Optical Inspection of SRF Cavities

Automated Defect Recognition

James Hayward, 2011

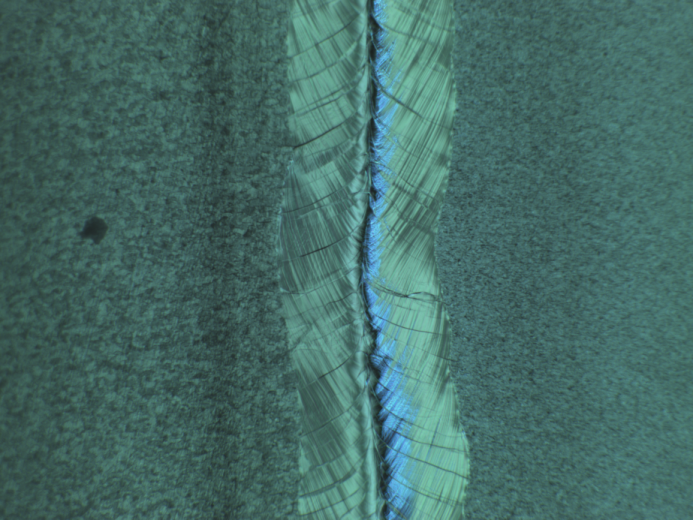
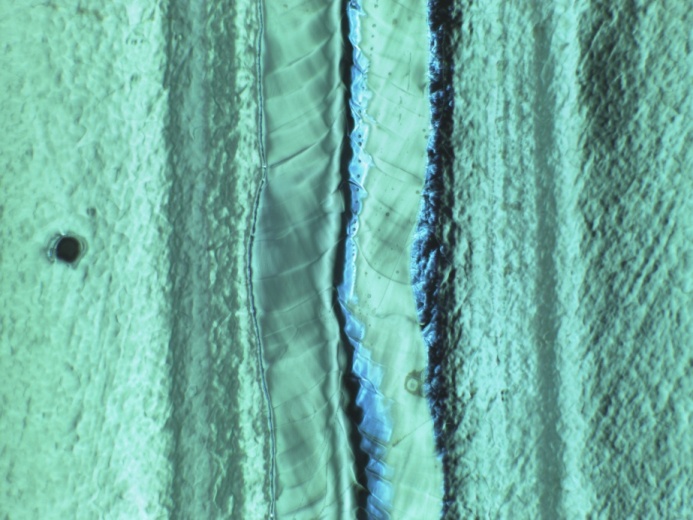
Supervisor: Sebastian Aderhold

**Abstract:**

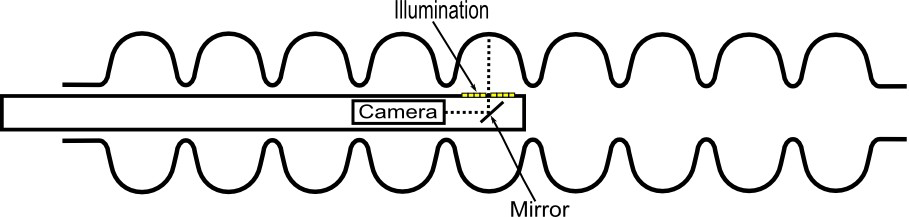
The aim of this project was to use an existing defect recognition program to decide upon a useful set of parameters and to investigate correlation between parameters. Such a set of parameters was found and certain correlations too.

**Introduction:**

Niobium superconducting radio-frequency cavities are used to accelerate particles, most commonly in linear accelerators. The maximum accelerating gradient is limited by the cavity surface quality. Quench spots are one of the main limiters on the maximal accelerating gradient of niobium cavities. Quench spots are areas of thermal breakdown on cavity surface, created during manufacture, although their origins are not fully understood. If precise defect location could be determined, this might lead to manufacture process improvement.



