

NPL REPORT MAT 107

**ROCKWELL INDENTATION TEST FOR EVALUATION OF ADHESION
OF COATINGS - AKA DAIMLER-BENZ ADHESION TEST**

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MARCH 2022

Rockwell Indentation Test for Evaluation of Adhesion of Coatings - aka Daimler-Benz adhesion test

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ABSTRACT

This report focuses on the development of a methodology to extract, and quantify features introduced to a coating system by the Rockwell Indentation Test for Evaluation of Adhesion of Coatings, which is also known as the Daimler-Benz Adhesion Test. The Daimler-Benz Adhesion Test (Test) is an established method for the evaluation of coating adhesion, an important metric for quantifying coating performance. Attempts have been made by other research institutions to apply supervised machine learning techniques to classify test images. These require large, labelled datasets and their performance is inherently difficult to evaluate. The primary aim of this project was to explore the possibility of developing conventional algorithmic solutions, these may include unsupervised clustering methods sometime referred to as a form of machine learning.

Damage to a coating within the vicinity of a Rockwell indentation can be used to classify coating adhesion performance. Indentations are performed in accordance with ISO 6506-1. Stresses induced in the coating by the Rockwell indent and due to material displacement can cause microcracking and delamination of the coating. These stresses are radially dependent decreasing with distance from the indent. Currently, the damage introduced by the test is classified manually by domain experts. The manual aspect of these processes is susceptible to unquantified bias and/or error and additionally inhibits the integration of such tests into an automated production or quality assurance pipeline. Furthermore, the classification does not provide a high level of granularity when comparing similar performing coatings.

Routines have been developed in MATLAB to analyse a set of test images captured on four coating systems, (WC/Co, Nitron MC, TiN, and Graphit-iC). Although some success has been demonstrated on the application of these routines to available test images using both the RANSAC and Pixel Classification methods there is still room for improvement both in the methodology and the implementation of the code. Potential avenues for further work are covered in Section 5, however, any further development will require the collection of more data using coating systems tailored to capture the range of potential test features.

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ISSN 1754-2979

DOI <https://doi.org/10.47120/npl.MAT107>

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This work was funded by the UK Government's Department for Business, Energy and Industrial Strategy (BEIS) through the UK's National Measurement System programmes.

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CONTENTS

1	INTRODUCTION	1
1.1	CORE PRINCIPLE AND MOTIVATION	1
1.2	CLASSIFICATIONS.....	1
1.2.1	BS ISO 26443:2016	1
1.2.2	DIN 4856:2018-02	3
1.2.3	VDI 3198 Indentation Test.....	3
1.3	FAILURE MODES	3
1.3.1	Fracture / Crack Formation	3
1.3.2	Delamination	4
1.3.3	Buckling.....	5
1.3.4	Spallation.....	5
1.4	EXAMPLES FROM LITERATURE	6
1.4.1	Light Microscopy	6
1.4.2	Scanning Electron Microscopy	7
2	DATA.....	8
2.1	SAMPLES.....	8
2.2	IMAGE CAPTURE.....	8
3	MATLAB ROUTINE DEVELOPMENT	9
3.1	STEP 1 - INDENT DETERMINATION.....	12
3.1.1	Outline	12
3.1.2	MATLAB code	12
3.1.3	Pseudocode	12
3.1.4	Evaluation.....	16
3.2	STEP 2 - FEATURE ENHANCEMENT	17
3.2.1	Outline	17
3.2.2	MATLAB code	17
3.2.3	Pseudocode	17
3.2.4	Evaluation.....	19
3.3	STEP 3 (ROUTE 1) - RANSAC MODEL FITTING TO CRACK SPATIAL INFORMATION	20
3.3.1	Outline	20
3.3.2	MATLAB code	20
3.3.3	Evaluation.....	21
3.4	STEP 3 (ROUTE 2) - PIXEL CLASSIFICATION – UNSUPERVISED MACHINE LEARNING	21
3.4.1	Outline	21
3.4.2	MATLAB code	22

3.4.3	Pseudocode	22
3.4.4	Evaluation.....	22
4	DISCUSSION	24
4.1	GUIDANCE ON IMAGE CAPTURE	24
5	FURTHER WORK	25
5.1	PROCESSING PIPELINE DECISION TREE	25
5.2	IMAGE SIMULATOR	25
5.3	IMAGE FEATURE SYNTHESISER.....	26
5.4	UNUSED CODE	26
6	REFERENCES	28
7	APPENDIX 1 – IMAGE DATA.....	29
7.1.1	Titanium Nitride Coating.....	29
7.1.2	Nitron MC Coating.....	30
7.1.3	Graphit-iC Coating.....	31
7.1.4	WC/Co Coating	32
8	APPENDIX 2 IMAGE PROCESSING EXAMPLES.....	33
8.1	IMAGE PROCESSING PIPELINE: EXAMPLE 2.....	33
8.2	IMAGE PROCESSING PIPELINE: EXAMPLE 3.....	38

1 INTRODUCTION

1.1 CORE PRINCIPLE AND MOTIVATION

Damage to a coating within the vicinity of a Rockwell indentation can be used to classify coating adhesion performance. Indentations are performed in accordance with ISO 6506-1 on a surface free of particulate or fluid contaminants. Stresses induced by the Rockwell indent and due to material displacement can cause microcracking and delamination of the coating. These stresses are radially dependent decreasing with distance from the indenter.

Currently, the damage introduced by the test is classified manually by domain experts. The manual aspect of this processes is susceptible to unquantified bias and additionally inhibits the integration of such tests into an automated production or quality assurance pipeline. Furthermore, the classification does not provide a high level of granularity in the comparison of similar performing coatings. A point which is becoming increasingly important as coating systems improve and therefore require greater discrimination to quantify marginal gains in performance, which, over time, can become substantial. A more rigorous treatment of the image data may yield useful metrics for the detailed characterisation of coating performance using this test.

1.2 CLASSIFICATIONS

1.2.1 BS ISO 26443:2016


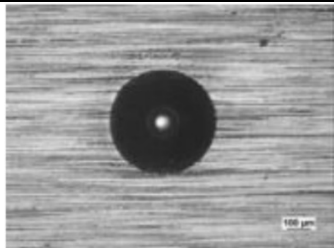

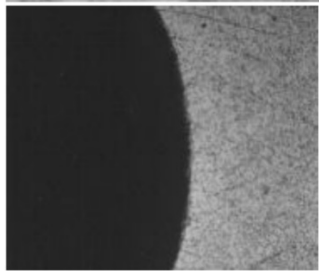

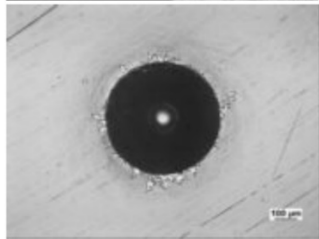

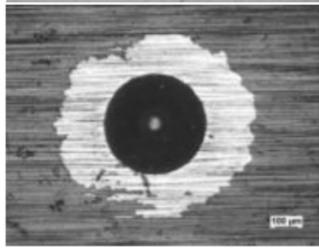
BS ISO 26443:2016 supersedes BS ISO 26443:2008 (without modification), and DD CEN/TS 1071-8:2004. Related standards pertaining to Rockwell Indentation include ISO 6508-1:2016, ISO 3738-2:1988 (current in 2021), ISO 4498:2010 (current in 2022).

According to BS ISO 26443:2016 damage induced by Rockwell indentation, made in accordance with ISO 6508-1, can be qualitatively classified as shown in Table 1. ISO 26443 pertains to all ceramic coating less than 20 μm in thickness. Images are taken using an optical microscope using a 100x objective. Examples of test images included in the standard are reproduced in Table 2.

Table 1 Daimler-Benz adhesion Test Output Classifications according to BS ISO 26443:2008

Class #	Cracking	Partial Delamination	Complete Delamination
Class 0	0	0	0
Class 1	1	0	0
Class 2	0 or 1	1	0
Class 3	0 or 1	0 or 1	1

Table 2 Example diagrams and images of the Daimler-Benz adhesion Test Output Classifications according to BS ISO 26443:2008

Class	Sketch	Example Image
Class 0		
Class 1		
Class 2		
Class 3		

Additional definitions for coating performance that pertain to different coating systems exist within the literature and are reproduced in Section 1.2.2 and Section 1.2.3.

1.2.2 DIN 4856:2018-02

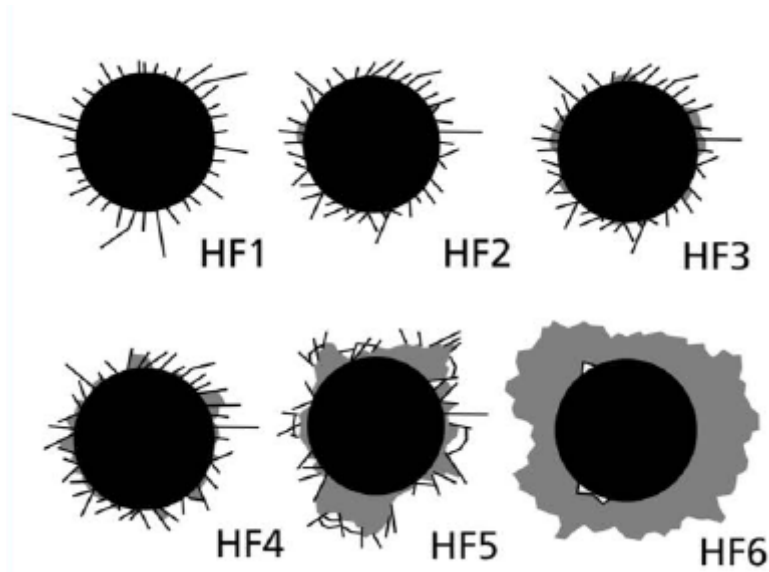


Figure 1 Example diagrams of indent classification features [1]

1.2.3 VDI 3198 Indentation Test

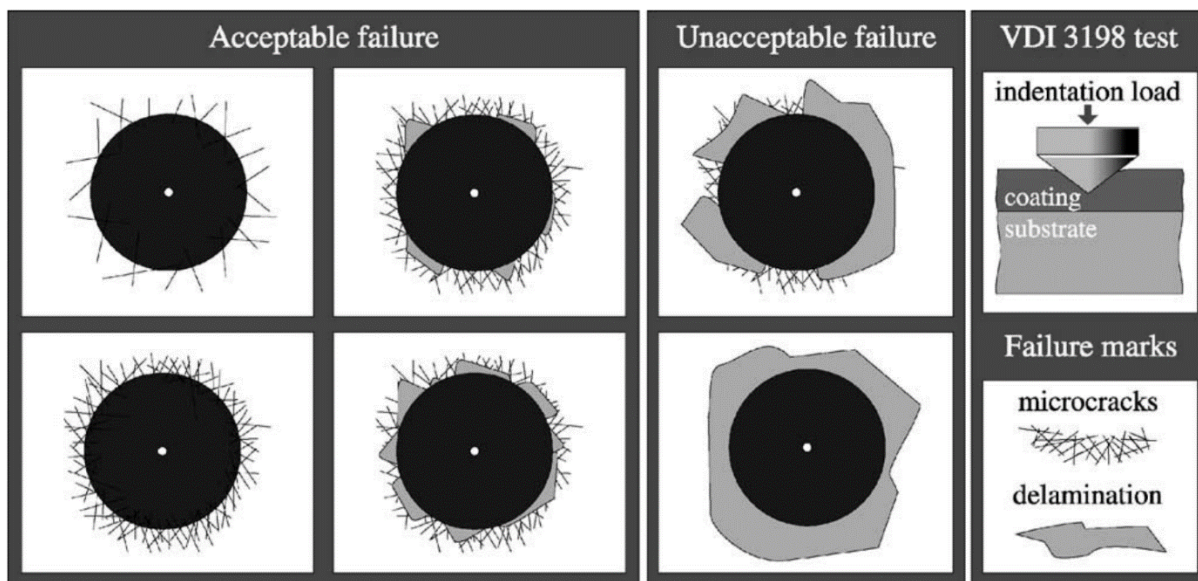


Figure 2 The principle of the VDI 3198 indentation test, reproduced from [2]

1.3 FAILURE MODES

1.3.1 Fracture / Crack Formation

Drobný et al. identified three main crack morphologies observed during indentation of hard coatings deposited on ductile substrates [2].

1. **Circumferential cracks**; appear at the periphery of plastic zone

2. **Channel cracks:** initiated under heavy stress caused by direct contact between the indenter and coating
3. **Radial cracks:** originate from the middle of the indentation imprint and propagate outwards in the form of beams

Figure 4a shows an example of a circumferential crack with Figure 4b showing both radial and channel cracks. Depending on the coating system there is the potential for apparent cracks to branch. The various mechanisms responsible for crack formation may require further elucidation. The classification of cracks by their respective formation mechanisms could inform a feature detection algorithm if such features can be associated with known physical properties of the substrate and coating system.

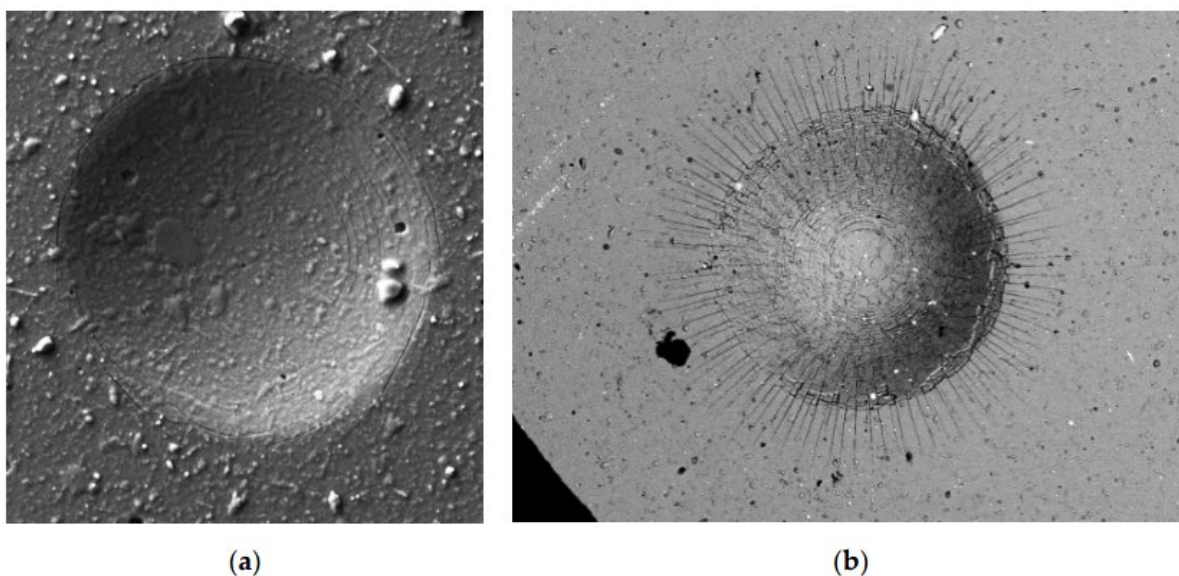


Figure 3 a) circumferential crack, b) radial and channel cracks. Reproduced from [2]

1.3.2 Delamination

Delamination describes the loss of contact between a coating and its substrate. Delamination can occur with or without buckling, fracture and/or spallation. Figure 5 provides examples of single and mixed failure modes.

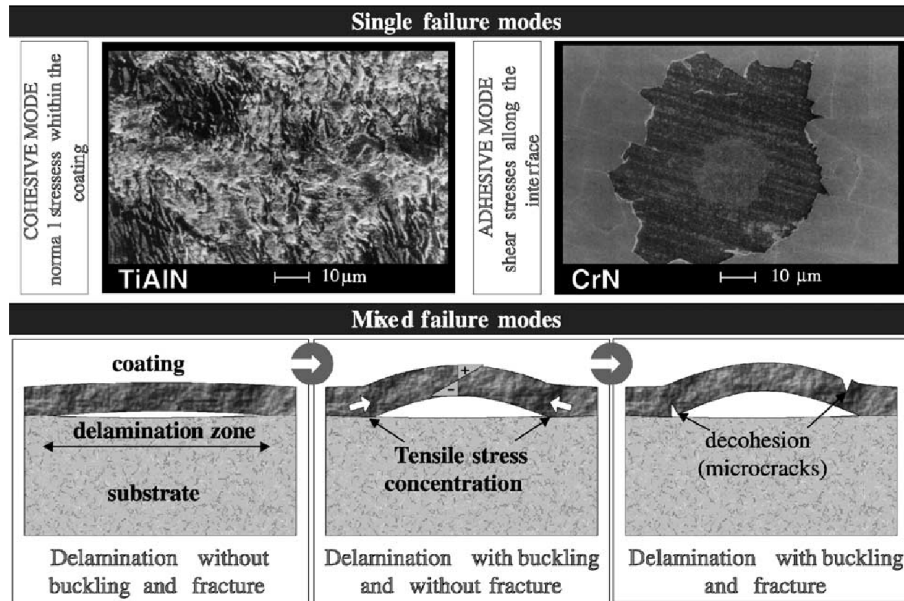


Figure 4 Potential failure types of coatings from overstressing. Reproduced from [3]

1.3.3 Buckling

Buckling is the deflection of a delaminated coating away from the substrate due to stress. Buckling, shown in Figure 5, can occur with or without fractures.

1.3.4 Spallation

Delamination and buckling of coatings can lead to coating spallation thus exposing the underlying substrate. Figure 6 and Figure 7 show examples of coating spallation.

