DEFECT IDENTIFICATION AND CHARACTERISATION ALGORITHMS FOR ASSESSING EFFECT ON COMPONENT STRENGTH

A. J McMillan

Aeronautical Engineering, Faculty of Advanced Technology, University of Glamorgan, Pontypridd, CF37 1DL, UK

alison.mcmillan@physics.org

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Abstract

The presence of defects, such as foreign matter inclusions or porosity, is a particular issue for composites. This paper demonstrates a defect sampling algorithm to characterize clusters of voids. This methodology has the potential to pass components as "fit for duty" where more traditional percentage porosity quality measurements would have designated these for scrap. For high value composites manufacturing, reduced scrap rates would yield important economic and material utilization benefits. The method might also be used to optimize the manufacturing process to reduce the effect, size or shape of porosity in regions of the component that would ultimately be most sensitive to it.

1 Introduction

It is well known that the presence of defects, such as foreign matter inclusions or porosity, can weaken materials, and that this is a particular issue for composites [1,2]. In the composites industry, manufacture quality is typically characterized in terms of the percentage porosity, and a composite component may be scrapped if the percentage level reaches a pre-determined maximum, or if particular individual voids are deemed to be too large.

In a production line environment, it is clearly impractical to perform a detailed mapping of the entire component to identify and characterize every defect. Typically an ultrasound scan will show a level of absorption, and this can be related to the porosity percentage, but it cannot identify or measure particular defects. Although this may predict percentage porosity to a respectable level of accuracy, it is well known that the strength knockdown of a material due to the presence of holes is derived from the stress concentration effects around the perimeter of the holes, and depends on the size, shape and orientation of the holes, and their relative proximity [3]. The stress concentrations due to small numbers of holes, or holes of regular size and distribution, can often be derived analytically and those results used to assess the strength of structures such as bolt flanges or weight reduction features [4]. In the case of composites however, the placing of the holes is obviously not deliberate, but random. Further, the manufacture process influences the porosity distribution, in as much as the localized temperatures, pressures and state of cure within the component during processing will influence the formation of pores and subsequent shaping of those pores [2]. The finished component, if of acceptable quality, will be placed into service where it will be subjected to the loads to which it was designed. Typically some parts of the component will be more heavily loaded than others, and it is therefore the more heavily loaded parts of the component which would be more sensitive to particular porosity distributions.

2 Representative geometry

2.1 Realism in geometry creation

It is self-evident that porosity weakens a material as a result of the localized increased stresses around the edges of voids in the material. Depending on how the porosity came to be there, these voids could range from being near spherical to being flattened or stretched out, and the boundary might be smooth, or jagged. Clearly the nature of such features would have a major influence on the increase of the localized stress above the nominal applied stress within the material. The strength of a material is usually determined through test, and failure initiates from the weakest point. Given that a test specimen of material prone to porosity will include some voids, this provides us with a strength baseline for a typical worst void. Testing specimens of different dimensions, and using Weibull statistical arguments is a known method for taking account of void size effects.

There are further issues which should be taken into effect. It is important to consider the void size variability, distribution of the voids within the material, and, in the case of flattened or elongated voids, whether there is any particular preferred orientation. While material samples might show the same percentage porosity, this could range from a single massive spherical void to a large number of tiny and well scattered smaller ones of various shapes, or the voids could be clustered. An obvious “worst” case example would be a row of perforations on a tear-off slip of paper.

To begin to a quantified analysis of the effect of porosity on strength knock-down it is first necessary to define what the nominal strength should be, from which the knock-down is calculated. To some extent this has been addressed [3], but investigation into void shape and material fracture mechanics should be employed to take this further. The second step is to quantify void spacing distribution, and to be able to recreate models of material with appropriate voids in order to perform stress analysis. In the examples shown in this paper, the basic geometry taken is 2D, and loading as defined in [3].The voids are taken to be circular of diameter 0.05 units, placed within a 5x5 unit square of material.

