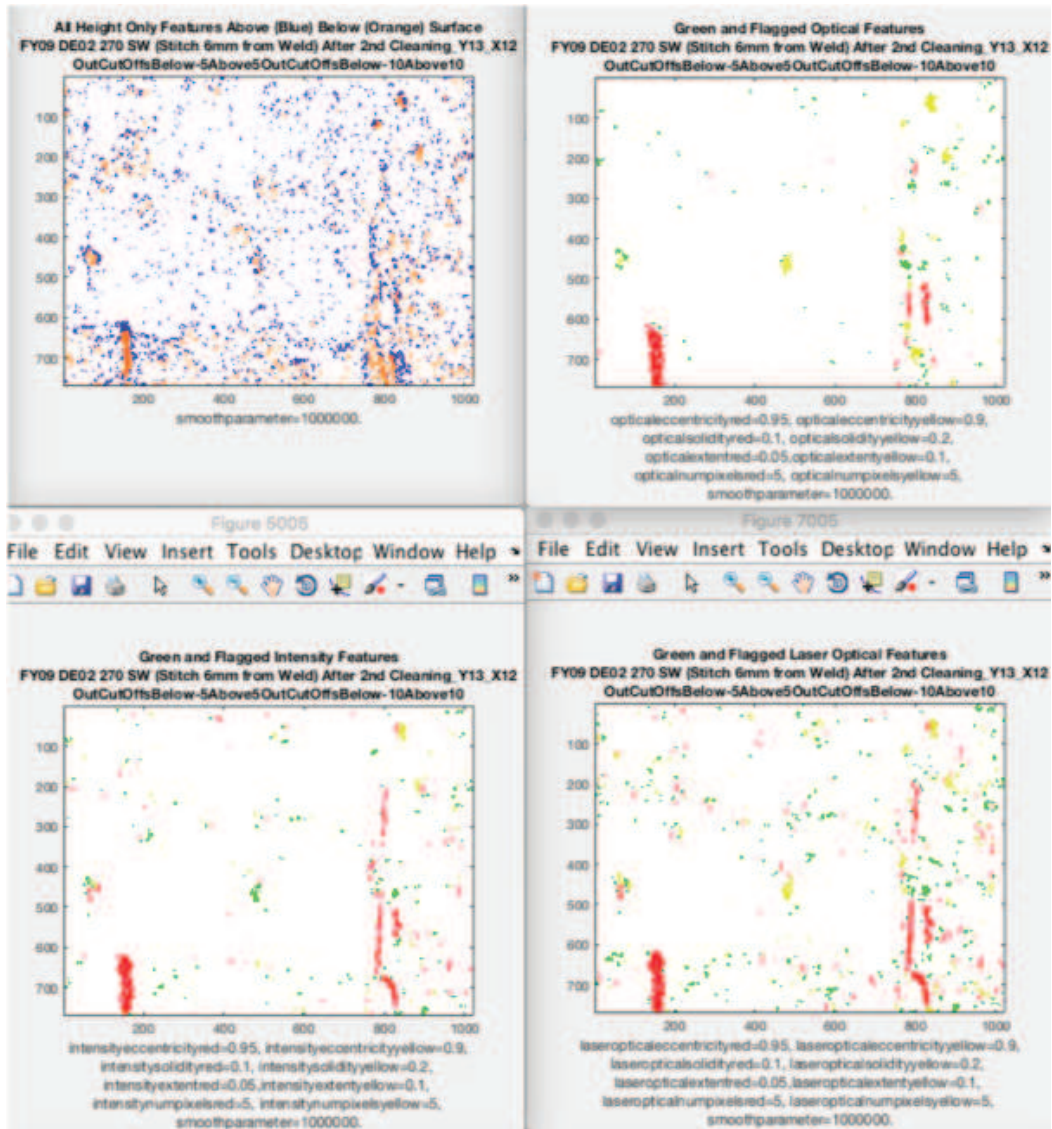


Figure 23: Classified Features Created in Image “FY09 DE02 Y13 X12”. Height in upper left, Intensity in lower left, Optical in upper right, and Laser Optical in lower right.

6.2 RGB Features in Image “FY09 DE02 Y13 X11”

There is a potential suspect crack in the image “FY09 DE02 Y13 X11” of Figure 24. The potential suspect crack spans from approximately (350,530) to approximately (325,420). It is hard to see and appears as a dark thin line in the optical image.

Using the analysis methodology detailed above we get the features displayed in Figure 25. Again we see that the different data types pick up different aspects of the surface as portrayed by the different features created.

Using the analysis methodology detailed above we get the features displayed in Figure 25. Using these features we classify them, as described previously above, to yield the classified features in Figure 26. The height/depth data did not pick up the suspect crack in the sense of finding linear features where the potential crack is located. The other three types of data, intensity, optical, and laser optical all not only picked up the crack-like features with high eccentricity but also classified them as red features. Intensity and laser optical data were the best at finding red linear features near the subject matter expert identified

crack.