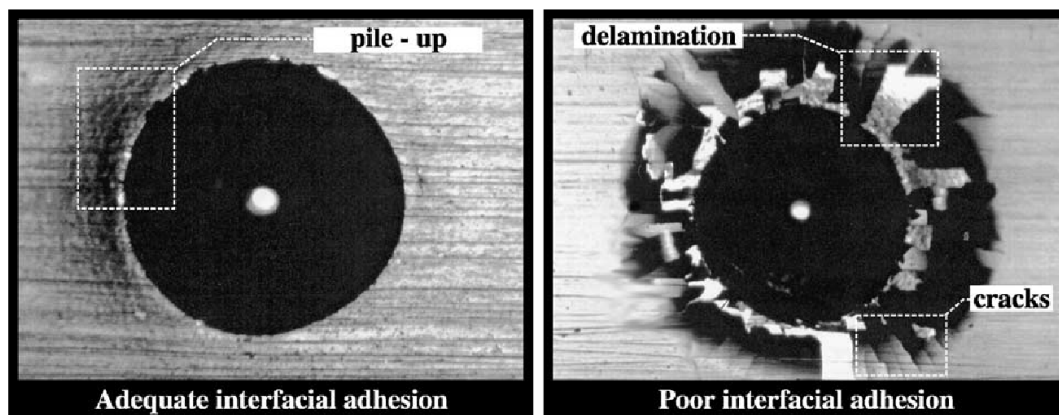


Figure 5 Example cases of the same coating, well and poor adherent on different substrates under identical conditions, exhibiting pile-up, delamination and crack formation. Images were taken using light microscopy. Figure reproduced from [3]

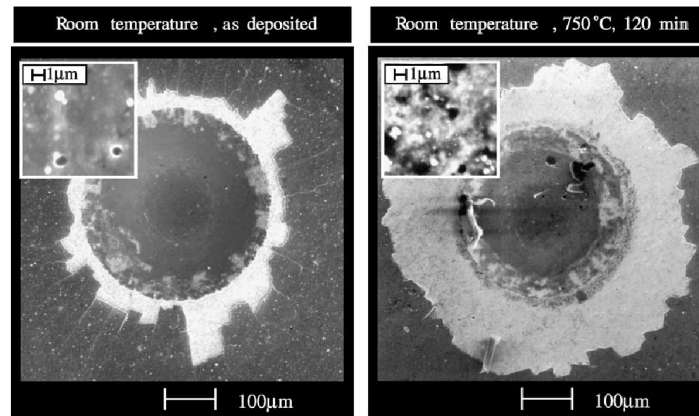


Figure 6 Example micrographs of coating delamination and spallation revealing a brightly contrasted substrate. Image were taken using electrom microscopy. Figuee reproduce from [3]

1.4 EXAMPLES FROM LITERATURE

To expand on the micrographs captured for this project, provided in Appendix 1, this section provides some example images extracted from the literature. These images are used to provide context to the image analysis challenge and aid in subsequent discussion/evaluation sections.

1.4.1 Light Microscopy

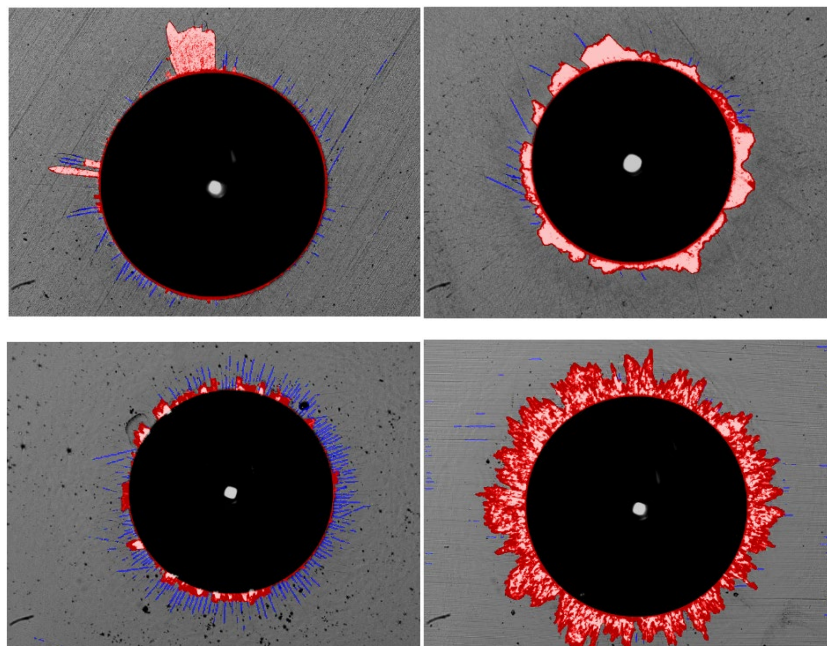


Figure 7 Example of resonably simple Diamler-Benz Adhesion Test images segmented using comperter vision techniques (deconvolusional neural net pixel classification). Figure reproduced from [1]

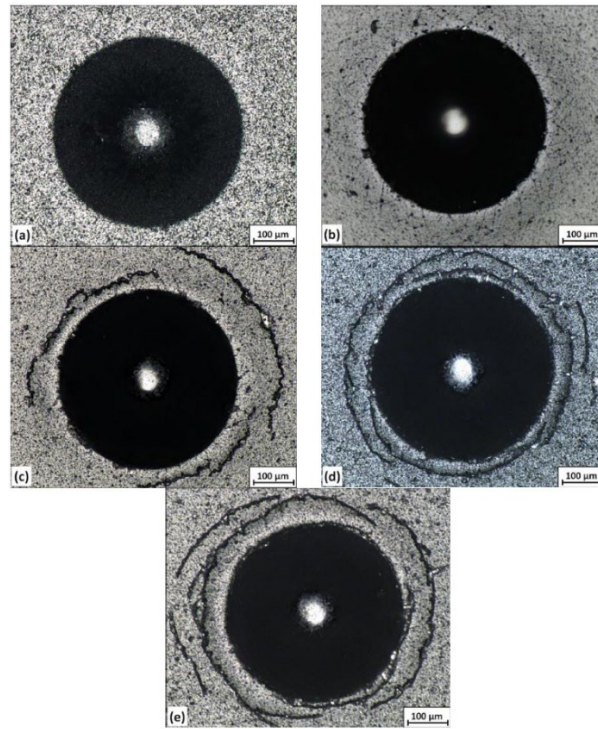


Figure 8 Example of Daimler-Benz Adhesion Test images exhibiting approximately circumferential cracks. Figure reproduced from [4]

1.4.2 Scanning Electron Microscopy

Analysis routines developed for light micrographs are unlikely to work for SEM micrographs due to the different contrast mechanisms that constitute the image. SEM micrographs have a much greater depth of focus, different topographic shadowing, generally greater stochastic noise, and charge artefacts at feature edges. In this current work, only light micrographs are considered.

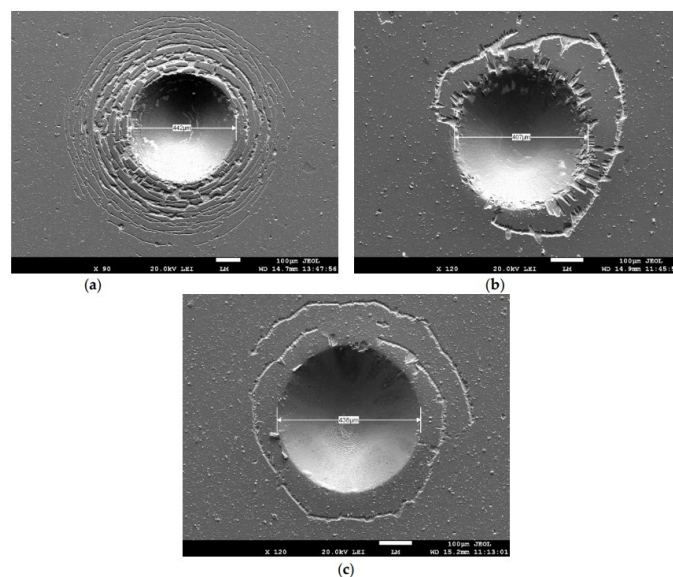


Figure 9 Example SEM micrographs of a Daimler-Benz adhesion test [2]

Regarding features of the Daimler-Benz adhesion test, the coatings in Figure 9 and Figure 10 do not exhibit radial cracks instead showing circumferential cracks or fissures. The potential for such features to evolve complicates the analysis which must be capable of discriminating between radial and circumferential features which may or may not be concurrent.

2 DATA

2.1 SAMPLES

Four coating systems, listed in Table 3, are included in the study. Micrographs used in the development of the analysis routines are provided in Appendix 1.

Table 3 Sample Overview.

Sample ID	Material	Coating Thickness
AKIT001	WC-Co Thermal Sprayed	150 μm
AKIU001	Nitron MC / (Nitron DLC)	3 μm
AKIV001	TiN	3 μm
AKJS001	Graphit-iC	3 μm

2.2 IMAGE CAPTURE

Indents were imaged using a Nikon Measuring Microscope MM-60 (serial number 2203181), with an Optronics MicroFire (serial number KC725323-H) digital camera. Images are provided in RGB, TIF format.

3 MATLAB ROUTINE DEVELOPMENT

This section is broken into subsections relating to each step in the analysis, an overview of which is provided in Figure 11. Each subsection will provide an outline of the analysis step, executable MATLAB code and outputted figures, and an evaluation of the codes' performance. Step 4 has not been included as further work is necessary to assess the robustness of the preceding steps on a larger dataset.

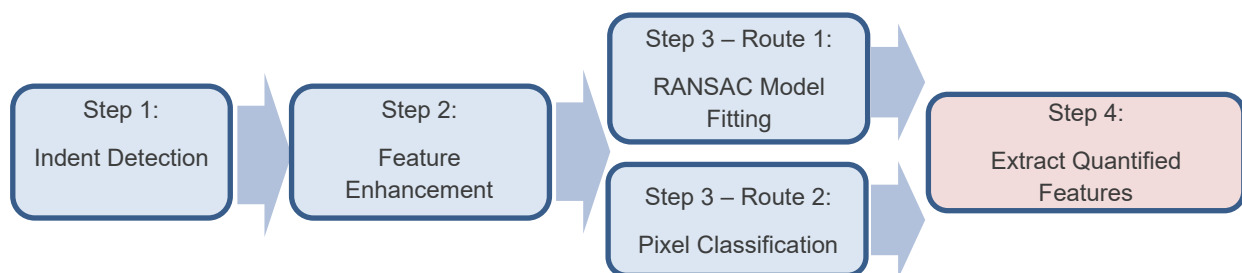


Figure 10 Overview of method steps

The number of potential coating systems, and therefore variability in image features, in addition to varying capabilities of imaging devices make it difficult to define a general solution for the image analysis. The initial approach is therefore to narrow the pool of coating systems down to a subgroup with features amenable to an automated solution. Once performance of the analysis routine(s) has been demonstrated on a subgroup of coating systems the capability of the routine(s) can be expanded.

Figure 12 shows an example of a Rockwell Indentation Adhesion Test on a ductile coated substrate. Figure 12 can be regarded as a simple example as there are no obvious crack-like features of the coating with any preferred orientation and there is no obvious delamination or spallation of the coating within the vicinity of the indent. Nevertheless, there is a lot of complexity in the image.

1. There is a dark central region associated with the indent.
2. There are radial contrast gradients caused by variations in surface topography related to displaced substrate around the indent.
3. There are two, possibly three, types of radial cracks. The smaller branching cracks may be better described as fissures caused by decoherence of the coating on the regions of displaced substrate.
4. There are outliers in coating surface features belonging to imperfections or contaminants.
5. There are subtle gradients associated with flatness or tilt of the coating surface which may or may not have been altered by the indent itself, see Figure 14.
6. The colour information can vary depending on imaging system settings or the data collection protocol
7. The image does not make use of the full bit depth of the format, even if it did, the method of image normalisation would impact contrast which can greatly influence the detectability of fine features such as cracks

8. There is an overlaid micron marker which, depending on the format of the image, may overwrite image data

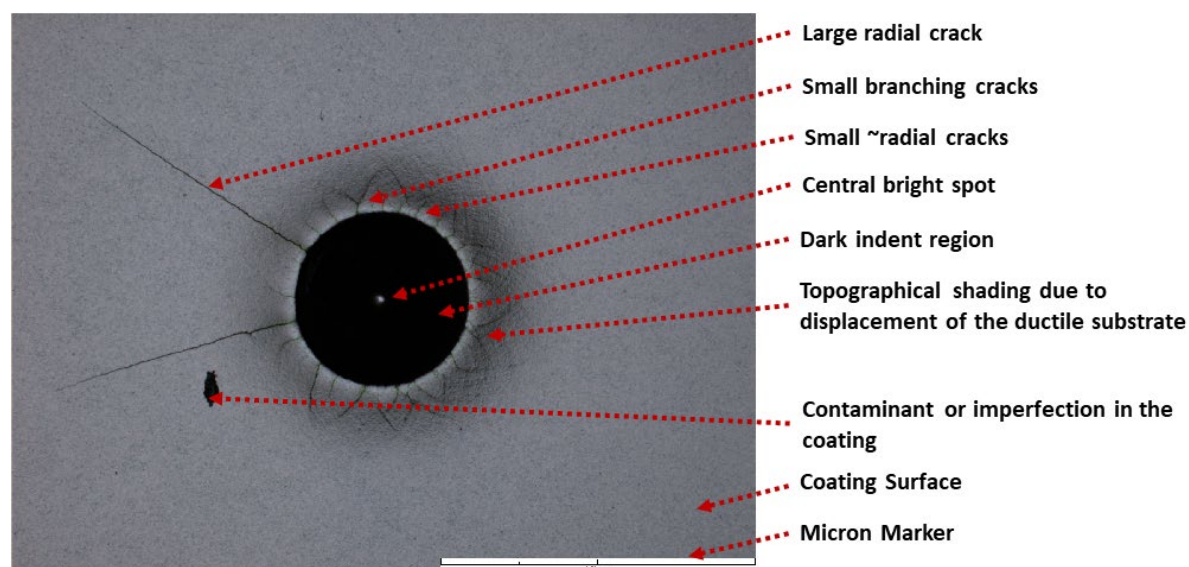


Figure 11 AKIT001 4.413kN Indent 5 - WC/Co

Figure 13 shows a second example of a Rockwell Indentation Adhesion Test on a ductile coated substrate. Naturally, there are many similarities between this, and the example provided in Figure 12, with some key differences.

1. There are no large radial cracks
2. There are no branching fissures
3. Contrast gradient introduced by displacement of the ductile substrate has produced a discontinuous pile-up of material
4. Bright regions associated with exposed substrate due to spalled coating are present

Figure 13 can also be regarded as a simple example as there are no obvious features of the coating with any preferred orientation and there are no obvious delaminated regions, however, there are regions of spalled coating.

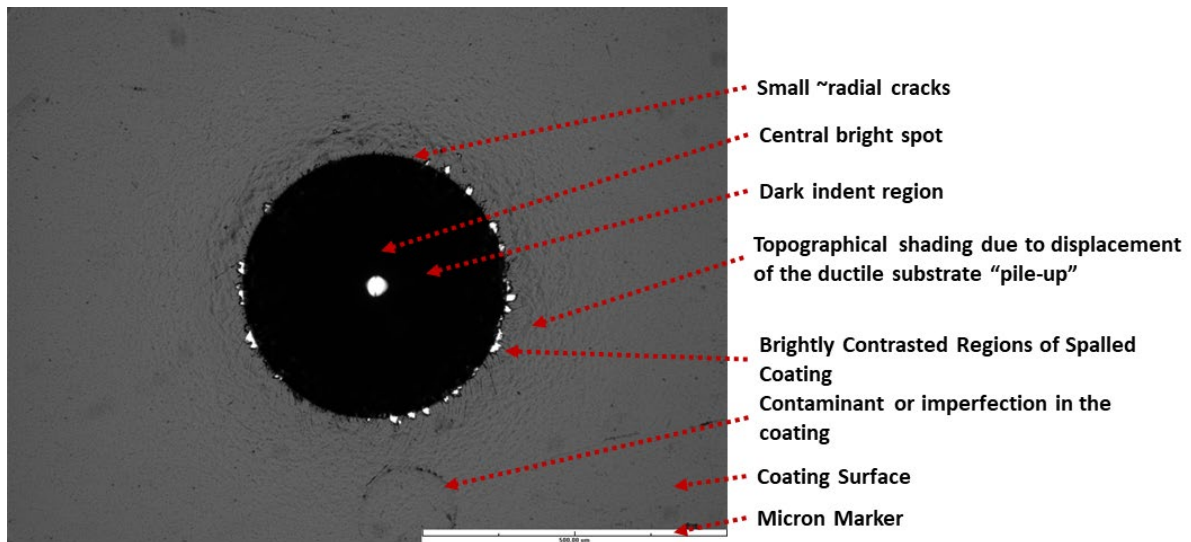


Figure 12 AKIU001 1 10x - Nitron MC

The potential absence of cracks complicates the analysis as relative segmentation methods such as k-means or auto thresholds will segment the image into subclasses regardless but would operate erroneously on the noise or subtle gradients in image features instead. An example of a subtle image gradient present in both previous examples is shown in Figure 14. Detecting the absence of a feature can be more problematic than detecting the presence of a feature.