2.2 Algorithms for random distribution of voids

The obvious approach to modeling a material with randomly spaced voids is to choose random numbers to represent the co-ordinates of the center for each void. Unfortunately this technique does not lead to an even coverage of the material domain, and some voids may overlap. Furthermore, looking to the physical processes that cause the porosity, this type of void distribution is probably not representative.

The problem of random placement is well known to the computer graphics art community, where the requirement is to position artistic features onto a background, such as daisies onto a lawn. One approach known as “jittering” is to divide the material domain up into regions, and place a void at a random location within each region. This then maintains a random aspect to the location of each void, while at the same time ensuring a given level of porosity across the whole domain. The problem with jittering is that it is visually very obvious: while the actual distance between neighboring voids is allowed to vary, the set of nearest neighbors remains the same. The implication is that this controls the distribution statistics, and would seem as unsatisfactory for a scientific application as it is for an artistic one.

An alternative approach is known as a "Poisson disk" distribution [5]. Here the co-ordinates are generated at random, as before, but an exclusion principle is introduced. As each new void center is placed onto the domain, the proximity to all previously added voids is checked, and the new void is only added if it lies outside the exclusion zone for each existing void. On the simplest level, a limit might be set for minimum distance between voids, and attempts to place new voids would continue until it become no longer feasible.

The difficulty with the Poisson disk approach is that for any given exclusion zone size, the maximum number of voids that can be contained will vary. At one extreme, the random packing could be close to the theoretical maximum density packing of the exclusion zones, and at the other, the random packing could fall such that voids are spaced almost twice as far apart (Figure 1). The latter case might be indistinguishable from a packing where the exclusion zone dimension were larger. In practice, this is unlikely to be a real problem, as the random nature of the packing will ensure that there are some instances of near minimum distance closely placed voids. This problem is illustrated in Figure 2, where in this example the number of voids ranges between 13 and 16, and the minimum distance between voids is 1 unit. An exclusion zone of 1 unit is also imposed around the boundary. Even for a small domain such as this, each of the examples illustrates some closely located pairs of voids.

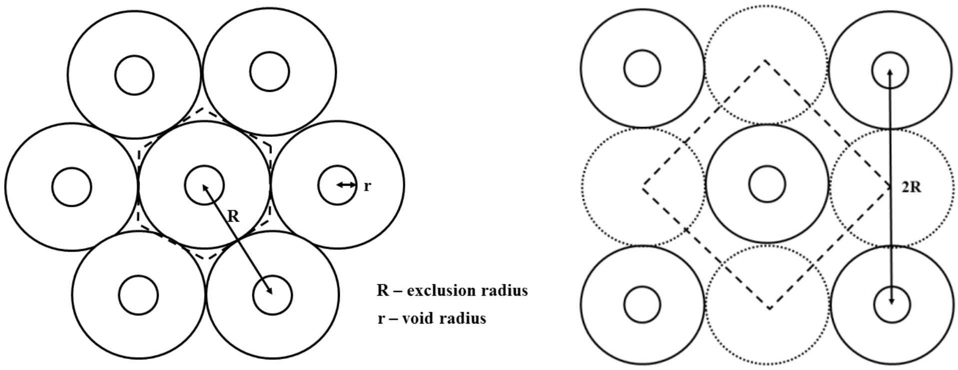

Figure 1. (a) Maximum packing density, (b) Minimum packing density

Working in 2D, the percentage porosity for a given void of radius r is given by

$$\frac{\text{area of void}}{\text{area controlled by exclusion radius}} \times 100\ \%$$

To obtain the maximum porosity, the area controlled by the exclusion radius is the area of the hexagon shown in Figure 1a. The minimum porosity for a fully dense arrangement of voids is given by the diamond shown in Figure 1b.

$$\text{maximum porosity} = \frac{2\pi}{\sqrt{3}}\left(\frac{r}{R}\right)^2 \times 100\%$$

$$\text{minimum porosity} = \frac{\pi}{2}\left(\frac{r}{R}\right)^2 \times 100\%$$

For the domain and exclusion radius sizes depicted in Figure 2, the theoretical maximum and minimum numbers of voids are 18 and 8 respectively.

