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ABSTRACT

This paper introduces a technique to quantify internal flaws in a ceramic body. The approach uses data images obtained from 3D X-ray computed tomography. An approach called guided segmentation uses image processing methods applied to a series of the data images to quantify the flaw volumes. The technique is tested on synthesized data for spheres. The technique is then applied to real images of known size to examine its use.

INTRODUCTION

As the uses of ceramics become more varied and widespread, the ability to examine the internal characteristics of ceramics becomes more critical. At Argonne National Laboratory, there is a significant amount of research directed at characterizing ceramics using three dimensional X-ray computerized tomography (XRCT) [1,2]. The effort includes work examining the effects of the convolution kernel to XRCT [3]. Current work includes the estimation of flaw sizes in ceramics. The long term goal is to use the information obtained about the flaws in fracture mechanics. Size and position of flaws are important factors in analyzing the potential for fractures [4]. It is felt that the approach presented in this paper is a first step in automated flaw analysis of ceramic images using XRCT.

Internal flaws in ceramics may be found by examining reconstructed 3-D images of the ceramic bodies. To obtain the images, the level of attenuation of an X-ray through the ceramic body is taken. This is then repeated at many angles. These individual attenuation levels are then reconstructed to form a 3-D image. The 3-D images are stored in horizontal slices. Each slice is a two dimensional array usually of an equal number of rows and columns. Each position in the array holds a value representing the density of the original body at that position. These positions are either pixels (2-D values) or in our case represent voxels (3-D values). The voxel values are obtained in a real-valued format. They can then be transformed to an integer scale (0 - 255) called a gray-scale.

Flaws in ceramic bodies tend to block less amounts of X-rays because of the void created. This allows more X-rays through the body which translates into a different (usually smaller) value showing the flaw as a lower valued gray-scale segment of the image.

PROCESSING OF XRCT IMAGES

Segmentation of images is usually attempted by two methods: edge based and region based. The edge based method examines the differences of an image, relying on the detection of dissimilarity of point values (gradients) as its basis of distinction. Dissimilarities can be used to detect edges where one gray-scale level segment meets the boundary of a different gray-scale level segment. This method is generally considered computationally efficient and linear in complexity. Its main drawback is that it is very sensitive to noise. The region based method relies on developing regions of similarity. Region based methods traditionally use extensive parallel processing which can be computationally expensive and usually slower. However, they tend to be algorithmically sturdier and are rugged in that they are less sensitive to noise [see 5,6,7]. Clearly, both of these approaches have some strengths that are desirable for examining ceramic bodies. Our algorithm combines some techniques from both approaches.

THE SEGMENTATION ALGORITHM

The algorithm is divided into three phases. Phases 1 and 2 are applied to image slices, while phase 3 is applied to the series of slices. A predetermined threshold for the difference in gray-scale is used as a basis for flaw candidates.

The Algorithm

Phase 1. Determine an area to be a candidate for a flaw.

Phase 2. Trace the outline of the flaw. If the image is closed, record it.

Return Phase 1 if there are points greater than prescribed threshold.

Phase 3. Sum flaws from neighboring slices to obtain volume.

The steps of the algorithm are to find a potential flaw, determine if it is a flaw, and add its contribution to the overall volume of that flaw. While this seems straight forward enough, the examination of details will show how we combine the use of similarities and dissimilarities.

Phase 1. Determine an area to be a candidate for a flaw.

To discover a potential flaw area, we examine the gradients of the gray-scale images for points on an edge of a flaw. The largest gradient of the image is used as a base point from which to search. From this point, eight vectors are obtained leading in the eight neighboring directions (N, NE, E, SE, S, SW, W, NW). The values of the vectors are compared to the values of the main body. If one direction proves to be significantly different from the main body, the area is considered a candidate for a flaw.

Two important parameters are obtained for the candidate. The first is a direction of the flaw from the point. Since the point is assumed to be an edge point, the edge would be in an orthogonal direction to the flaw. Therefore the search for the edge is given a starting direction.

The other parameter is the value of the vector called the characteristic vector. The characteristic vector is used as an indicator of what value the flaw has produced. This is used as a basis for that entire flaw.

Phase 2. Trace the outline of the flaw.

Finding a candidate for a volume flaw does not necessarily mean that a volume flaw exists. If a flaw exists, we assume that it should be a closed (outside edge connected) segment. To determine if we have found a volume flaw, we trace around the outer edge of the segment. To trace the edge we compare, in the orthogonal direction to the flaw, the gradients searching for the largest values of one direction and its neighbors. For example, if the flaw is in the East, we search in the North, Northwest, and the Northeast for the largest gradient. However, we do not only look for dissimilarity for the edge trace. The algorithm requires a vector of similarity to be maintained in the body of the flaw. This has the effect of stabilizing the tracing of the edge. It also reduces the dependence of the algorithm on the gradients, because they are so susceptible to noise. This allows the segmentation to be guided around the desired feature while being anchored in the flaw itself. It is this way that we combine both approaches to minimize our weaknesses while maintaining computational efficiency.