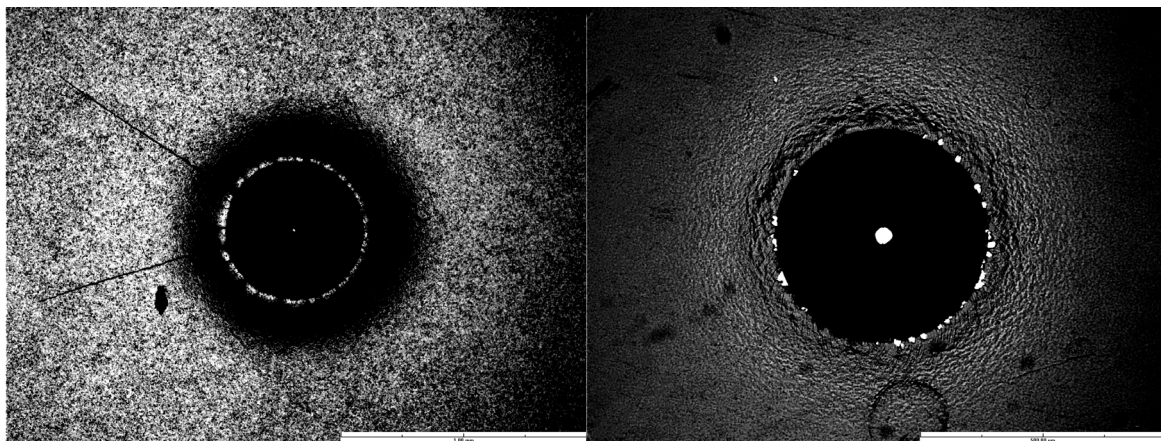


Figure 13 Both examples provided in Figure 12 and Figure 13 exhibit a subtle contrast gradient around the indent

The following sections will introduce methods for feature extraction. The features under consideration are as follows

- Dark indent approximately central to the image
- Bright spot at centre of indent
- Contrast gradient around the indent due to topography introduced by material displacement.
- Radial cracks
- Brightly contrasted regions connected to the perimeter of the indent and assumed to be exposed substrate due to spalled coating

3.1 STEP 1 - INDENT DETERMINATION

3.1.1 Outline

The first step in automating the analysis is to accurately determine the location and extent of the indent. To simplify the process the indent is positioned approximately central to the image according to the data collection protocol. Rockwell indenters have a spherical or conical form depending on the hardness of the material being tested. Both forms should result in a circular impression when imaged normal to the surface, however, material displacement and topographically dependant contrast mechanisms of the imaging method combined with the complex behaviour of the coating lead to uncertainty on the exact position of the edge of the indent. As part of this study multiple methods were trialled.

1. Foreground/Background Automated Threshold followed by conversion to equivalent diameter circle, the Otsu method was used initially, however, numerous alternative auto threshold definitions exist
2. Hough Circle Transformation on image gradient information
3. Graph cuts pixel segmentation optionally based on both intensity and image texture information, requires initial guess of boundary
4. Active contours optionally based on both intensity and texture information using the Chan-Vese method, requires an approximate initial guess

Once the indent has been segmented the image can be cropped as to only include the square bounding box of the maximum inscribed circle centred on the indent. The image is interpolated to centre the indent at the subpixel level. This is done as later analysis steps exclude regions outside of the maximum inscribed circle to be sympathetic to the rotational symmetry of the test. It should be noted, however, that interpolating the image alters the noise profile and may influence subsequent analysis.

3.1.2 MATLAB code

MATLAB code is embedded in this document. Code was written in MATLAB version R2022a. All Steps should be run sequentially.

Executable MATLAB code



Stage
1_ImageFormatting_

3.1.3 Pseudocode

Image Formatting

- crop image to remove the micron marker
- convert image to greyscale with value ranging 0 to 1.

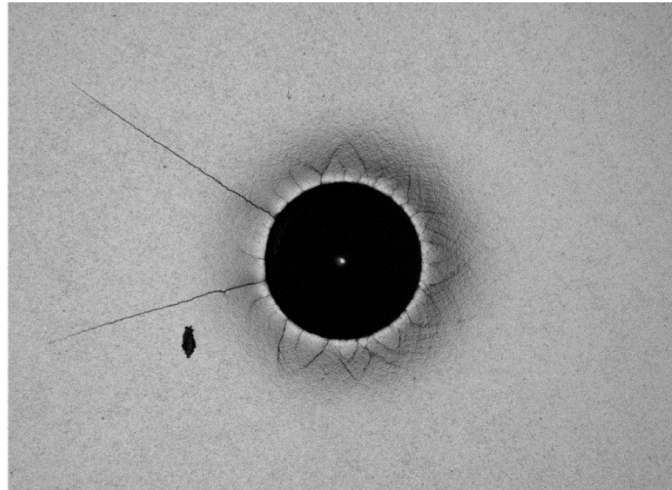


Figure 14 Original image, normalised and cropped to remove the micronmarker

Approximate Determination of Indent location

- Method 1.1 Auto threshold
 - Determine threshold automatically using Otsu method
 - Apply threshold to image to generate mask
 - Isolate largest feature within mask which is assumed to be the indent, generate indent mask
- Method 1.2 Hough Circle Transformation
 - Determine image gradient magnitude image
 - Apply Hough Transformation to gradient magnitude defining the centre points and radii of any circular features
 - Assume the largest and most pronounced circular feature is the indent
 - Generate a binary mask indent centre point and radius

Removal of the Bright Spot in Centre of Indent

This step is necessary as the bright spot has an intensity profile similar to that of spalled regions. Removing this image feature early on reduces image complexity.

- The indent mask is filled, where indent mask does not equal filled indent mask defines the region of the inner bright spot in the centre of the indent
- The region of the inner bright spot is assigned the mean value of the indent mask

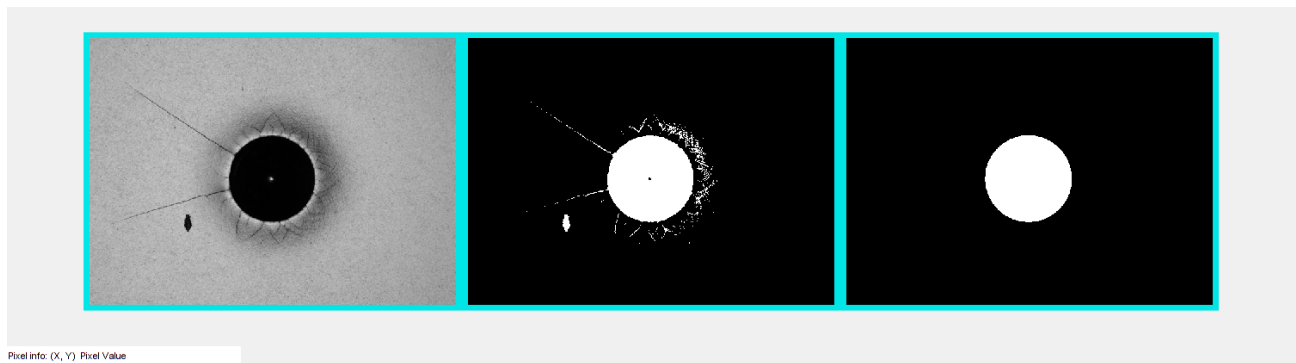


Figure 15 image generated by the MATLAB routine showing the indent segmentation and subsequent removal of the dot at the centre of the indent.

Centre the Indent in the Image

- The image is translated so that the centre of the indent aligns with the corner of a pixel
- The image is cropped to a bounding box of the maximum inscribed circle centred on the indent

Figure 15 shows the processed image after initial guess of indent position with the red and blue overlays indicating the extracted indent using the Otsu threshold and Hough Circle transform methods, respectively.

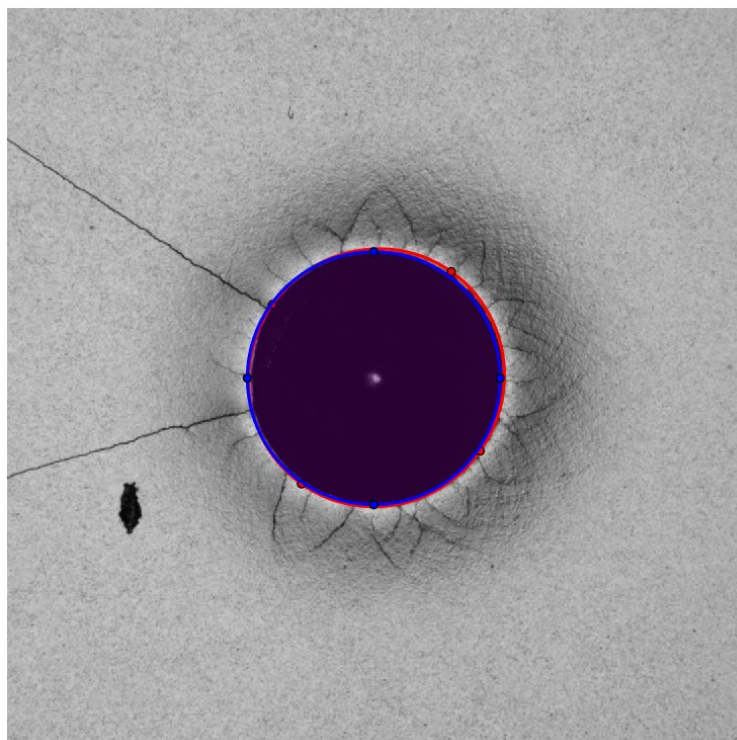


Figure 16 Processed image showing the indent region defined used Otsu (red) and Hough Circle methods (blue)

Indent Refinement

Multiple methods of enhancing the information within the image to include radial position and/or texture information were explored and remain in the MATLAB code. Both active contours and Lazy snapping can operate on multi-channel images that include layers of enhanced images. Image enhancement improved the segmentation in some images and inhibited it in others. Due to inconsistent performance, these methods have been commented out in the code. For the currently available dataset, active contours based solely on intensity information was the most consistent. One potential expansion of the work could be to train a decision tree to analyse individual images and choose the best subset of algorithmic processing steps to produce the best segmentation.

- Method 2.1 Active Contour
 - Run active contours on test image using Otsu threshold as initial guess
 - Active contours is based on Chan-Vese method without bias to grow or shrink segmented region
- Method 2.2 Lazy snapping (k-means)
 - Graph cuts using texture information from Gabour features

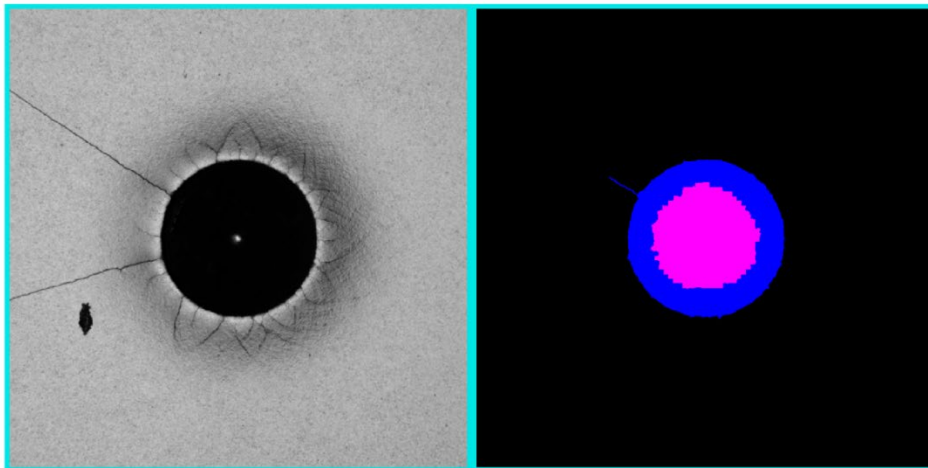


Figure 17 Images output by the AMTLAB routine comparing the performance of (blue) active contour and (red) lazy snapping segmentation refinement algorithm.

Recentre the Indent in the Image using the Refined Indent location

- The image is translated so that the centre of the indent aligns with the corner of a pixel
- The image is cropped to bounding box of the maximum inscribed circle centred on the indent

Determine Uncertainty of Indent Edge Determination (deviation from circular form)

- Take the refined indent mask and convert to equivalent circle
- Take the refined indent mask and determine the perimeter pixels
- Plot the perimeter pixels radius as a function of theta
- Remove outliers (Generalized Extreme Studentized Deviate (gesd)), this is approximate and could be improved perhaps by fitting a sine function and determining local uncertainty

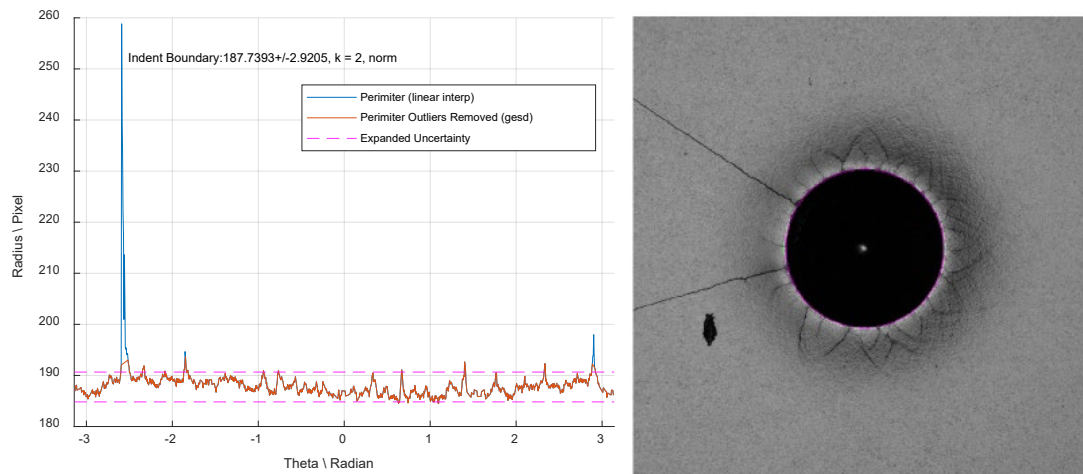


Figure 18 Figure output by the MATLAB routine showing the removal of cracks that were included in the indent segmentation and the resulting uncertainty on the indent-coting interfact location.

3.1.4 Evaluation

The auto threshold method performed well but was susceptible to error based on other features within the image e.g., surface texture, topographical contrast, or spalled regions. Hough Circle Transform provided inconsistent results due to irregularities of the indent edge, however, it did perform better than the auto threshold method in several instances. Graph cuts performed well but requires an initial sample of the image data which, if chosen incorrectly and without oversight, could cause the algorithm to fail. Active contours performed well by visual inspection of the limited sample of image available for this work. The Chan-Vese method uses k-means segmentation to maximise the difference between the background and the entire region segmented by the contour (foreground). The initial approximate guess could be defined *a priori* by the test protocol or adjusted depending on an approximate initial guess using the auto threshold or Hough Circle transform method. In the interest of simplicity an *a priori* definition is preferable but may need to be adjusted as a function of substrate/coating material properties and/or the applied force or other test parameters.

Depending on the image, including texture features in addition to the intensity information either improved or worsened the indent segmentation based on visual inspection. The potential for different segmentation methods to perform better, or fail completely, depending on image qualities presents an issue. Should the most appropriate method be selected based on a quantitative evaluation of the resulting segmentation, e.g., circularity of the largest segmented feature, centrality of the largest segmented feature, similarity of results using multiple methods, etc? Or should a single general solution be sought even if it is suboptimal?

Active contour was the most consistent method employed based on visual inspection of available images. It would be necessary to include a larger sample of images to ensure this method is truly robust. To make the algorithm more robust, it may be necessary to define image derived quality metrics that can identify when this initial indent detection step fails.

3.2 STEP 2 - FEATURE ENHANCEMENT

3.2.1 Outline

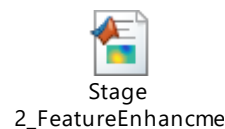
Step 2 enhances qualities of the image to facilitate feature quantification. As the indent has already been segmented in Step 1, the image can be simplified by masking the indent and excluding it from further analysis. An alternative approach is to convert the image into polar co-ordinates and crop the indent entirely. Converting the image to polar co-ordinates also simplifies filtering in either spatial or frequency domain and allows the rotational symmetry of the image to be exploited. It does, however, distort information in the spatial domain and increases the computational burden of image processing.

Multiple methods for feature enhancement exist that could be used to enhance crack-like features. One of the more accessible methods is to apply a deconvolution kernel based on a Laplace of a Gaussian (LoG). LoG filters are edge aware filters that can reduce noise whilst enhancing spatial features such as edges and cracks.

After image enhancement a simple adaptive threshold has been applied to segment the image. The features of the resulting binary mask can then be filtered based on connectivity with the top edge of the image (the edge of the indent).

3.2.2 MATLAB code

Executable MATLAB code



3.2.3 Pseudocode

Feature Enhancement + Noise reduction (Local Laplace of a Gaussian Filter)

- apply LoG filter to the image

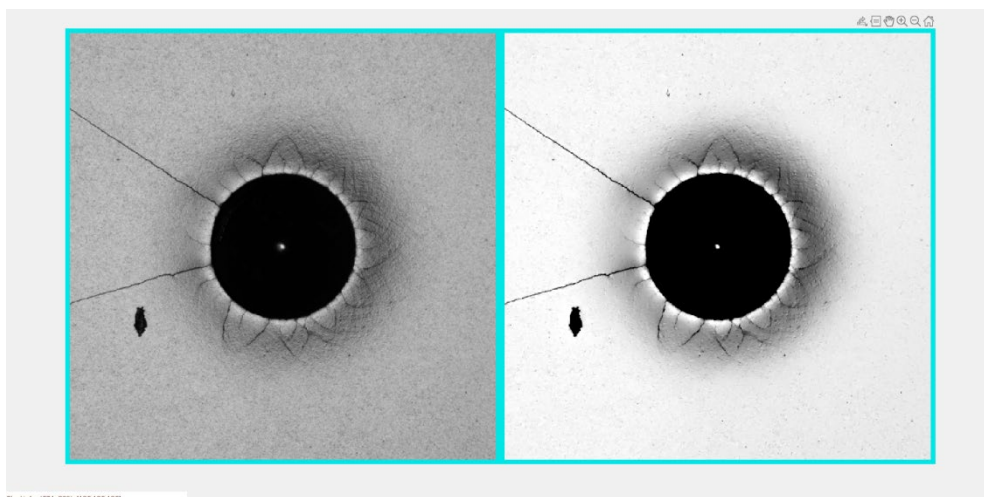


Figure 19 generated by the MATLAB routine showing the effect of applying a local Laplace of a Gaussian filter

Conversion to Polar Image

- convert image to polar co-ordinates and crop indent + region of uncertainty indent edge.