*Fig. 1 – Left: image of inner niobium cavity surface prior to electropolishing. Right: image of inner niobium cavity surface post-electropolishing.*

Defect recognition is currently carried out by first use of Second Sound, which locates the defects spatially, and then further information can be gained from optical inspection. At DESY, he system currently used for this is the Kyoto camera system, shown below:

*Fig.2 – Diagram of experimental set-up of Kyoto camera system at DESY.*

Automisation of this process is required due to the typically large number of cavities used in an operating system.

A program is currently under development to classify surface defects from images of the cavity inner surface.

However, several image processing operations must be applied to the surface photo, before this program can be run: Greyscale conversion; Shadow subtraction; Edge enhancement; Segmentation (i.e. decision as to whether a pixel is a part of the background or a region of interest). The end result a binary image and its complement.

Subsequent analysis provides various parameters for objects in the images. Once said parameters obtained, one can compare objects‘ parameters to their neighbours‘ by use of the Mahanalobis distance. The Mahanalobis distance is a metric in higher-dimensional vector space, defined by1:

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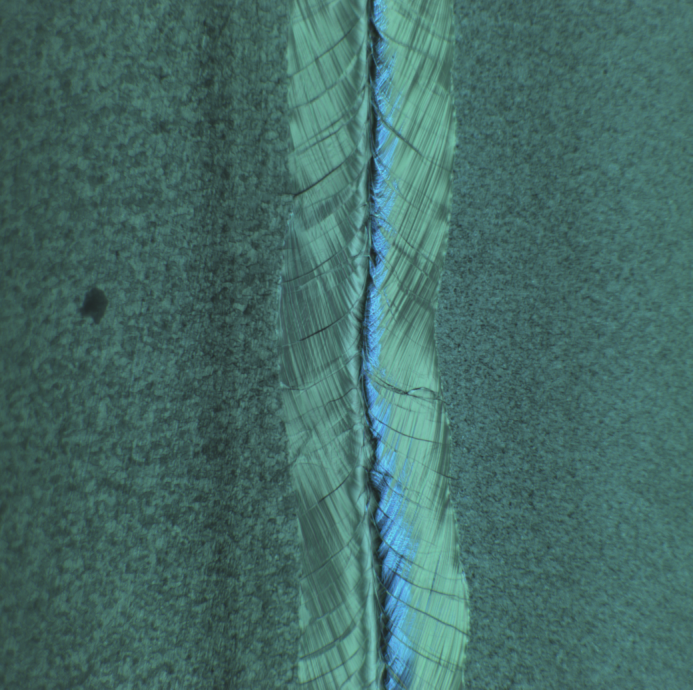
where the vectors are the parameter sets of each object and S the covariance matrix of objects in the image. It effectively normalises the different parameters of an object to make them comparable. If the Mahanalobis distance between an object and the average properties of its neighbours is large, that object could be classed as a defect.