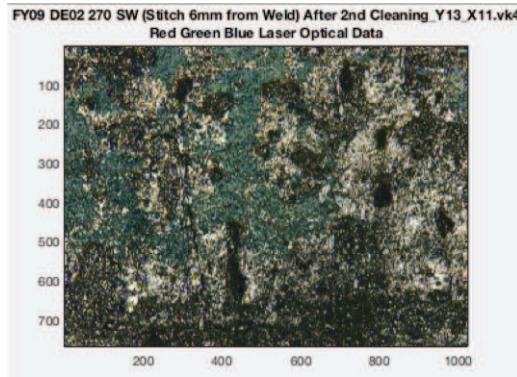


Figure 24: Optical image of “FY09 DE02 Y13 X11”. Potential suspect crack approximately from the point (350,530) to (325,420).

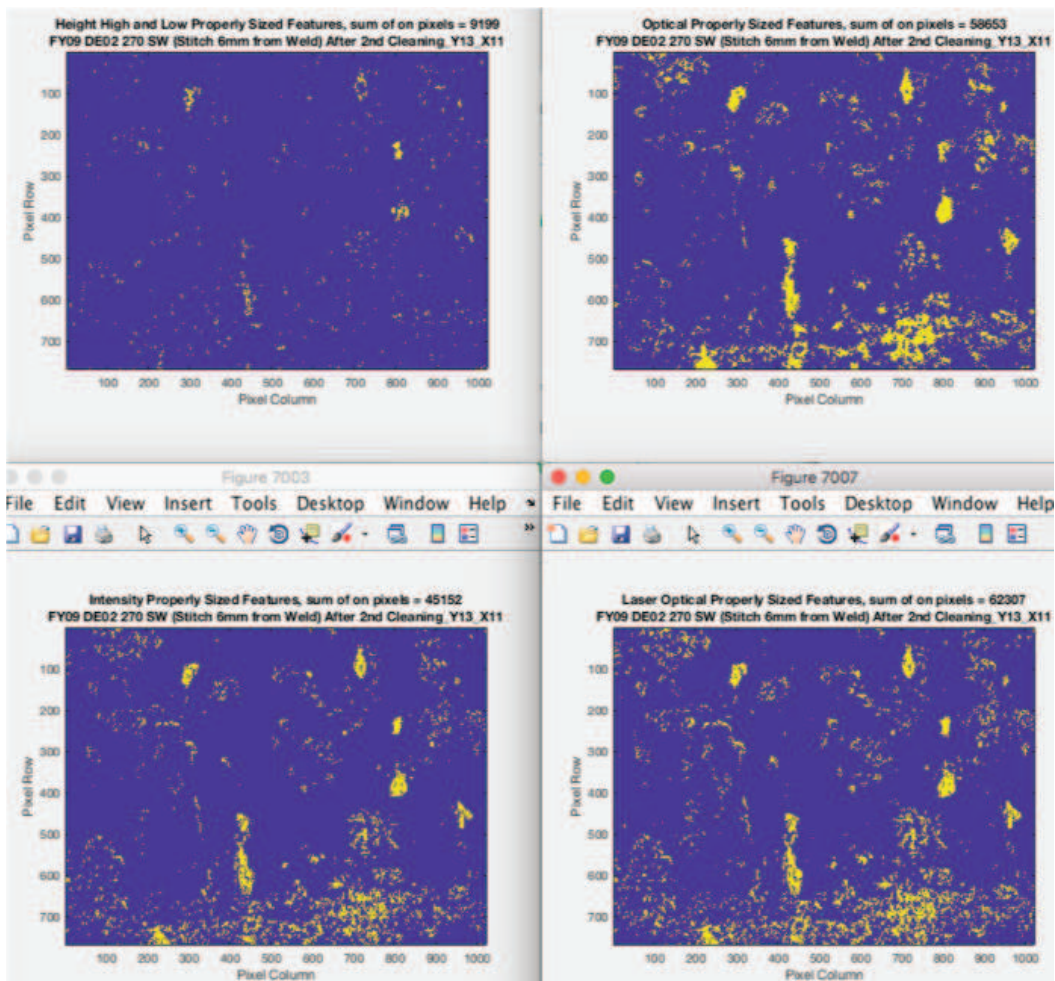


Figure 25: Possible Features Created in Image “FY09 DE02 Y13 X11”. Height in upper left, Intensity in lower left, Optical in upper right, and Laser Optical in lower right.