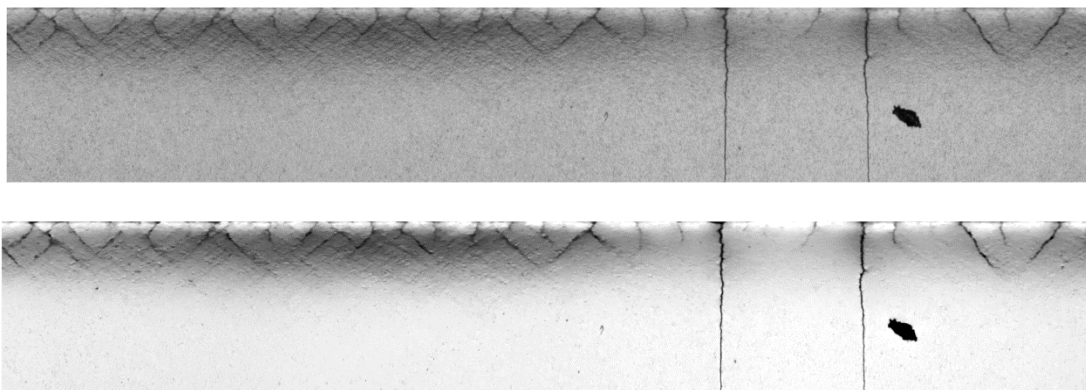


Figure 20 generated by the MATLAB routine showing image warped into polar co-ordinate space and the indent subsequently cropped.

Median Filter to Remove Background Gradient

- apply median filter to polar image using kernel of size [2, image width / 4]

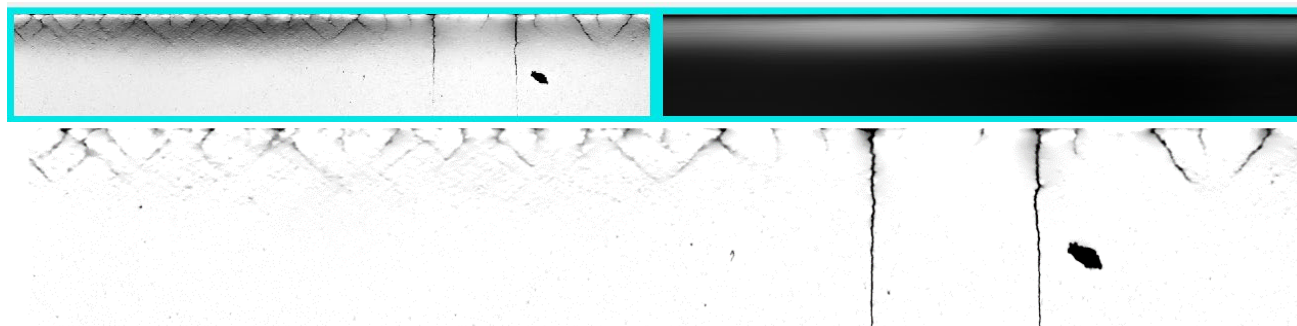


Figure 21 images generated by the MATLAB routine showing image reduction of radial features using a median filter with high-aspect ratio anisotropic kernel.

Detect Bright Outliers on Indent Edge

- Define normal range of intensity values for the coating. Sample region of polar test image connected to the bottom edge of the image and including the full width and 20% of image height
- Create spalled region mask by defining bright outliers in the polar image that are outside of the normal range of values of the coating, assumes the substrate has a higher albedo than the coating, normal range defined as $\text{mean} \pm 2\sigma$
- Remove all segmented features in the spalled region mask that are not connected to the top edge of the polar test image.

Detect Cracks

- Apply Adaptive Threshold to create initial crack mask
- Dilate segmented mask by circular structural element of radius 5
- Remove all features that are not connected to the top edge of the image
- Define cracks as pixels present in both initial crack mask and dilated filtered crack mask.

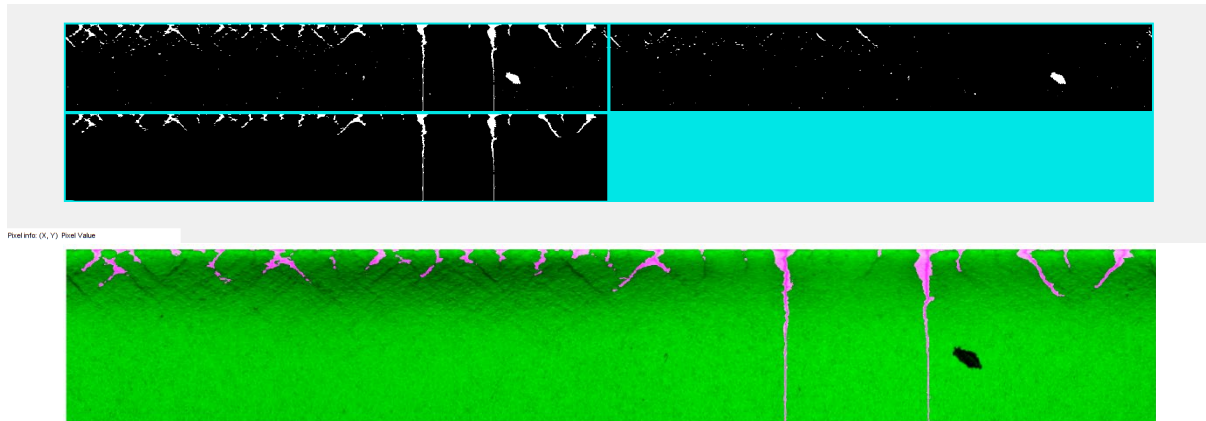


Figure 22 images generated by the MATLAB routine showing simple thresholding of the enhanced crack-like features

3.2.4 Evaluation

Feature enhancement works well for all available test images. Notably, it works whether cracks are present or not. The presence of pile-up in the sample does however obscure cracks within their vicinity. Uncertainty varies as a function of local contrast within the image, it may be necessary to characterise the variation in the background intensity gradient when calculating uncertainty or tune proceeding analysis based on the result. A method to overcome residual variation in background intensity is to apply an adaptive threshold, they are however susceptible to errors particularly in the absence of any crack features. A more robust method may be to define cracks as “not coating”, essentially define cracks as outliers from the normal coating surface. This could be achieved whilst making use of spatial, intensity and texture information. It would, however, be sensitive to the presence of crack like features in the coating especially along the radial direction.

It can be seen in Figure 15 that many cracks are missed. The routine can be tuned to improve the detection in the sample but doing so lessens performance on other samples. Unless a robust method of tuning inputs to the various analysis steps can be created, the detection sensitivity is limited by the worse-case scenario for the set. A larger set of example image would be necessary to tune the routines based on image derive qualities.

All available examples exhibit little to no crack-like features in the coating surface texture e.g. grinding striations. These features have the potential to be misclassified as cracks. For future iterations of the analysis routine(s) it will likely be necessary to characterise coating surface texture to reduce false positives and define the detection sensitivity. Detection sensitivity, or uncertainty, will likely be dependent on theta. An example of orientation dependent misclassification of crack-like surface texture can be observed in the literature and is shown in Figure 8.

The treatment of the data could potentially be improved if the resolution of the optical measurement system was known opposed to inferred from the image.

Currently, the routine identifies the edges of spalled regions as cracks. This means features relating to spalled regions of the coatings may be double counted in Stage 4 – Extract Quantified Features. A convention will have to be established and code added to organise the results.

3.3 STEP 3 (ROUTE 1) - RANSAC MODEL FITTING TO CRACK SPATIAL INFORMATION

3.3.1 Outline

Applying an adaptive threshold to the enhanced image followed by filtering the resulting mask for features not connected to the top edge of the image as performed in Step 2 is highly sensitive to discontinuities in the crack. Such discontinuities may be caused by noise or contrast variation due to the apparent crack depth or width when viewed normal to the surface. Potentially, reflected light from exposed substrate could also complicate the image, assuming the substate is brightly contrasted and under co-axial illumination. Step 3 introduces methods to overcome limitations of this initial segmentation.

An attempt was made to refine the initial segmentation by fitting a linear equation to pixels surrounding the initial segmented regions weighted by the inverse of the image contrast using Random Sample Consensus (RANSAC). This method quantifies the crack morphology and is robust to apparent discontinuities in the crack.

At least two crack morphologies are observed, linear cracks along the radial direction and branching fissure-like crack near the indent edge. The model fit the radial crack well, however, the fissures were curved and tended to branch. RANSAC is not limited to fitting simple linear models. The curving fissures can be fit using higher polynomials, however, branching cracks require more complicated models and/or iterative routines. This method shows a lot of potential.

3.3.2 MATLAB code

Executable MATLAB code



Stage
3_Rout1_RANSAC_M

RANSAC Model fitting to Crack

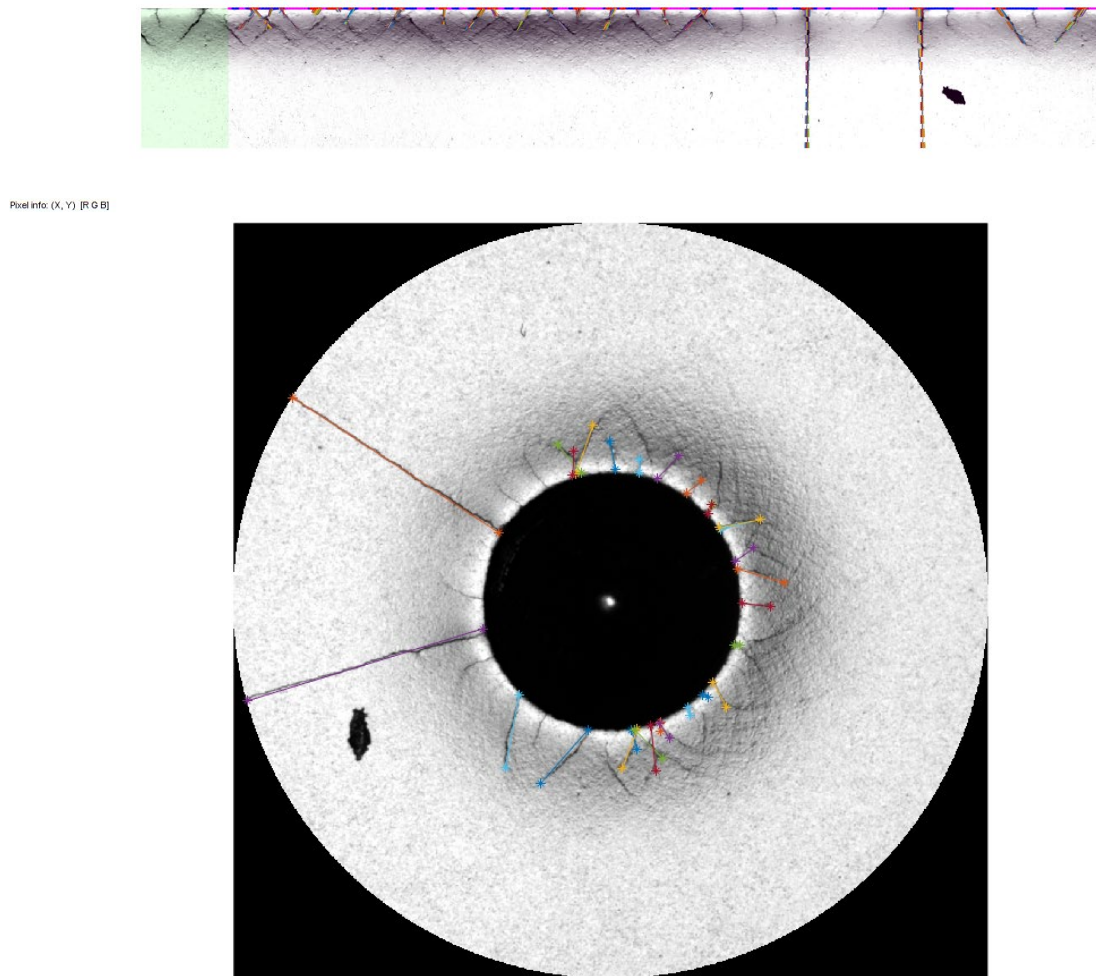


Figure 23 images generated by the MATLAB routine showing linear fits of the enhanced and segmented crack information in both cartesian and polar co-ordinates

3.3.3 Evaluation

Detecting and quantifying cracks is a notoriously difficult task in image analysis. The method makes use of the *a priori* assumption that cracks extend from the boundary of the indent simplifying analysis and providing a method to filter out false positives that may occur depending on coating surface texture. The implemented code is time consuming and in need of optimisation, however, it does demonstrate the principle of model fitting to intensity information. There is the potential to develop more complex models that allow for curvature of the crack or even branching.

3.4 STEP 3 (ROUTE 2) - PIXEL CLASSIFICATION – UNSUPERVISED MACHINE LEARNING

3.4.1 Outline

This method uses texture information to segment the crack regions. The method shows promise in the available image data, however, a large set of example images is needed to evaluate its performance under less ideal circumstances.

3.4.2 MATLAB code

Executable MATLAB code



3.4.3 Pseudocode

- Segment enhanced polar image based on k-means of Gabor image features

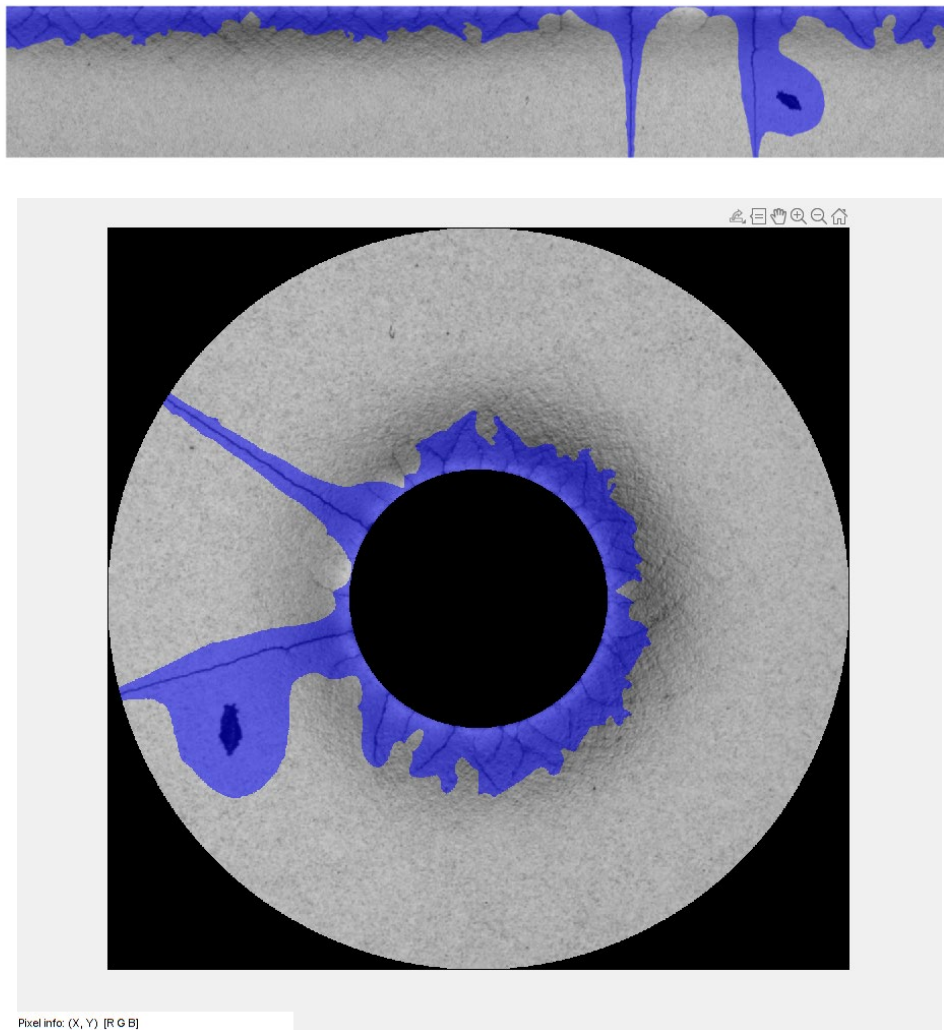


Figure 24 images generated by the MATLAB routine showing a k-means (k=2) segmentation of Gabor image features derived from the enhanced images in both Cartesian and polar co-ordinates

3.4.4 Evaluation

This method is highly dependent on the preceding analysis steps that simplify the image and enhance the crack features. The number of process steps results in a complex workflow that will require

evaluation on a larger dataset before an informed decision can be made on the most appropriate method for crack feature quantification.