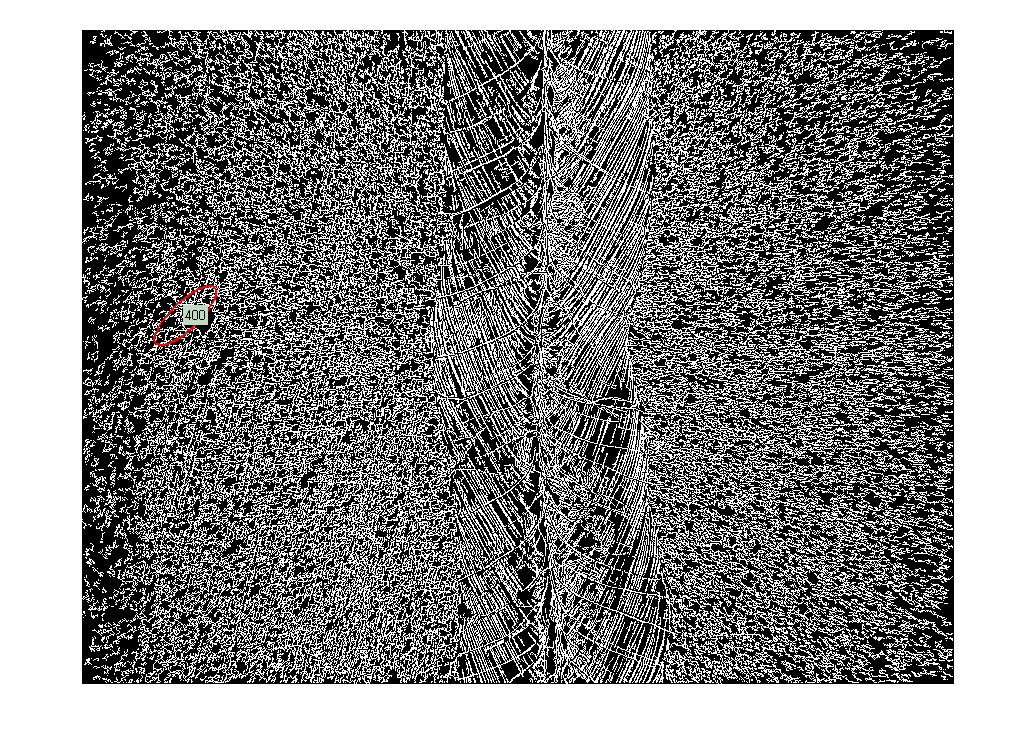
**Experimental**

The aim was to identify defects by maximising the mean Mahanalobis distance of such objects in relation to surrounding objects. Initially the program took into account 13 properties of each object. The first step was to remove a number of parameters whose inclusion in the original program had since been judged unnecessary: Distance to welding seam; Euler number; Area; Orientation; Mean colour. By a system of trial and error, the optimal parameter set maximising the mean Mahanalobis distance for defects in each image available was: Extent (no. pixels of object / no. pixels of bounding box); Major Axis length; Minor Axis length; Eccentricity; Solidity (no. pixels of object / no. pixels of convex hull)

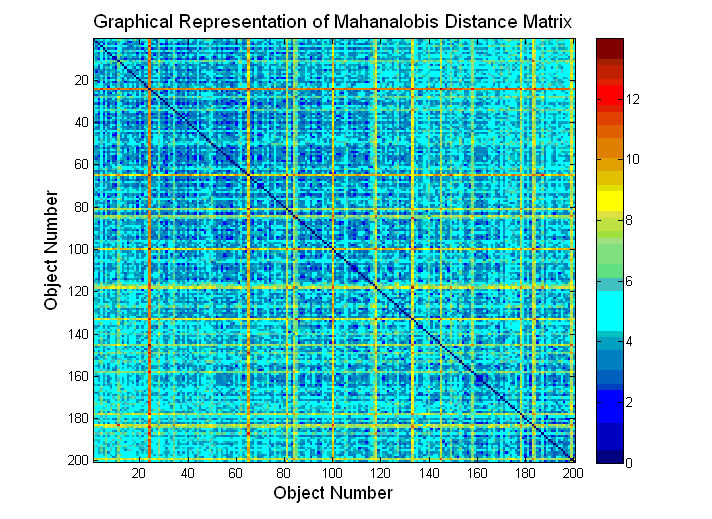
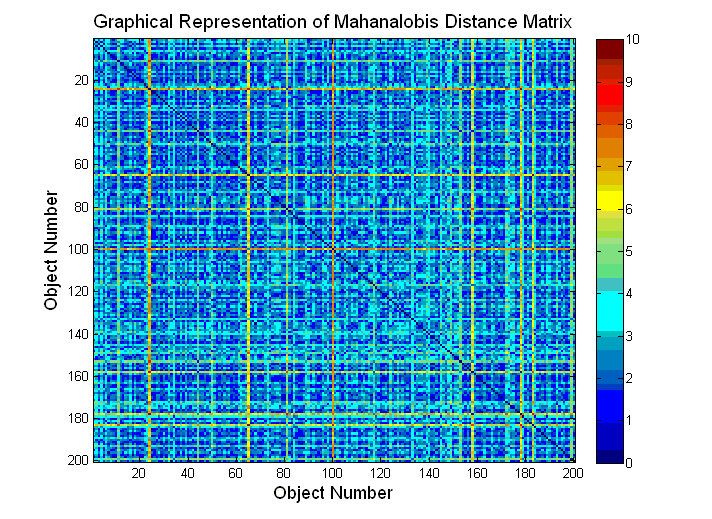
In order to investigate inter-parameter correlation, it was also necessary to see whether there was any variation across the image, i.e. was there any difference between the seam and not on the seam.