Phase 3. Summing correlated areas of slices.

As the program goes from one slice to the following slice, it stores the position of each flaw in the previous slice. When it finds a flaw in the slice that

follows a flawed slice, it compares the position of the flaws in the previous slice with the position of the flaws in the next slice. If they are found to be from similar locations relative to each slice they are assumed to be from the same flaw. The algorithm combines the volume obtained from the flaw of the first slice to the volume from the next slice.

RESULTS

The algorithm has been applied to both synthetic and real data. The synthetic data contains spherical and elliptical flaws of predetermined sizes. The real data is obtained from a ceramic body (Si_3N_4) that has five known flaws contained in it. In the synthesized data, the ability to assign sizes to the flaw gave us the ability to test the effect of varying the prescribed number of expected voxels (3D pixel elements). The real data gave us the ability to know if the approach actually worked.

It should also be noted that the program at this time is inclusive in nature. That is, when a voxel is thought to contain an edge of the flaw, the program includes the voxels with the flaw. This means that the volumes obtained by the program have as a lower bound the volume of the flaw.

Tables 1 and 2 compare the capabilities of the algorithm on spherical flaws with an equal expected number of voxels. However the volume of a voxel is diminished by one-half. This reduces the volume of the expected flaw by one-half.

Table 1. Voxels of size 0.66 X 0.66 X 0.77 simulated sphere flaws

Expected	202	300	400	500	600
Observed	222	319	423	536	637
% difference	9.4	6.33	5.75	6.4	6.16

Table 2. Voxels of size 0.66 X 0.33 X 0.77 simulated sphere flaws

Expected	200	300	400	500	600
Observed	235	322	432	542	641
% difference	17.5	7.33	8.0	8.4	6.83

It appears that the algorithm is not dependent on the size of the flaw as it achieved similar results with the smaller flaws and larger flaws. It is also noted that as the number of voxels increased, the estimate remained approximately the same.

We obtained real data from a ceramic body (Si_3N_4) which contained known flaws of specific size. Figure 1 shows the reconstructed picture of the body

that was used for testing. The body contained five holes or flaws ranging from 1mm to 5mm in size, these are quite apparent as the five blacker segments seen on the figure. Table 3 lists the results from this slice. The number of voxels obtained from the 1 mm flaw was slightly higher, probably due to the influence of the crack in the ceramic body running through the 1 mm flaw. (see Figure 1) Of note is the fact that the algorithm, as programmed, did not pick up any voxels from the crack. This is the way the program should perform. It was designed to discover volumes, not cracks.

Figure 1. A ceramic image with known flaws

Table 3. Results of known flaws contained in real data

flaw size	1 mm	2 mm	3 mm	4 mm	5 mm
expected	160	641	1,443	2,564	4,006
observed	192	686	1,579	2,659	4,182
% difference	20	7	9	3.7	4.4

These results are as expected. We should note that the variation of values from one size to another was not consistent. That is, the percentage of voxels that were included in our estimate above the expected was not consistent from one number to the next.

DISCUSSION

The algorithm works quite well on the data tested. However, the algorithm as it is programmed has some inherent weaknesses. Of particular note is that it cannot handle flaws with pointed or sharp edges. If these edges amount to a significant amount of volume or give information as to the connection of one flaw to another, they may be lost in this algorithm. In general, concave flaws, because of their corners, give this algorithm a problem unless the corners are well rounded and have a wide distance from flaw edge to flaw edge.

If a crescent shaped or cap shaped flaw forms a slice image that has a solid area within the flaw, this algorithm may overestimate the actual flaw. In fact, this would happen if the distance from the edge to the contained solid was greater than the vector length. If the distance is not greater, the characteristic vector may be fooled into misinterpreting the density of the flaw. Either way this could easily cause problems.

These two particular problems may be solved with a method that determines the flaw regions and then attempts to determine an edge. One such approach we are exploring is the use of a neural network to "learn" the characteristics of a candidate and determine the "region" with flaw characteristics.

CONCLUSIONS AND FUTURE WORK

The problem of quantifying volumes is a complex and difficult problem. Our work to date is encouraging. The performance of the software developed is highly dependent on the quality of the gray-scale images. The main difficulty arises from the noise in the system, making the tracing of a closed edge difficult even with a flaw characteristic vector used as an anchor for the tracing process. It does seem quite promising that the combination of edge and region detection can work in a synergistic manner in the evaluation of flaws and flaw sizes.

To eliminate a great many of the current problems, we are examining the use of neural networks in conjunction with the edge detection approach. We believe that the combination of these would improve the results obtained on highly noisy images.

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The Guided Segmentation Algorithm

Results (cont.)Real data Si_3N_4

flaw size	1 mm	2 mm	3 mm	4 mm	5 mm
expected	160	641	1,443	2,564	4,006
observed	192	686	1,579	2,659	4,182
% difference	20	7	9	3.7	4.4

* note the crack in the phantom of 1 mm flaw

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