4 DISCUSSION

4.1 GUIDANCE ON IMAGE CAPTURE

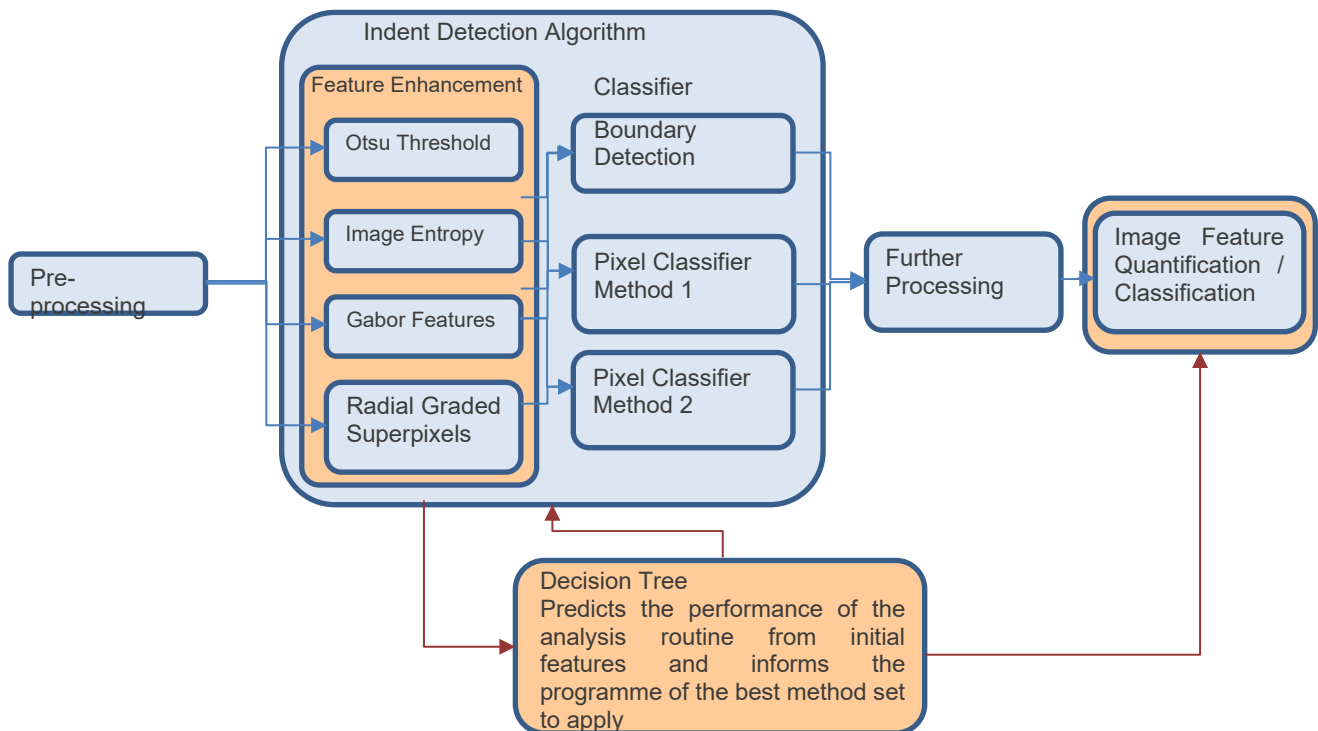
To aid the image analysis, test images should conform to the following, where possible.

1. images should be captured with the same pixel size.
2. the indent should be approximately central in the test image.
3. scalebars should not be present in the image, scale information should be contained in the meta data or saved as an overlay.
4. the minimum height or width of the image, whichever is the smallest, should be at least twice the diameter of the indent.
5. there must be adequate unaffected background (coating) visible within the image
 - a boarder, ~5th the height/width of the image, should contain no features associated with the Daimler-Benz test and be representative of the coating.
 - alternatively, images representative of the background could be supplied alongside the test images. All images should have the same contrast/brightness settings.
6. If the coating exhibits any directionality in textural features all images should be captured in the sample orientation.
7. contrast and brightness should be optimised on the coating surface and regions of observable crack and/or pile-up, clipping of the intensity information in bright fully delaminated regions or in the dark indent region is acceptable.

5 FURTHER WORK

5.1 PROCESSING PIPELINE DECISION TREE

To extend the routines to account for more complex coating-test interactions it may be necessary to tailor the analysis for a given subgroup of coating systems. One method could be to use input into a decision tree based on the prophetic qualities of the coating or measurement system e.g., physical, and optical properties of the substrate and coating.



5.2 IMAGE SIMULATOR

Figure 16 shows a mock-up of an image simulator that constructs a test image from a list of input parameters. The simulated image would have a known ground-truth of quantified features. The simulated image could be used either to benchmark the performance of an analysis routine or provide labelled images to train a computer vision-based solution. Assuming the simulated images were of sufficient fidelity to real images the simulator could provide an uncertainty estimate, or detection sensitivity estimate based on measurable image qualities (e.g., contrast to noise ratio, coating surface texture, system resolution etc.). This process would involve performing a parameter sweep of the image simulator and producing a look-up table of values for any given combination of inputs. Qualities of a real test image could then be measured and used to look up its corresponding performance estimate.

Coating Surface Texture

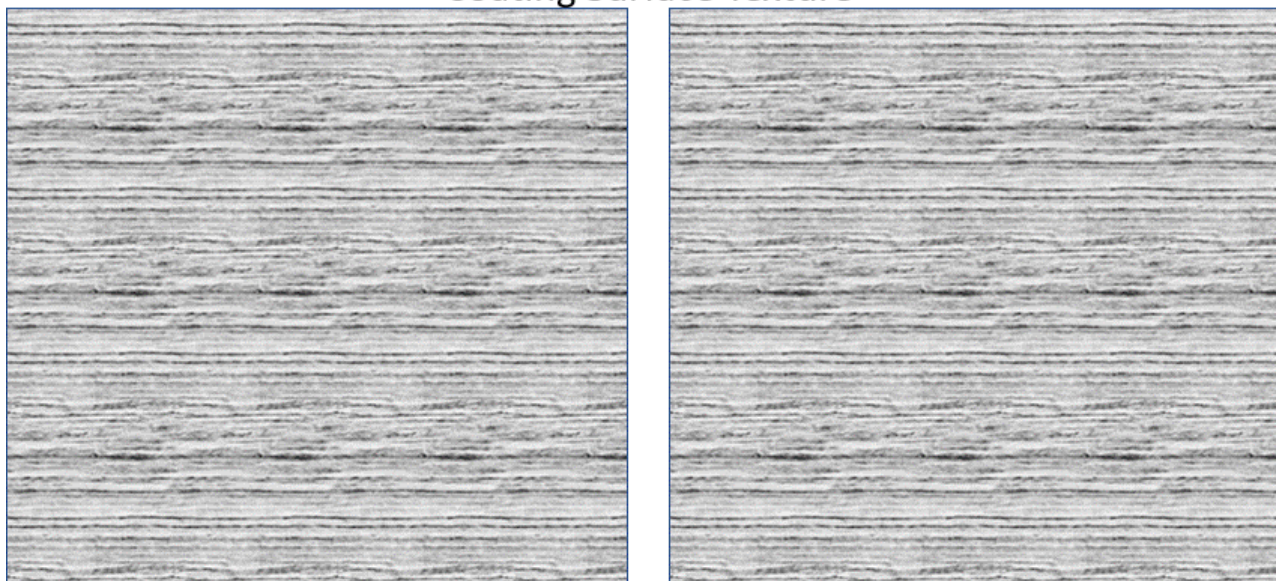


Figure 25 Mock-up of Daimler-Benz Test image feature simulaiton

Feature Obscuration / Image Augmentation

- Synthetic Noise
- Synthetic Blur
- Brightness/Contrast Jitter
- Hue/Saturation Jitter (colour)
- Image Scale / Discretisation

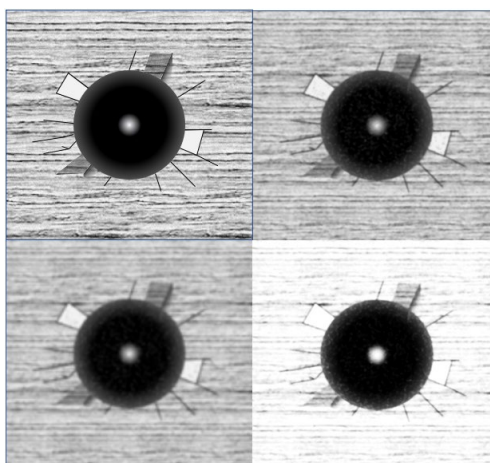


Figure 26 Mock-up of Daimler-Benz Test image simulaiton further processing

5.3 IMAGE FEATURE SYNTHESISER

A less onerous task than creating an image simulator could be to synthesise features to add to a test image, such as cracks. Then use these synthesised features as input to tune an existing neural net pixel classifier for the given image. The tuned network could then be applied to the test image to improve network performance. It is potentially very computationally expensive to perform this for each image.

5.4 UNUSED CODE

Some operations are best applied in the original cartesian co-ordinate system but are not compatible with region masking. Therefore, to simplify the image a method was developed to mirror the indent

along the boundary determined in Step 1, an example is provided in Figure 15. This may be a useful tool for future iterations of the analysis routines but has not featured in the current pipeline.

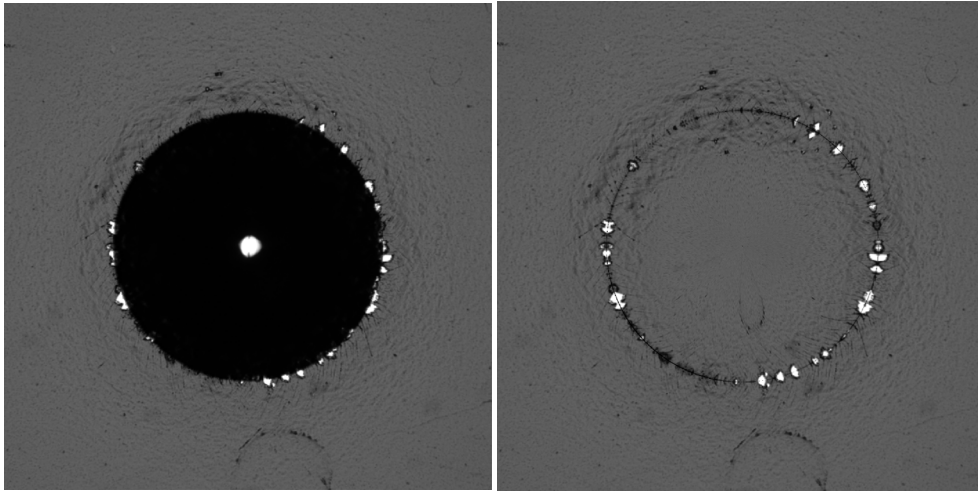


Figure 27 Example of image mirroring in polar co-ordinates to remove the indent

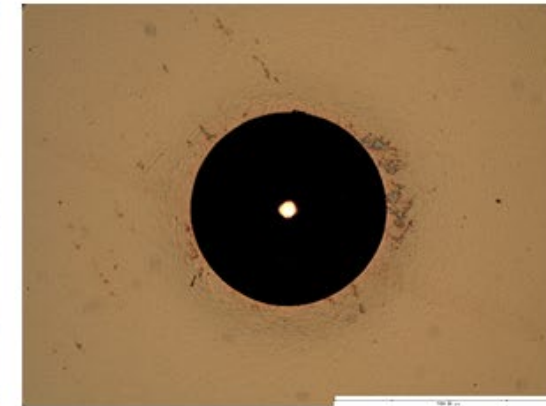
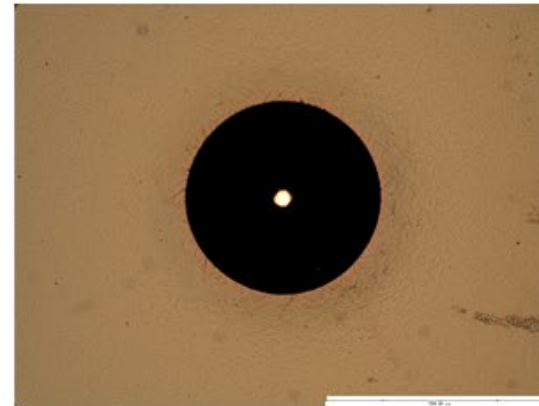
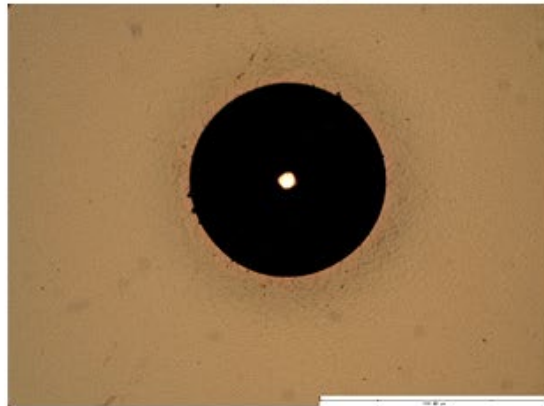
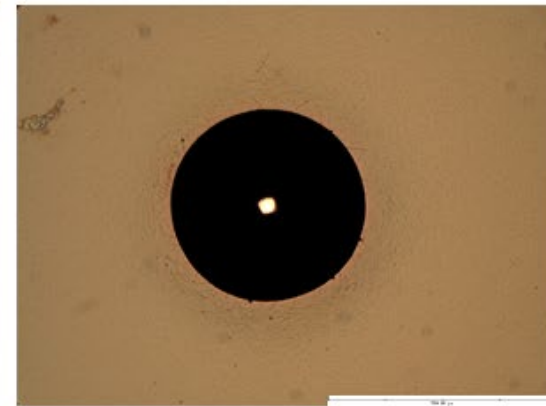
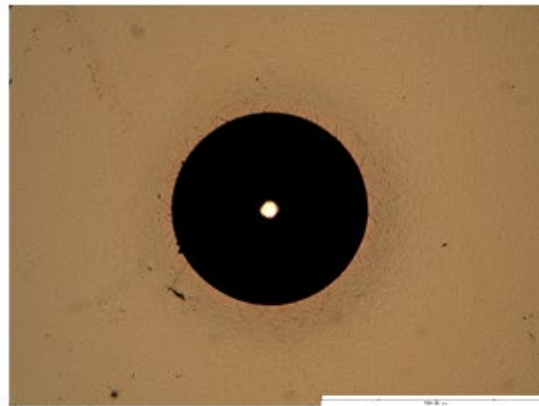
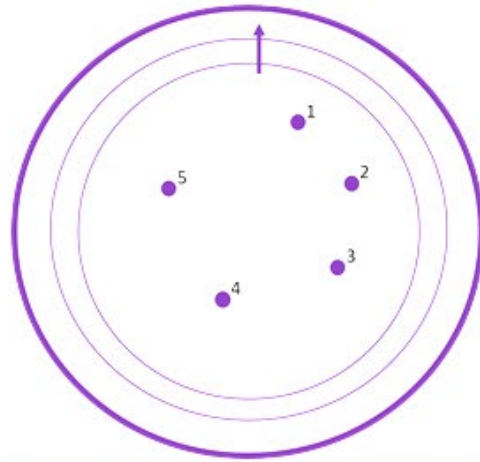
6 REFERENCES

- [1] Hatic D, Cheng X, Weibel T, Rauhut M and Hagen H 2020 Rockwell Adhesion Test- Approach to Standard Modernization. *EuroVis (Posters)* pp 29–31
- [2] Drobný P, Mercier D, Koula V, Škrobáková S I, Caplovič L and Sahul M 2021 Evaluation of Adhesion Properties of Hard Coatings by Means of Indentation and Acoustic Emission *Coatings* **11** 919
- [3] Vidakis N, Antoniadis A and Bilalis N 2003 The VDI 3198 indentation test evaluation of a reliable qualitative control for layered compounds *Journal of materials processing technology* **143** 481–5
- [4] Warcholinski B, Gilewicz A, Myslinski P, Dobruchowska E, Murzynski D and Kuznetsova T A 2020 Effect of silicon concentration on the properties of Al-Cr-Si-N coatings deposited using cathodic arc evaporation *Materials* **13** 4717