**Results and Analysis**

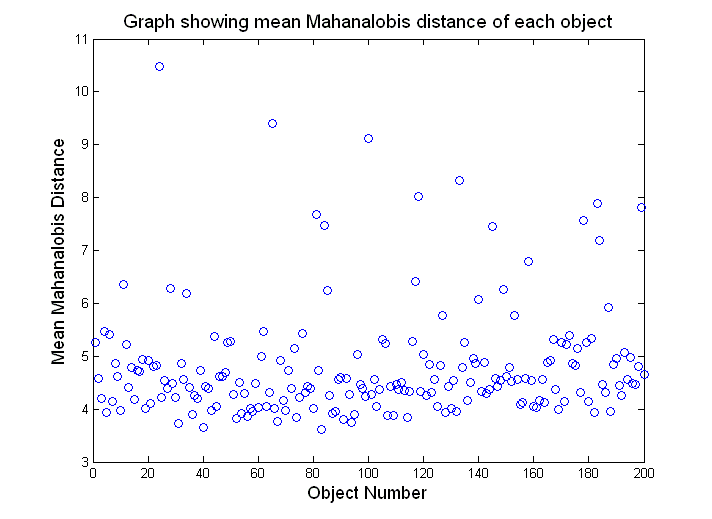
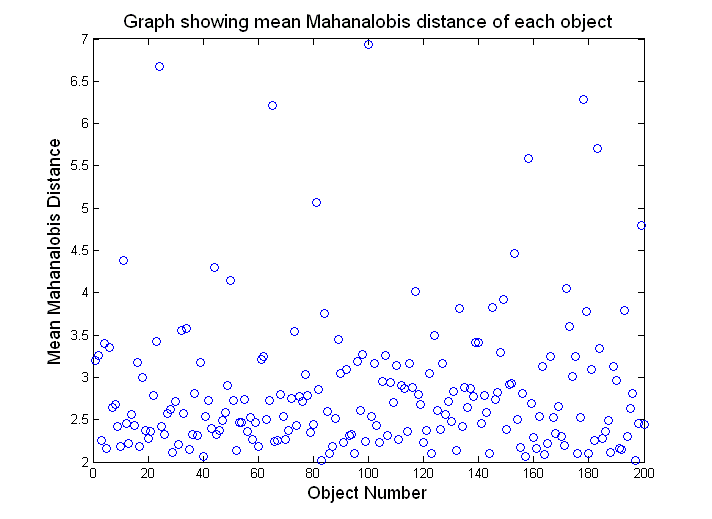
For a defect far from the seam:



*Fig. 3 – Left: Photo of seam of niobium cavity with defect on left, Right: Defect object encircled on processed image.*