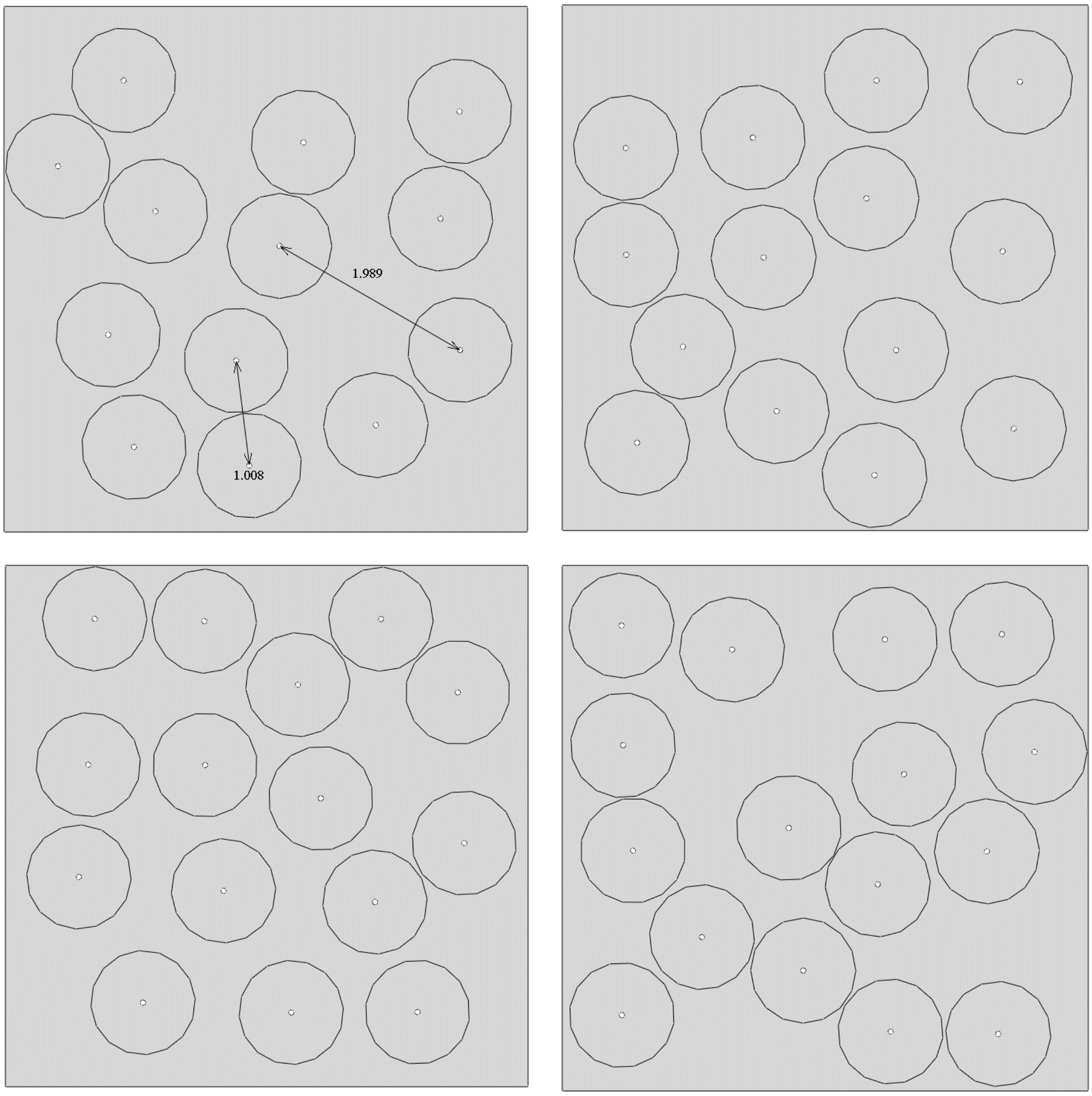

Figure 2. Poisson disk distributions with exclusion radius = 1 unit.