7 APPENDIX 1 – IMAGE DATA

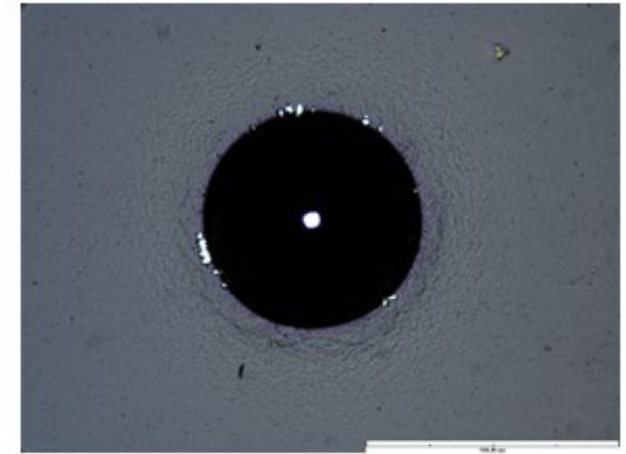
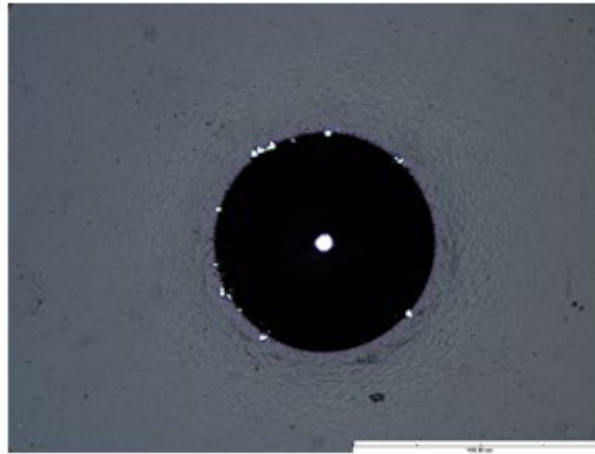
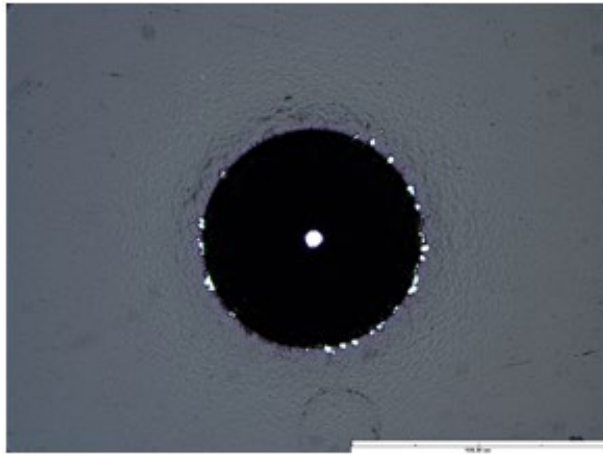
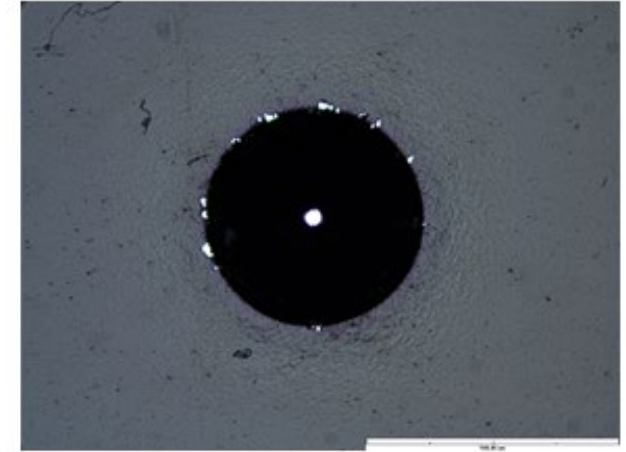
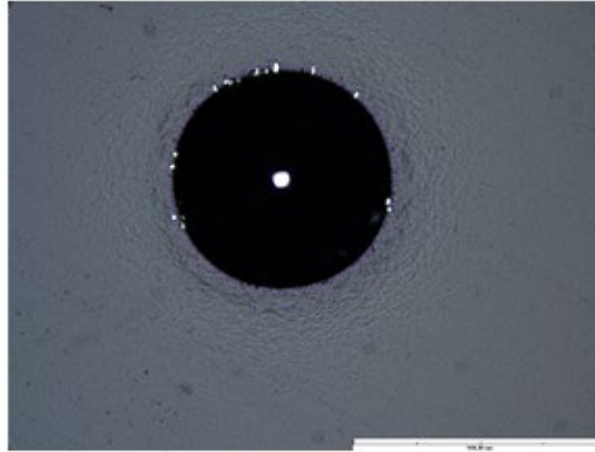
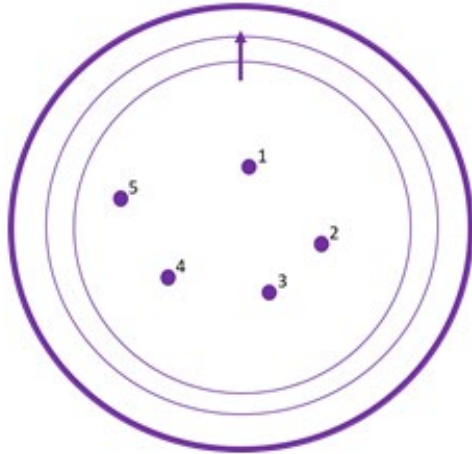
7.1.1 Titanium Nitride Coating

AKIV001 Titanium Nitride Coating



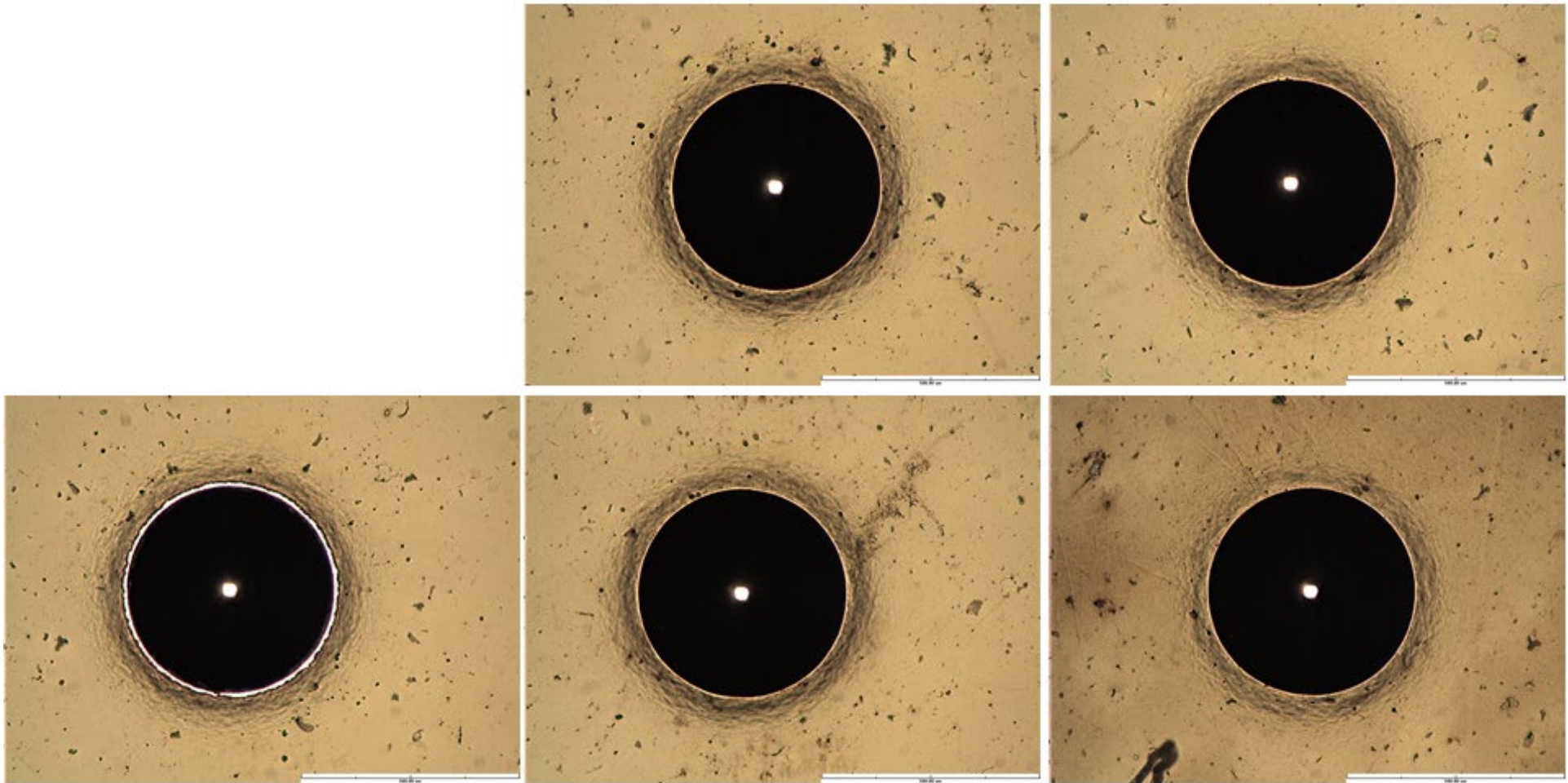
7.1.2 Nitron MC Coating

AKIU001 Nitron MC Coating



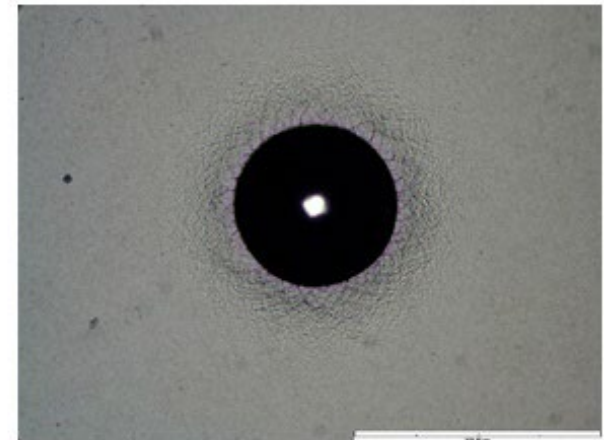
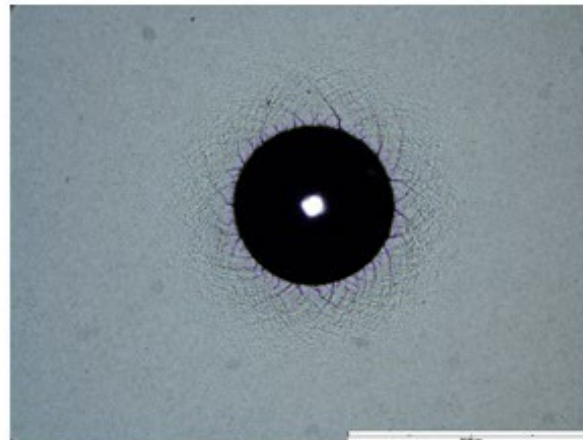
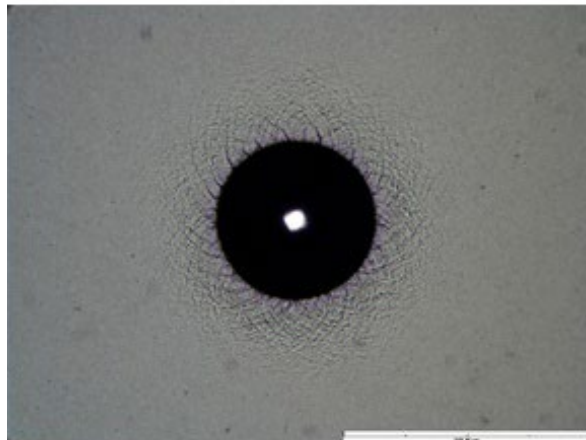
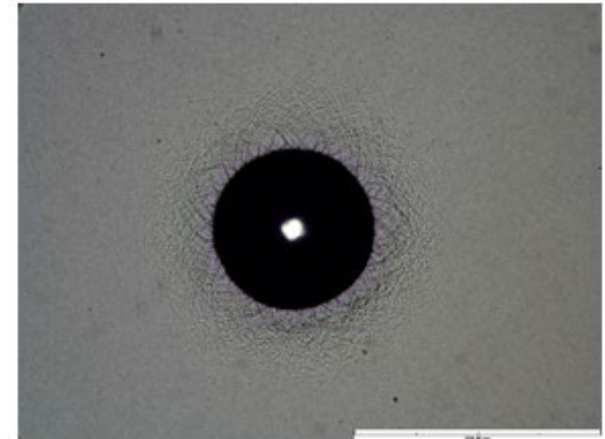
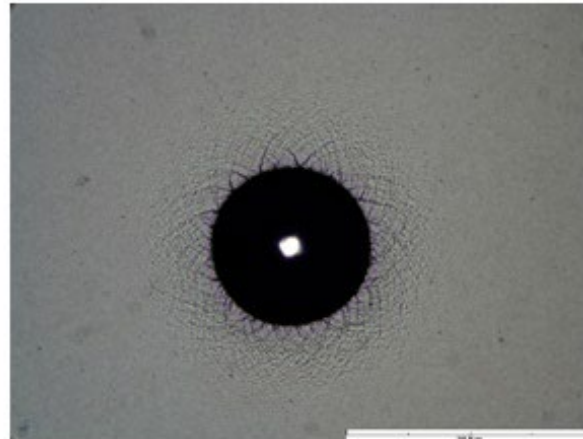
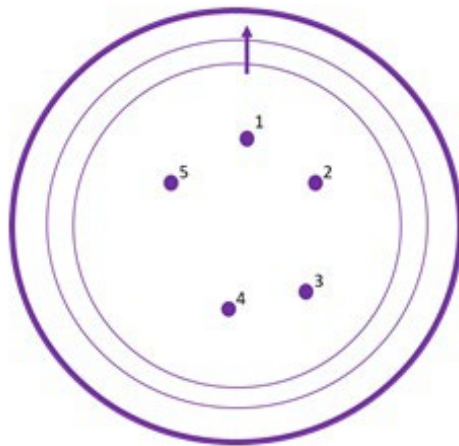
7.1.3 Graphit-iC Coating

Graphit-iC



7.1.4 WC/Co Coating

AKIT001 WC/Co

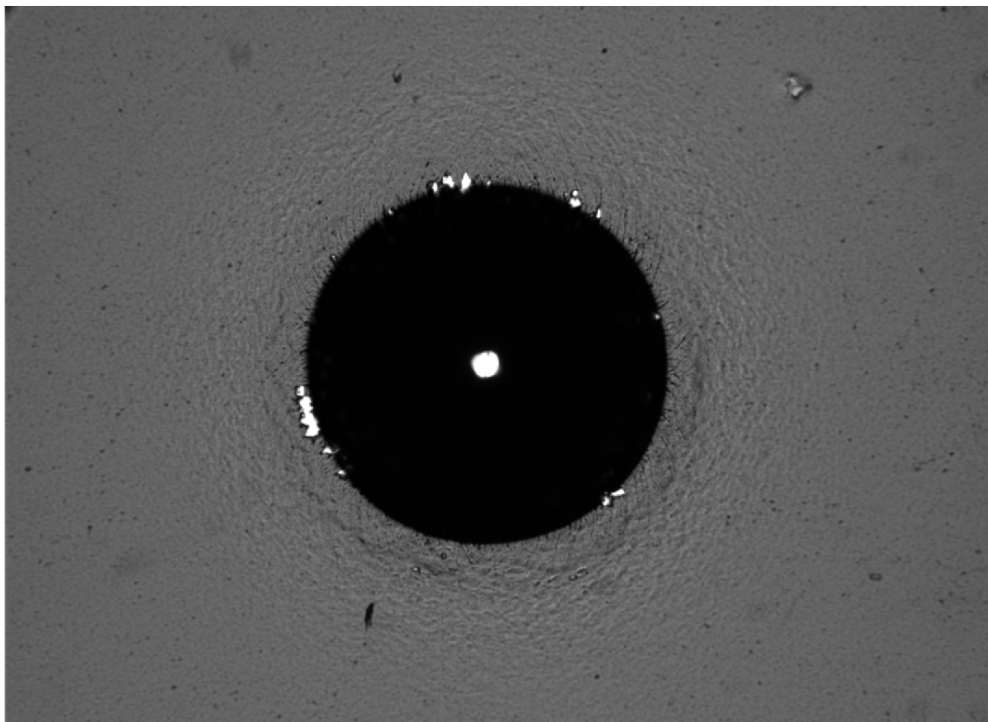


8 APPENDIX 2 IMAGE PROCESSING EXAMPLES

Images within the following annex follow the same pipeline as described in the main body of text. The Reader is directed to the main body of text for context. This section is to illustrate the pipeline performance on two other images/coating systems

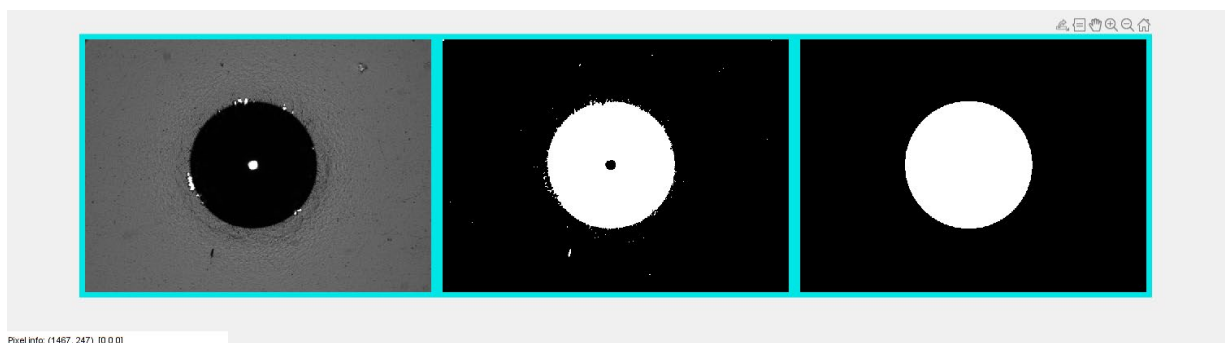
8.1 IMAGE PROCESSING PIPELINE: EXAMPLE 2

```
ImageFileName = '\\Images\\2021.11.01\\AKIU001 3 10x.tif'; %small faint cracks,  
some spalling
```