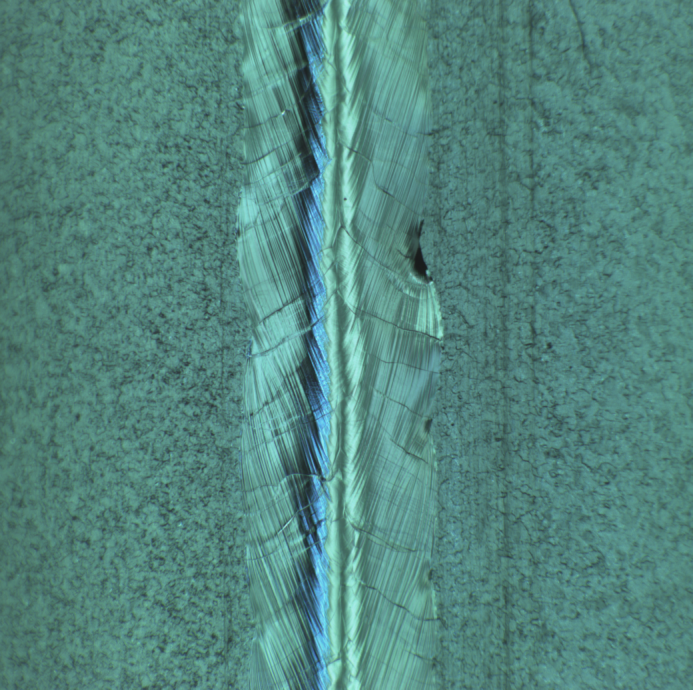


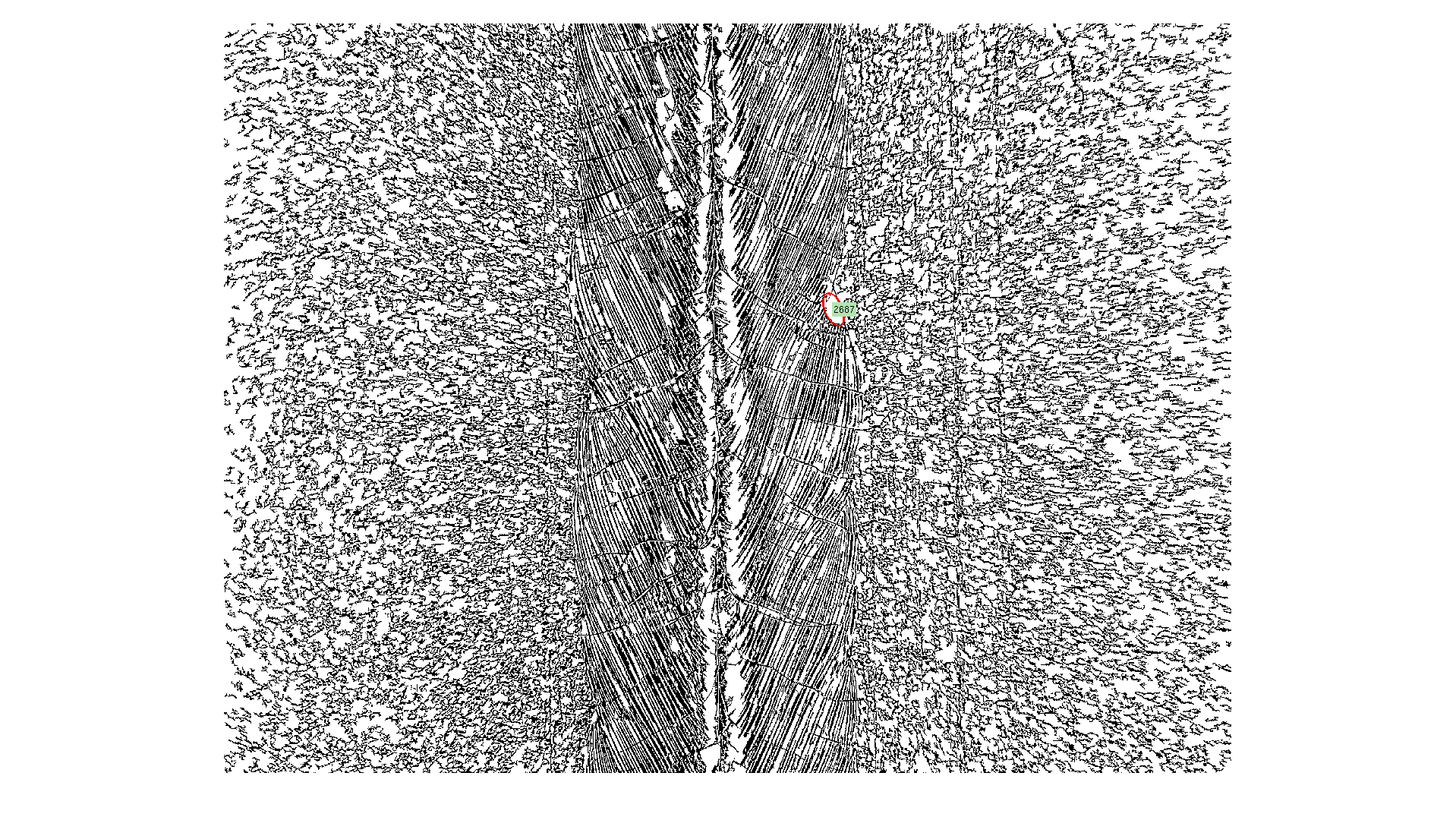
*Fig.4 – Graph showing colour representation of calculated Mahanalobis distance matrix – red indicates large distance, blue small distance. Right is that calculated when using all parameter, Left is that calculated when using only selected parameters.*