2.3 Potential issues

Although variability of number of voids may not seem ideal, for a body of material containing statistically significant numbers, the variation in distribution should be sufficient. A more difficult issue to be overcome is in the efficiency of the placing algorithm. Although it may be visually easy to spot when no further voids may be added (i.e. the Poisson disk is fully dense), this is less easy to do computationally. A more practical solution is to continue to attempt to place voids until the number of attempts exceeds some large number. It may be reasonable to accept a definition of “feasibly dense”, implying that for the majority of the domain, the distribution is fully dense.

From a practical perspective, partially dense packing can be classified according to the actual number of voids placed, and the imposed exclusion zone size. The latter can be related to the theoretical maximum or minimum packing density, to provide a quantifiable measure of clustering.

Note that while the figures shown here are for relatively small numbers of voids in a limited size domain, this is only for the purpose of illustration and development of the algorithms. In practice, statistically large numbers of voids are required.

3 Defect search and characterization

3.1 Sampling Algorithms

For full evaluation of a material specimen, a 3D representation of the specimen would be obtained, either directly by multiple cut-ups, or using NDE techniques. The image would then be analyzed for flaws such as voids or inclusions. Such an image would usually be represented by 3D pixels, and a search for flaws would be based on assessing each pixel, to determine whether it represents parent material or something else. The exhaustive search of the entire domain would give an accurate account of the relative volume of parent material and porosity, but much more sophisticated graphical analysis would be required to quantify void size, shape, orientation, and clustering aspects. Such analysis would be expected to require considerable computational power. Once this information is obtained as statistical data, it is then necessary to correlate it with some stress analysis based criteria, so that the material specimen can be sentenced as fit, or not fit, for the engineering duty it is intended to perform.

It is clear that to obtain a full 3D image is a major undertaking, and much of the information gathered will be similar from one specimen to the next. For manufacture production, the time required for exhaustive NDE would not be appropriate, and an indicative inspection would be more appropriate. For example, instead of imaging the whole specimen, it might be possible to image regions or individual pixels of each specimen. If sufficient of these regions or pixels were selected and assessed at random, then this data could provide a good approximation to the porosity level. A clustering analysis of the regions or pixels selected might then provide the basis for establishing void size, shape, orientation and clustering statistics. This latter process could be as computationally demanding as that for full image analysis. Thus, for fast sentencing of material specimens, a systematic method of selecting data should be developed that does not demand intensive post-sampling analysis.

The sampling algorithm presented here is based on the definition of a one dimensional path drawn through the material, with samples taken at incremental intervals [6]. For example, the output from each sample could then be in the form of long binary number, where each digit represents an increment on the path; a 1 being parent material, and 0 being a void. The number of 0s would define the porosity level, while the relative proportion of 1s and 0s at different points in the path could potentially be related to the void characteristics. Figure 3 shows such a sampling path, where each small circle represents a sample increment.

Here, it is clear that the path has a range of straight sections of varying length, and it is obvious that consecutive 0s on a long section of the path would indicate a void with a large dimension, whereas the same number of consecutive 0s at the end of the path with the rapid direction changes would indicate the area or volume of the void. The search path show here has just 128 sample increments, but this can be expanded by factors of powers of 2, in order to span a much wider range of void size, and provide data over a wider region of the specimen domain. The incremental distance is $\Delta l = 0.01$ unit.