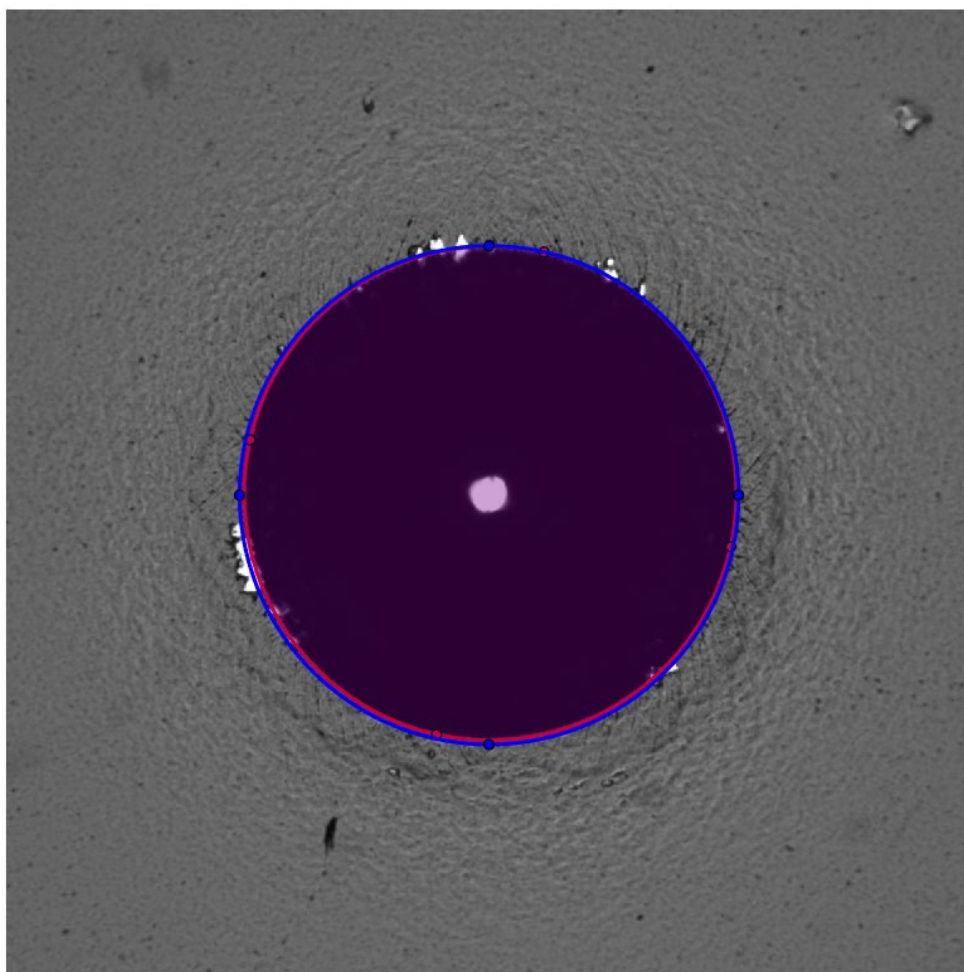
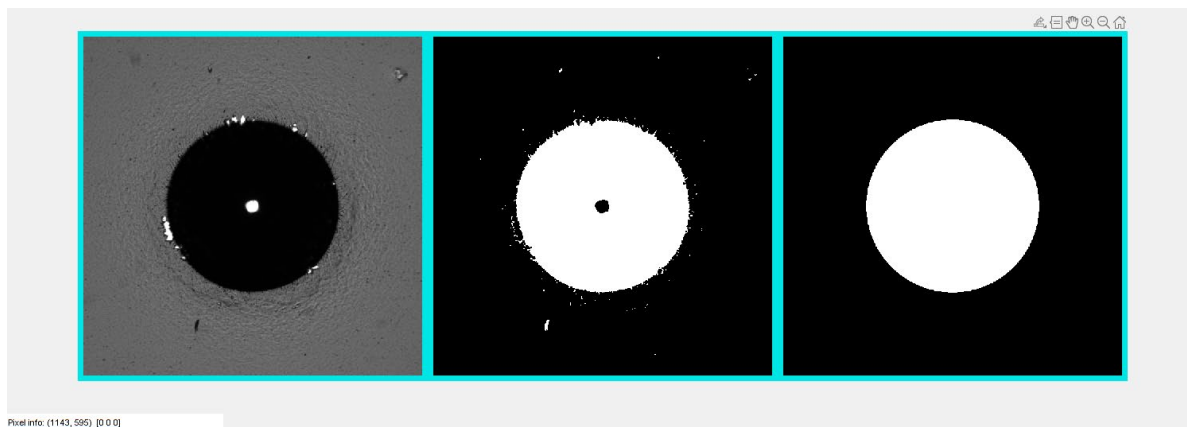
Approximate Determination of Indent location

Test Image, Otsu threshold, Otsu threshold + hole fill of largest blob



Centre the Indent in the Image

Test Image, Otsu threshold, Otsu threshold + hole fill of largest blob
Test image with overlay showing, (red) otsu + hole fill of largest blob, (blue) Hough Circle Determination

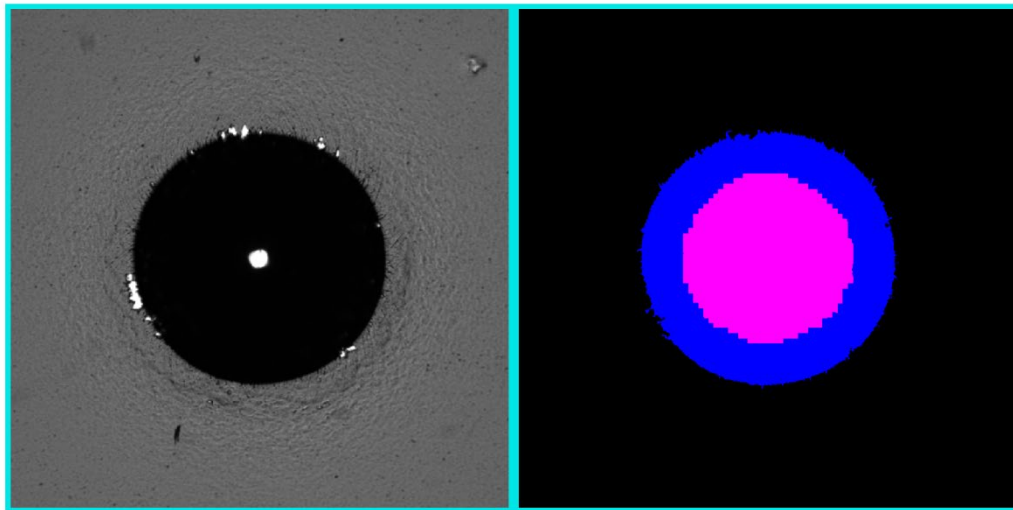


Refine Indent location - Method #1 Active Contour

Refine Indent location - Method #2 Graph Cuts

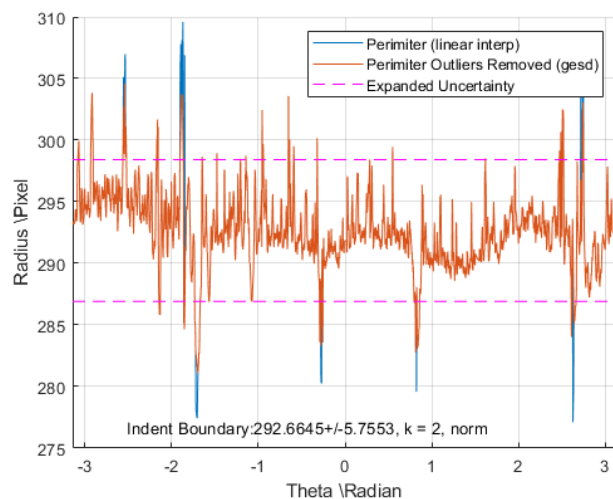
Graph cuts using lazysnapping

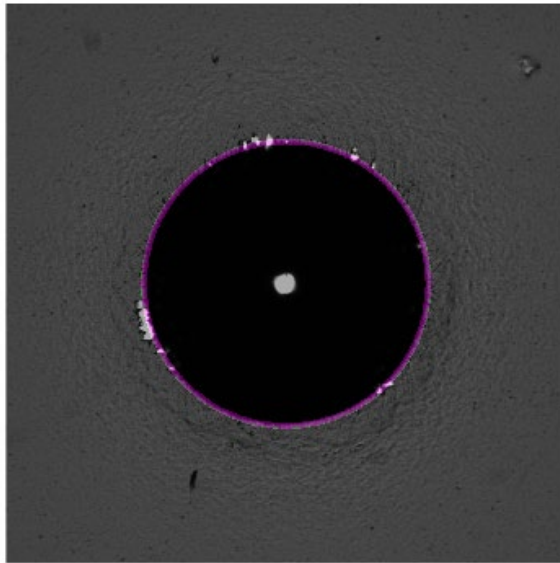
Original Cropped Image, GraphCut (red) Vs ActiveContour (blue)



Centre the Indent in the Image using IndentMask_Refined.ActiveContour

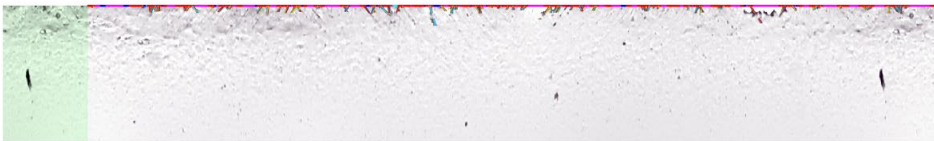
Determine Uncertainty of Indent Edge Determination (deviation from Circular Form)



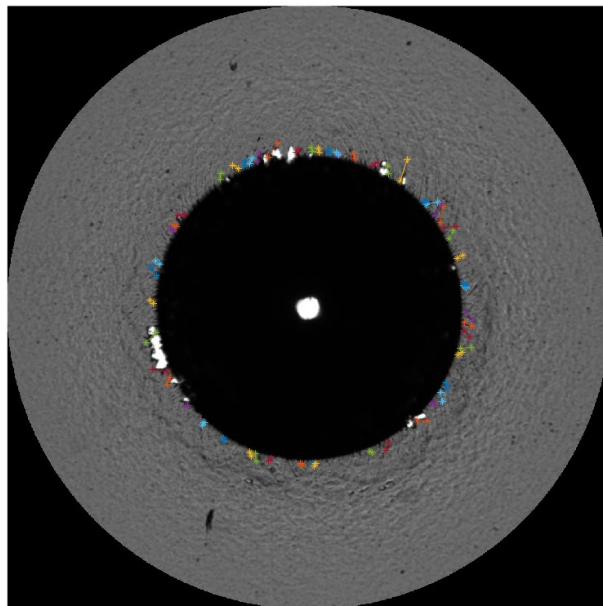


RANSAC Model fitting to Crack

Cracks Detected:54

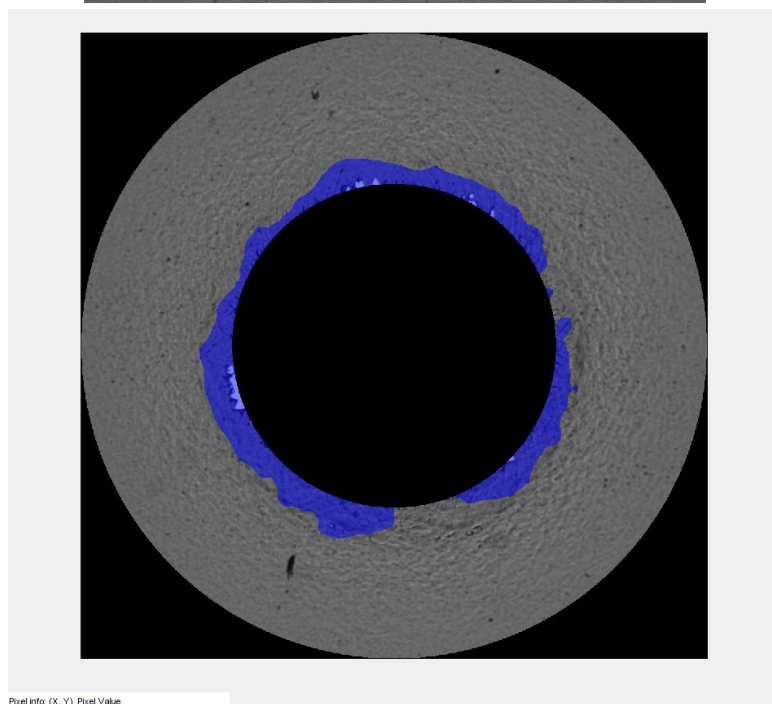
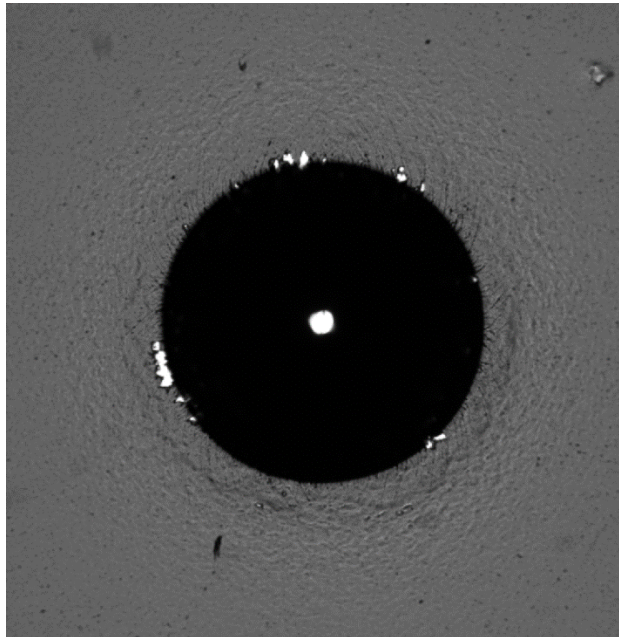
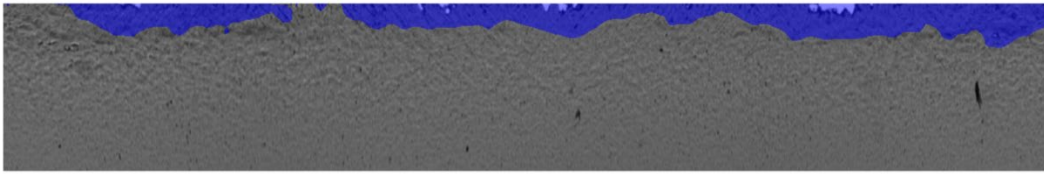


Pixel info: (X, Y) [R G B]



Pixel info: (X, Y) Pixel Value

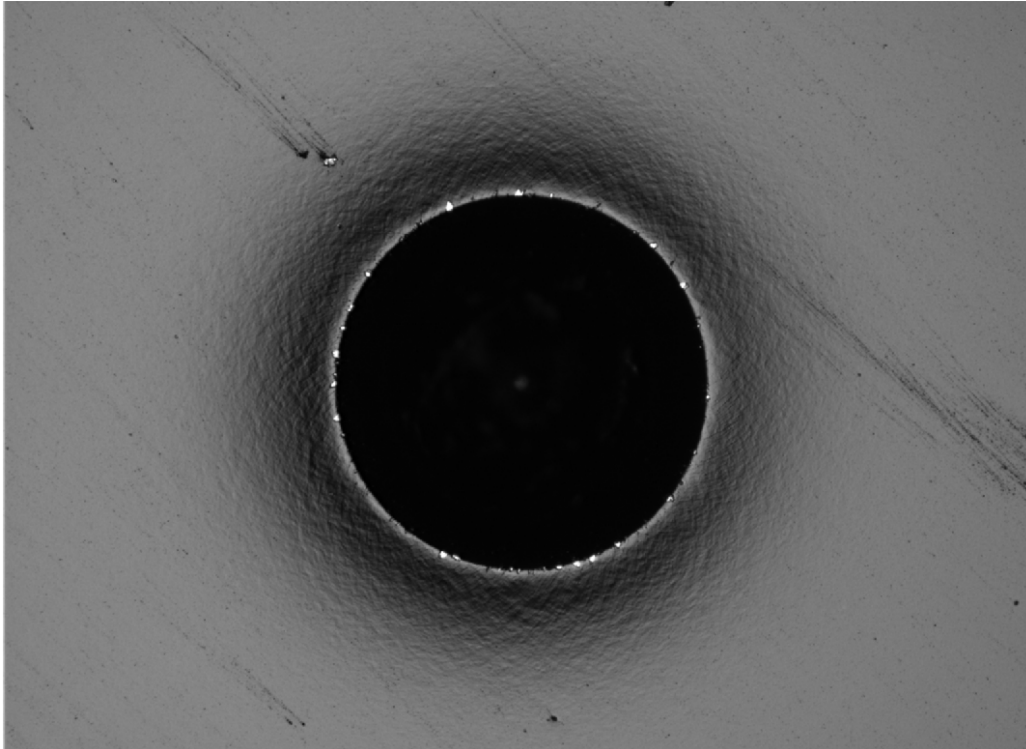
Pixel Classification



Pixel Info: (X, Y) Pixel Value

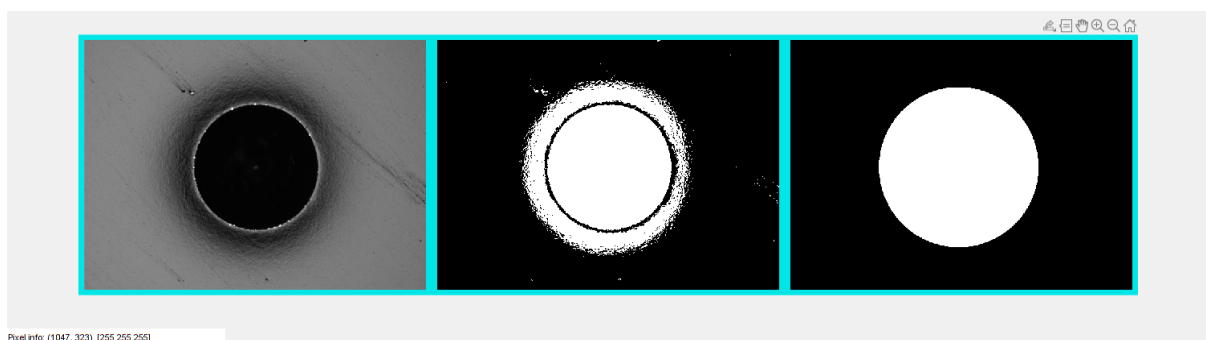
8.2 IMAGE PROCESSING PIPELINE: EXAMPLE 3

```
ImageFileName = '\Images\2022.10.03 High Load\AKIU001\AKIU001 5.884kN Indent  
1.tif'; % no cracks, very small amount of spalling
```