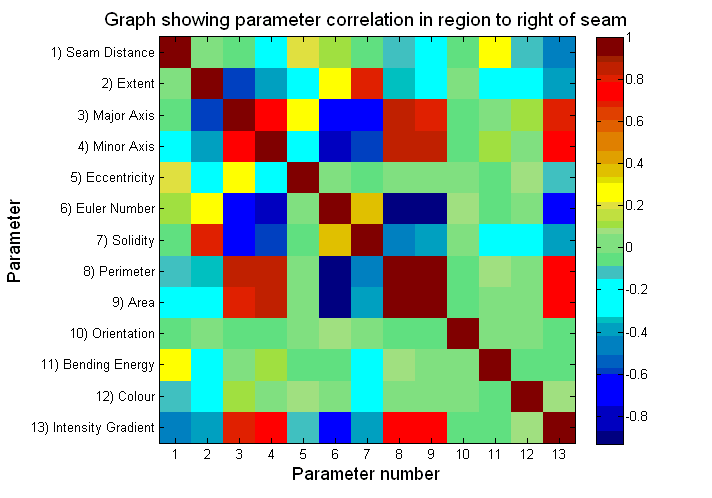
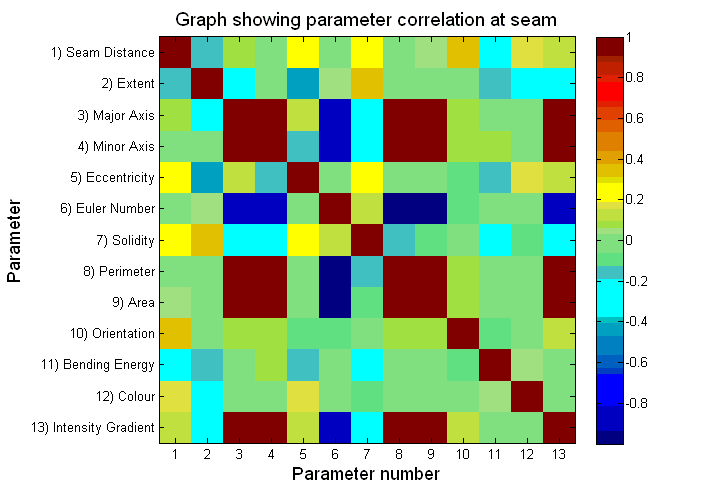
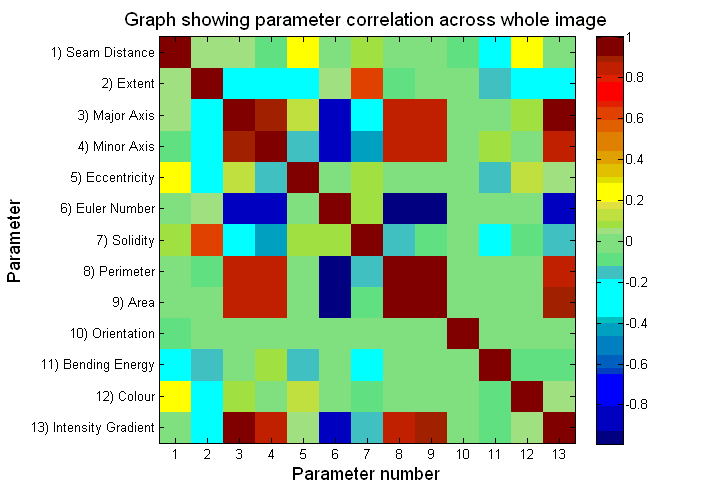
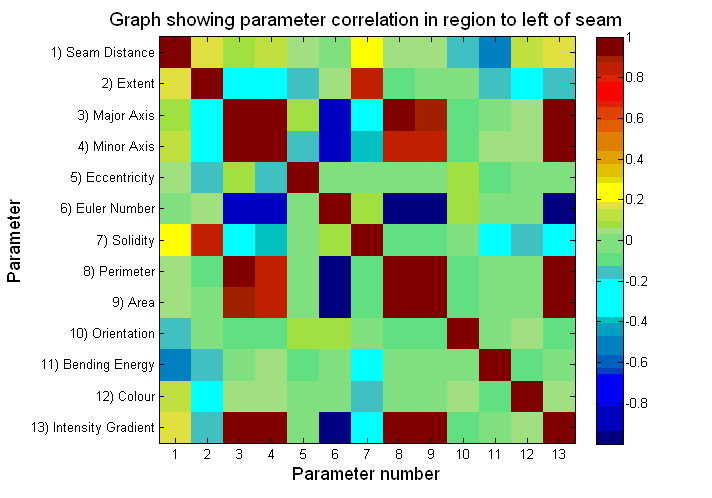
*Fig.5 – Graph showing Object number against mean Mahanalobis distance. Right is that when using all parameters, Left is that when using only selected parameters.*