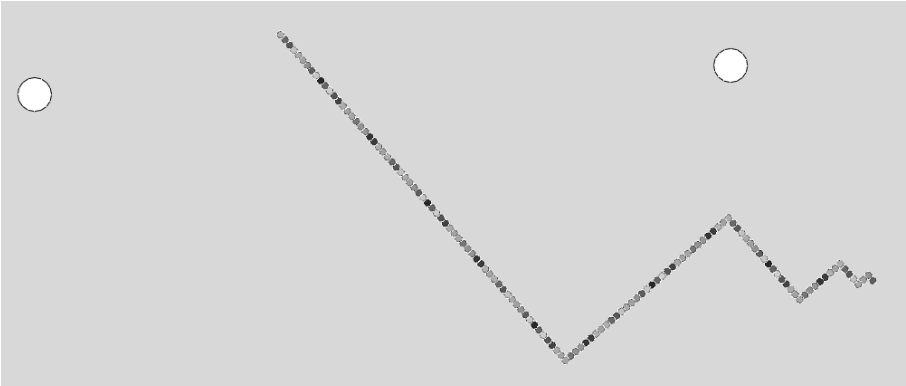

Figure 3. Sampling path

The equations to generate this particular path shape are as follows. The coordinates of the first point (x_0, y_0) are given by random numbers, confined within the domain of the specimen. A random initial orientation θ is given, from which the x and y components of the increment Δl can be calculated:

$$\xi = \Delta \mathrm{l} \cos\theta \ ; \ \eta = \Delta l \sin\theta$$

The i^{th} sample point is given in terms of the $(i-1)^{\text{th}}$ point as follows:

$$(x_i, y_i) = \begin{cases} (x_{i-1} + \xi, y_{i-1} + \eta)\text{: even legs of the path} \\ (x_{i-1} - \eta, y_{i-1} + \xi)\text{: odd legs of the path} \end{cases}$$

The path is defined by 2^n search points; the zero$^{\text{th}}$ leg having $2^{(n-1)}$ points, the 1$^{\text{st}}$ leg having $2^{(n-2)}$ points, and so on.

The search path length can also be determined. The circuitous length (following the path exactly) is given by $(2^n - 1)\Delta l$, and the distances travelled in the even and odd legs of the path are 2+8+32+… and 1+4+16+… respectively. It is obvious that the sum of the even legs is twice that of the odd legs, and therefore equal to 2/3 of the circuitous length. The direct distance, H, from the initial search point to the final search point is thus given by

$$H = \sqrt{(L_{\text{even}})^2 + (L_{\text{odd}})^2} = \frac{\sqrt{5}}{2} L_{\text{even}} = \frac{\sqrt{5}}{3}(2^n - 1)\Delta l$$

This provides a useful means to determine appropriate values for n and Δl. Although these equations are given in 2D it is easy to see how this can be generalized to 3D.

The key feature of this, or similar search paths, is the inclusion of multiple length scales in order to probe different features. Suitable shapes can be derived from fractal definitions, such as are employed in wavelets. This particular simple path is based on the Haar wavelet form. For full image analysis, wavelet signal processing analysis is very sensitive to edge detection, and it is anticipated that this desirable characteristic will apply in this random search context also.

For each specimen to be assessed, the use of a large number of such search paths would clearly be necessary. Each search path would target a different region of the domain, and would sample at a different orientation. To define a search path, it is first necessary to choose a search path definition: this specifies the shape of the search path, and the number and size of sample increments. Then the start position co-ordinates and the start orientation should be chosen. These should be chosen randomly to avoid systematic errors. Potentially multiple search sampling paths could intersect (Figure 4).