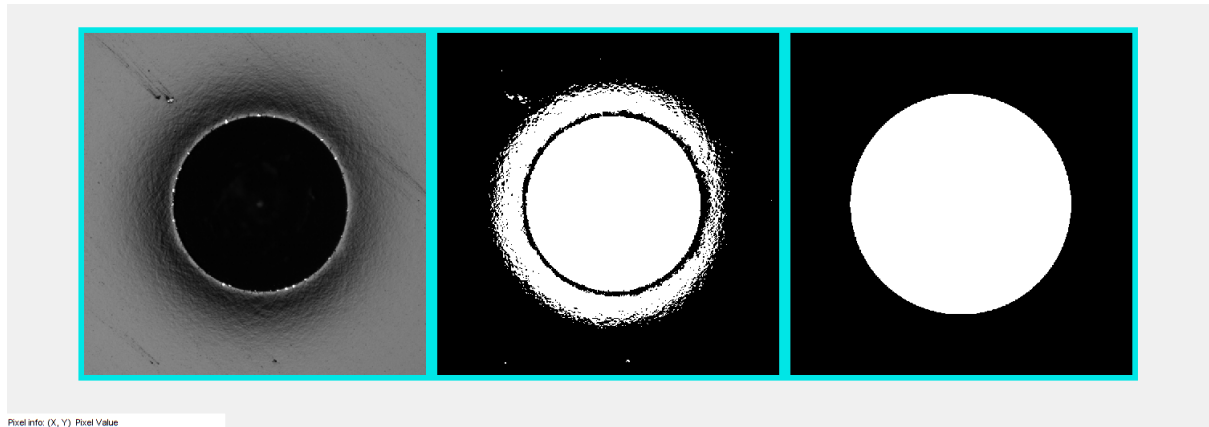
Approximate Determination of Indent location

Test Image, Otsu threshold, Otsu threshold + hole fill of largest blob

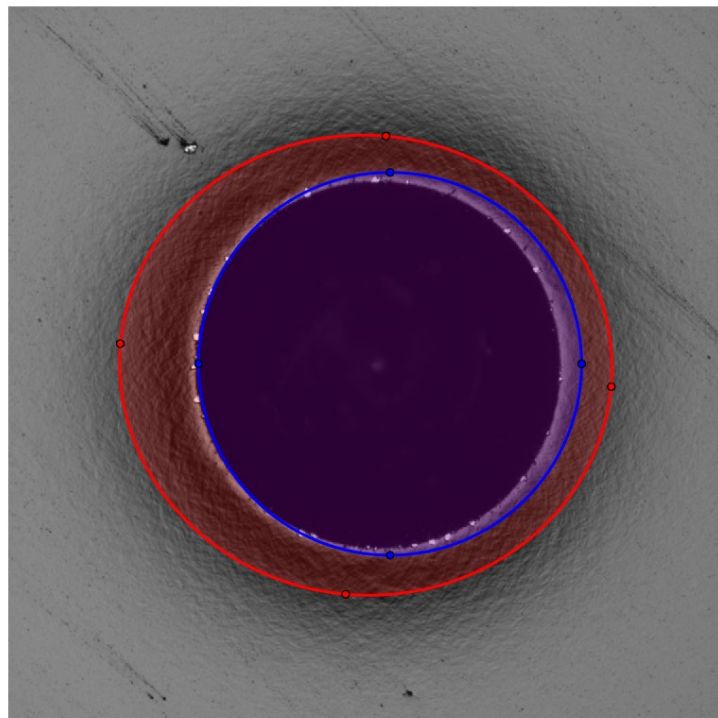


Centre the Indent in the Image

Test Image, Otsu threshold, Otsu threshold + hole fill of largest blob



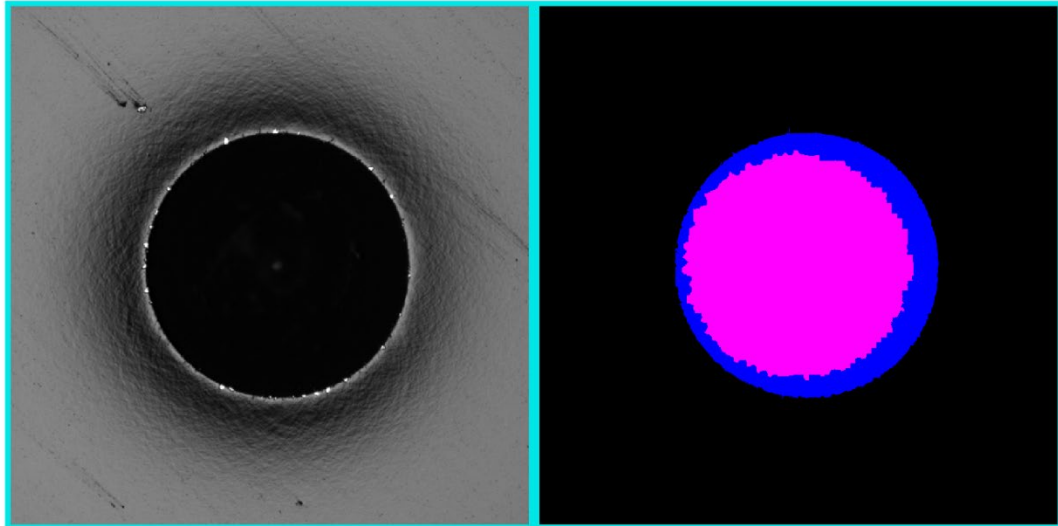
Test image with overlay showing, (red) otsu + hole fill of largest blob, (blue) Hough Circle Determination



Refine Indent location - Method #1 Active Contour

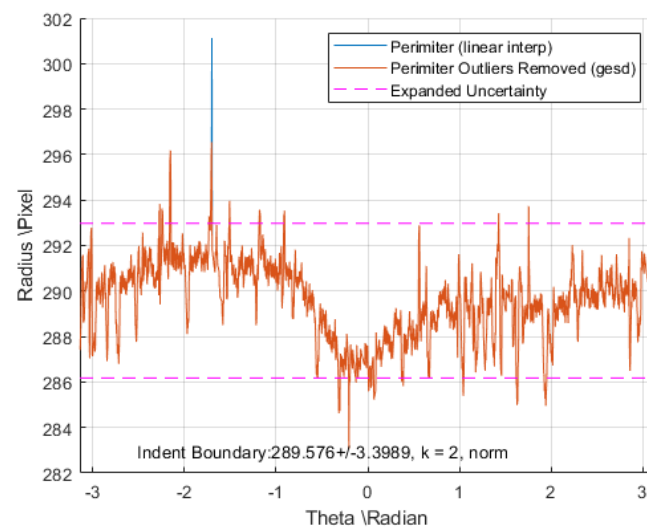
Refine Indent location - Method #2 Graph Cuts

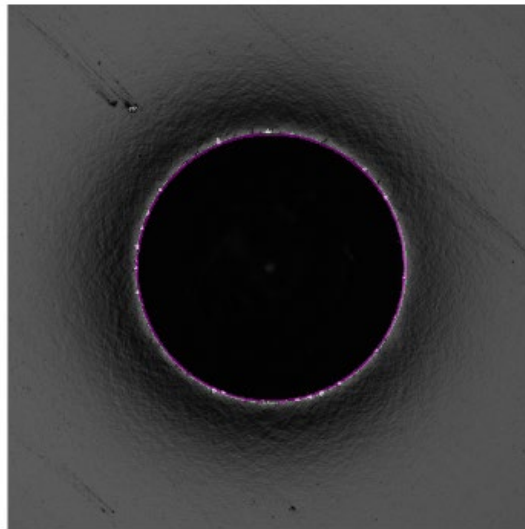
Graph cuts using lazysnapping



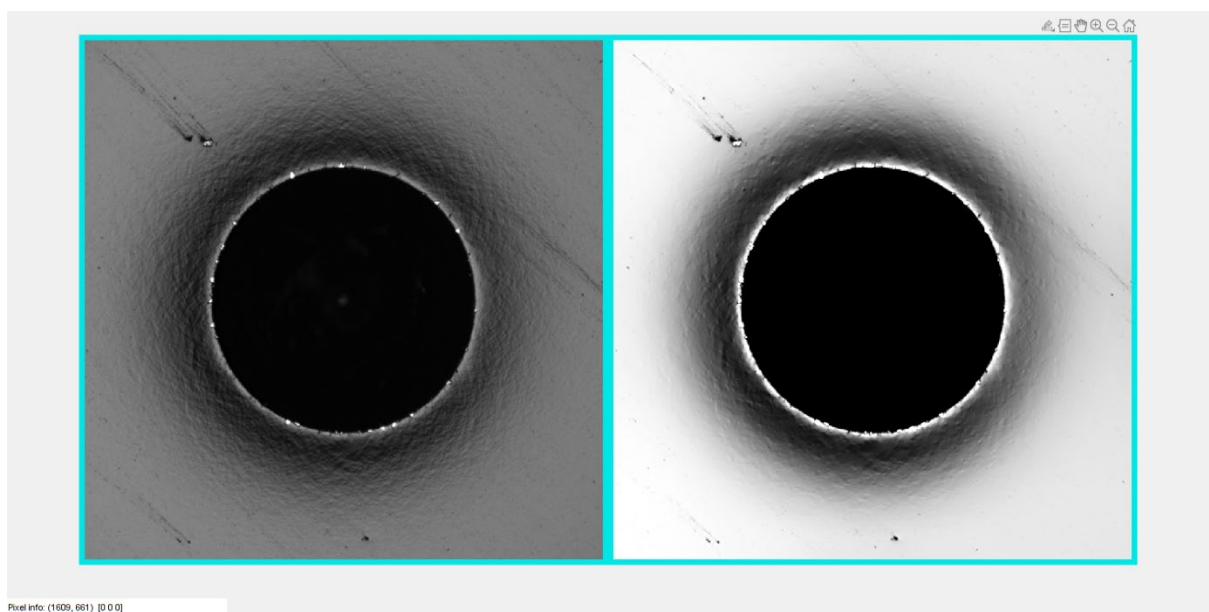
Centre the Indent in the Image using `IndentMask_Refined.ActiveContour`

Determine Uncertainty of Indent Edge Determination (deviation from Circular Form)

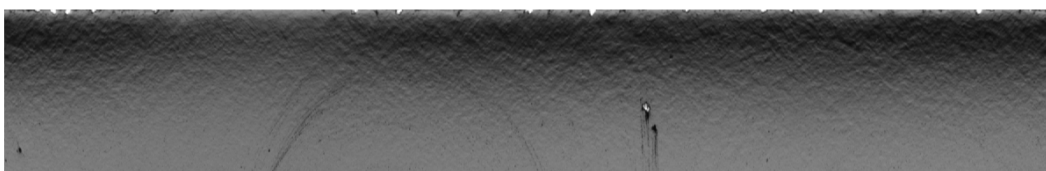


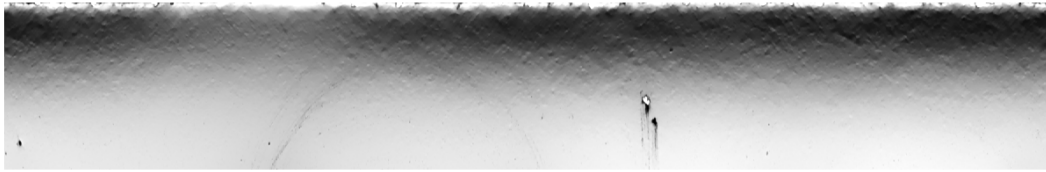


Feature Enhancement + Noise reduction (Local Laplace of a Gaussian Filter)



Conversion to Polar Image





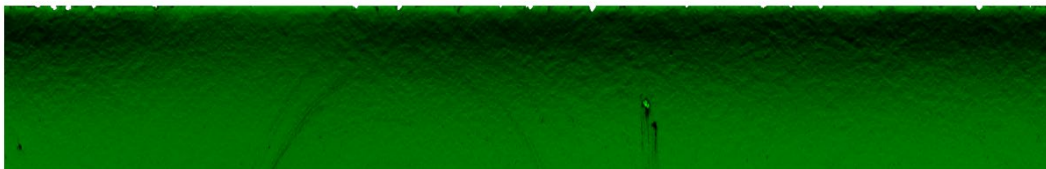
Median Filter to Remove Background Gradient



Pixel Info (X,Y) Pixel Value

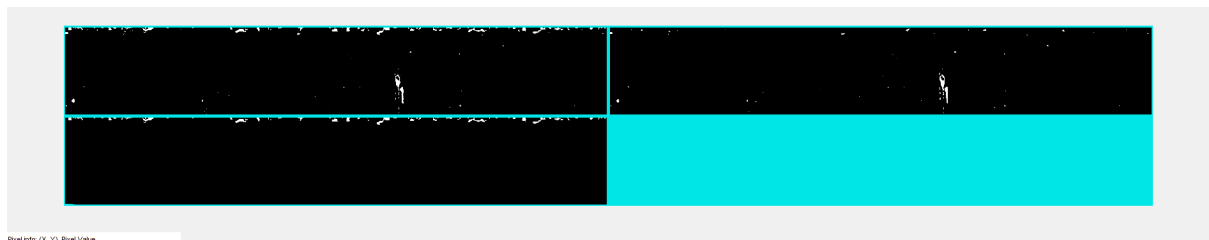


Detect Bright Outliers on Indent Edge

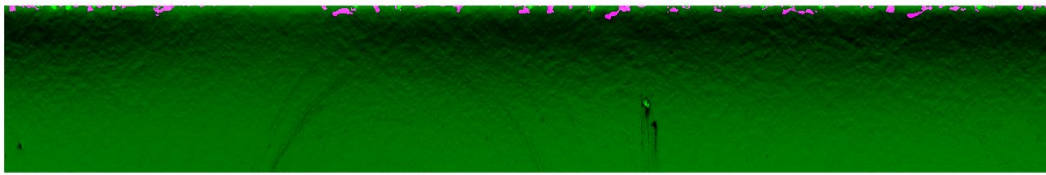


Bright spalled regions detected

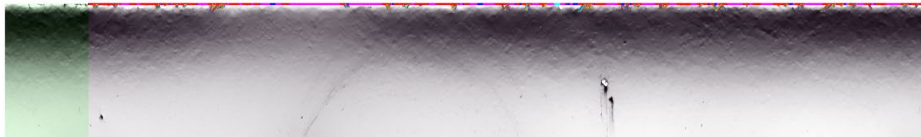
Apply Adaptive Threhsold



Pixel Info (X,Y) Pixel Value

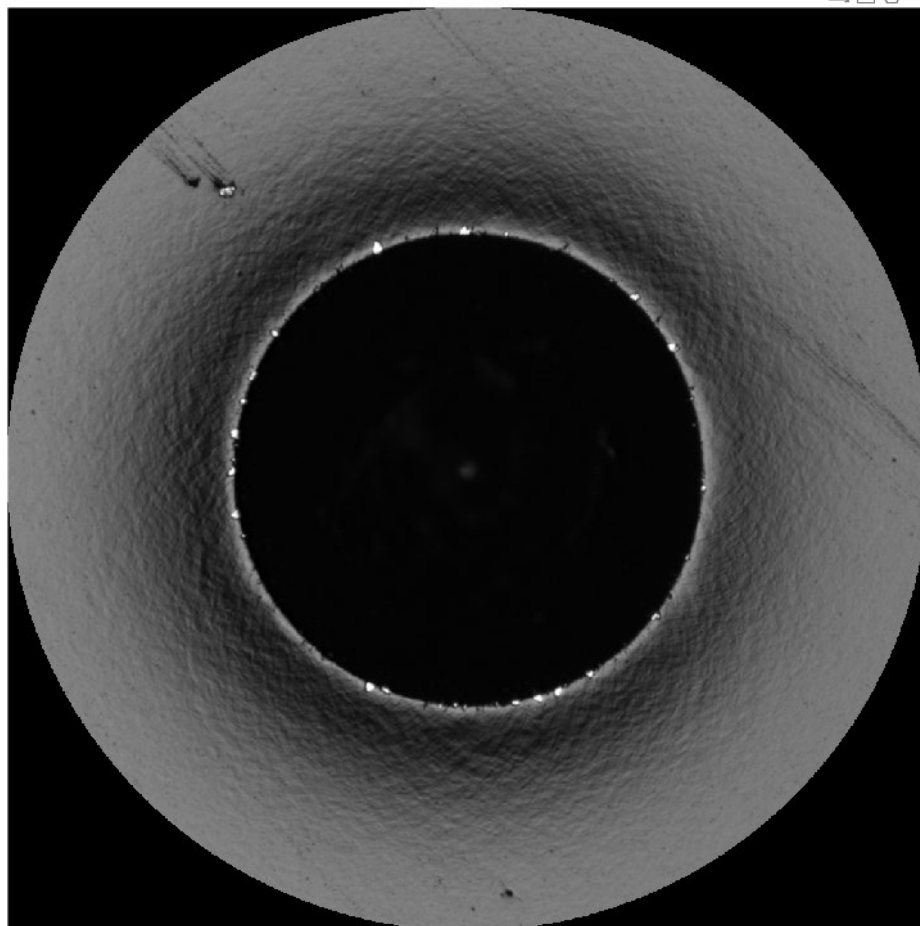


RANSAC Model fitting to Crack



Pixel info: (X, Y) Pixel Value

Cracks Detected:42



Pixel info: (1021.90, 572.30) 0.42

Pixel Classification