It can clearly be seen that the Mahanalobis distance is maximised for the selected parameter set compared to using all of them – object 100 is the defect object in question (as 100 objects on either side of the defect object were included.)

For a defect on the right seam edge, it was necessary to use the complement image, due to large size of objects at seam.



*Fig.6 – Right: Photo of niobium cavity seam with defect on right edge of seam, Left: Processed complement image with defect object encircled.*

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*Fig. 7 – Graphs showing correlation between parameters – red indicates high positive correlation, blue indicates high negative correlation, green indicates no correlation. Top-left: whole image, Top-Right: region to left of seam, Bottom-left: seam, Bottom-right: region to right of seam.*

It can be seen that there are the same general trends across different regions. There is one exception, in that the correlation between object extent and solidity is significantly less pronounced at the seam than in the bounding regions. There are obvious correlations between parameters related to size: area; perimeter etc. The correlations related to Euler Number are not especially important, as it was a previously discarded parameter. There is an interesting correlation between parameters related to size and the Rdq parameter. Rdq is proportional to the object surface roughness and here relates to the RMS of the object’s intensity gradient. Therefore, the surface roughness of an object increases with size (and vice versa).

**Conclusion:**

An optimal parameter set for identification of defects in images of SRF cavity surfaces was found, namely: Extent; Major Axis length; Minor Axis length; Eccentricity; Solidity.

The parameter correlation was found not to vary significantly across the image, except for a lower correlation between solidity and extent at the seam. A positive correlation was found between object surface roughness and size.

**Acknowledgements:**

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**References:**

[1] M.Wenskat, E. Elsen, ILC Higrade Report, 2011