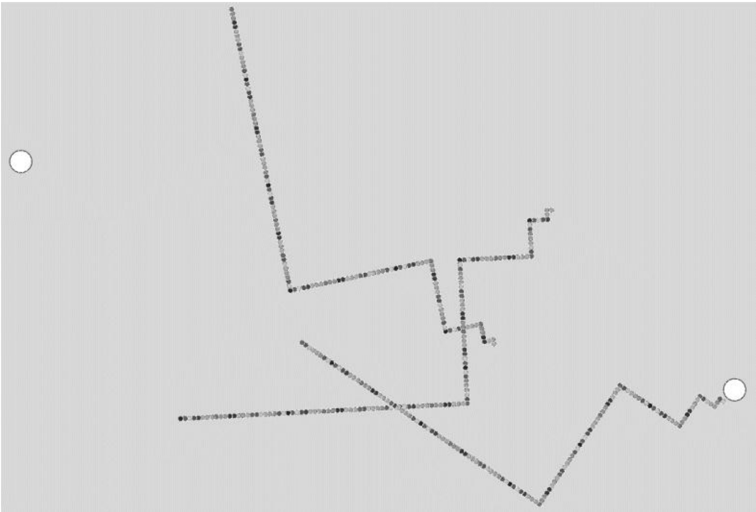

Figure 4. Intersecting search sampling paths

3.2 Stress analysis

For practical purposes, the designer of a component may place restrictions regarding maximum void size and maximum allowable percentage porosity, but these are derived from working experience and an appreciation of what is practically feasible to measure. To place the sentencing of a material specimen on a more scientific basis requires both a thorough understanding of the required loading duties and an assessment of the material flaws within the specimen. This should not only validate the extreme limits of the more pragmatic methodology, but also recognize and provide better interpretation of the “grey areas”. A component with a large rounded void in a low stressed region is more likely to acceptable than one containing a smaller void with sharp features in a highly stressed region.

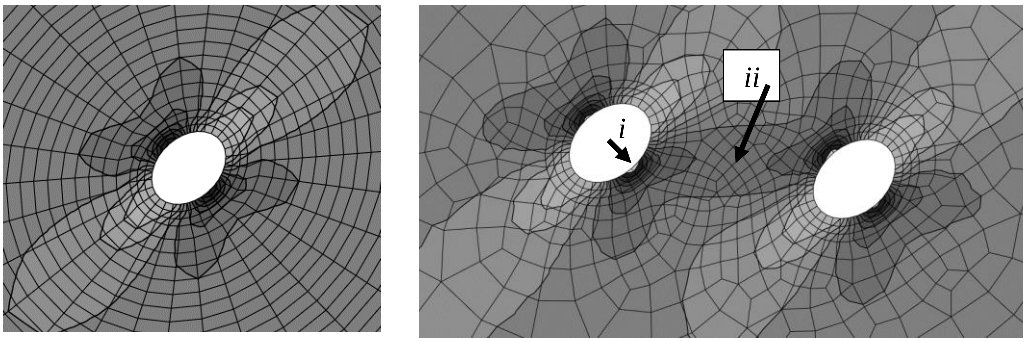

Figure 5. Maximum principal stress in void regions, for (a) a well separated void, and (b) two clustered voids.

For materials where the voids are expected to be of a similar rounded shape and size, the relative spacing or clustering is expected the deciding feature regards strength knock-down. The two examples (Figure 5) show circular voids in the same nominal stress field. The stress distributions and values are similar for both cases, except that the maximum value for stress is somewhat higher around the perimeter of the clustered voids *(i)* than around the single void, and there is a distribution of higher stress levels than nominal in the region between the two voids *(ii)*. It is clear that appropriate assessment of the void distribution variation statistics is essential for effective NDE sentencing.

4 Further work

4.1 Experimental verification of porosity distribution

Computationally based studies are useful to provide insight into real phenomena, but to progress this work further it is essential to measure real porosity in real material specimens. It is anticipated that actual void distribution statistics will vary from material to material, and with the manufacturing process variabilities. Ultimately this work should be linked to industrial process improvement activities.

4.2 Assessment and sampling using real NDE data

The search paths suggested in this paper assume that NDE techniques probe the domain of a material pixel by pixel. In fact, such observations are made using beams of ultra-sound or x-ray, and the image is created by the re-construction of detected signals, taking account of reflections and refractions at material interfaces. Efficient use of NDE data should take account of the cost of full domain scanning, and the potential for the use of medium or low fidelity scanning with quantified uncertainty, to obtain a suitably representative data set from which void distribution statistics can be deduced.

5 Conclusions

5.1 Experimental verification of porosity distribution

This paper demonstrates a defect sampling algorithm for characterizing the sizes, shapes, orientations and relative proximities for clusters of voids or inclusions. This methodology has the potential to pass components as “fit for duty” where more traditional percentage porosity quality measurements would have designated these for scrap. For high value composites manufacturing, reduced scrap rates would yield important economic and material utilization benefits. The method might also be used to optimize the manufacturing process to reduce the effect, size or shape of porosity in regions of the component that would ultimately be most sensitive to it.

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