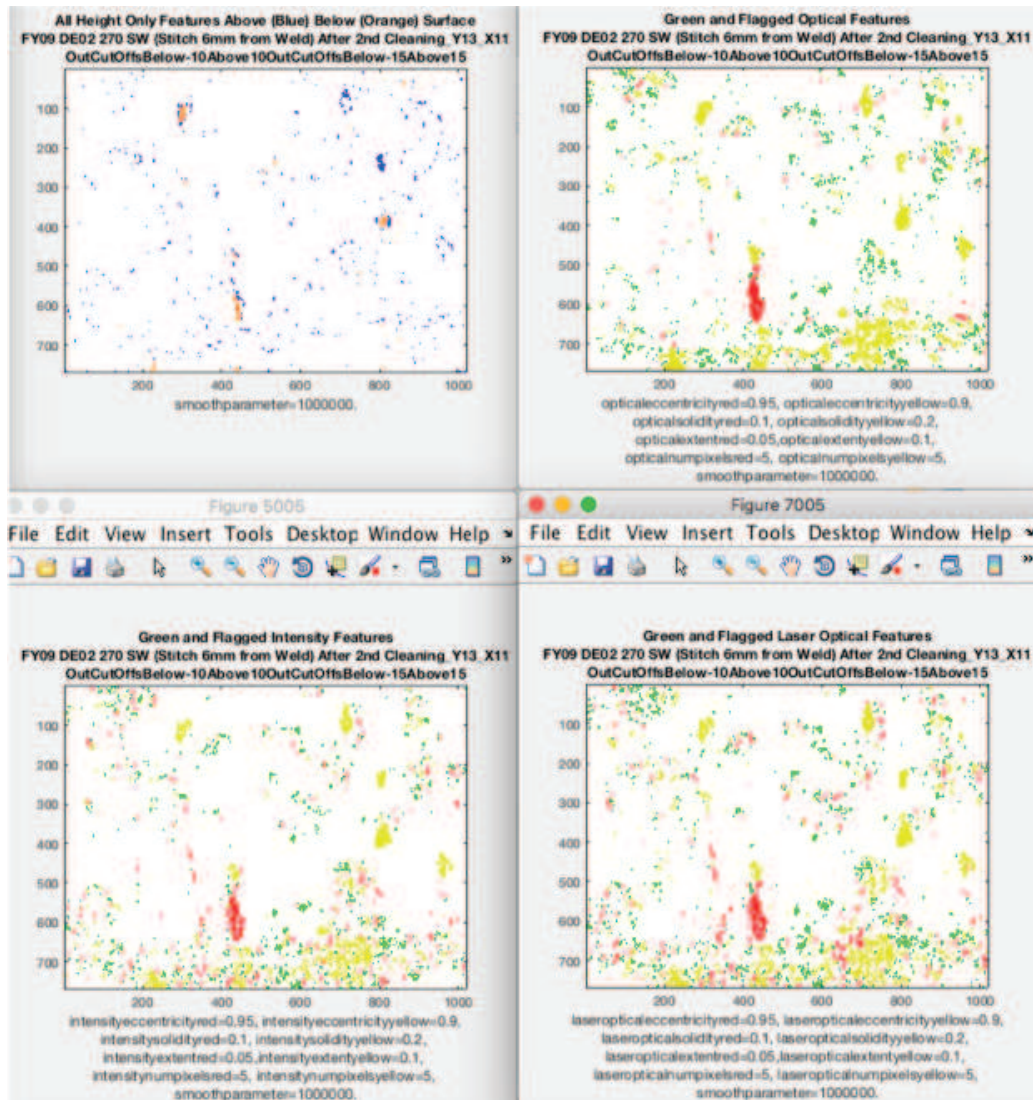


Figure 26: Classified Features Created in Image “FY09 DE02 Y13 X11”. Height in upper left, Intensity in lower left, Optical in upper right, and Laser Optical in lower right.

7. Ongoing and Future Work

7.1 Verification

The subject matter expert verified the maximum depths of identified features matched the depths obtained by careful examination with the microscope. The further analysis requires parameters so that potential or actual cracks are identified.

7.2 Cross Sections of the Sample

Another methodology we are investigating is use cross sections of the sample to verify the existence of below surface cracks indicated by surface features.

7.3 Ongoing and Future Analysis

The following methodologies are to be used for future investigation.

1. Classification of 6,000 images from one container
2. Multiple containers
3. Refinement of potential feature definitions
4. Refinement of image classifications
5. Incorporation of additional data (proximity, eccentricity and orientation) to form “super” features
6. Feature type agglomeration

7.4 Other Possible Methodologies

1. Other Container Types – Hagan/SAVY 4000
2. Other inspection methodologies – acoustic
3. Other measurement types - photographs

It remains to be seen how much of this image analysis process may be accomplished by the automated analysis as compared to the human analysis.

8. Conclusion

Automated image analysis may be used to categorize sample images as needing further examination, possible further evaluation and no features of concern. Images with features of concern also contain the location and feature shape as well as associated statistics about the shape, area, volume, orientation, solidity, extent, and eccentricity of the feature. These attributes may be used to characterize the features within an image. The attributes may also serve as an aid to subsequent human analysis of important features in images needing further examination or evaluation.

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