Crack's Detection, Measuring and Counting for Resistance's Tests Using Images

Carlos Briceño, Jorge Rivera-Rovelo, and Narciso Acuña

Universidad Anahuac Mayab
krlozgod@gmail.com, {jorge.rivera,narciso.acuna}@anahuac.mx

Abstract. Currently, material resistance research is looking for biomaterials where mechanical properties (like fatigure resistance) and biocompatibility are the main characteristics to take into account. To understand the behavior of materials subject to fatigue, usually we analyze how the material responds to cyclic forces. Failures due to fatigue are the first cause of cracks in materials. Normally, failures start with a superficial deficiency and produce micro cracks, which grow until a total break of the material. In this work we deal with the early detection of micro cracks on the surface of bone cement, while they are under fatigue tests, in order to characterize the material and design better and more resistant materials according to where they would be applied. The method presented for crack detection consists in several stages: noise reduction, shadow elimination, image segmentation and path detection for crack analysis. At the end of the analysis of one image, the number of cracks and the length of each one can be obtained (based on the maximum length of crack candidates). If a video is analyzed, the evolution of cracks in the material can be observed.

1 Introduction

Tests with new biomaterials like bone cements with monomers of amino group, should be conducted in similar conditions to the real use; in the case of bone cements, it is very important because they are used inside the human body (implants, prosthesis). Particularly important is the analysis of the resistance of the material, and the study of the material under stress (by external forces applied on it).

To understand the behavior of materials subject to fatigue, usually we analyze how the material responds to cyclic forces. Such forces can cause cumulative damage in the material, and depending on the intrinsic properties of the material, as well as to external factors which can be under control in laboratory experiments, the service life of the material could be reduced.

Fatigue is a kind of failure observed in materials under dynamic and fluctuant forces. Such failure can be observed even in cases where the force is below the resistance threshold; they can appear suddenly and can be catastrophic. Failures due to fatigue are the first cause of cracks in materials.

Normally, failures start with a superficial deficiency and in conditions where the local force induced is greater than the resistance value of the weaker grain,

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or microstructural barriers. In most cases, the superficial fault results in one or more micro cracks, which can be observed with a microscope. The micro crack start growing by discontinuity points in the material, which concentrates the efforts.

Crack detection and tracking of its growth in materials like bone cements, gives useful information about early stages in fatigue damage; this kind of damage is similar to the one the bones suffer in daily activities. Such information can be used to develop better materials (ie. more resistant materials).

Prosthetic bone cement can be used in orthopedics and odontology; it is an acrylic resin used to fix the prosthesis to the bone [1]. This kind of cement is used in orthopedics for hip, knee or shoulder surgery (for example, to replace by a prosthesis), as well as in spinal surgery and dental prosthesis. In such surgery, the bone cement is used to fill the spaces or holes between the (metal) prosthesis and the bone cavity where it should be fixed. Currently, we can find commercially bone cements with different characteristics like viscosity (high, low, extra-low), or concentration (20g, 40g, 50g, 60g), and we choose among them depending of the application.

According to the norm ASTM E206 described in [2], fatigue is a structural and progressive change, located and persistent, which occurs in materials subject to efforts and fluctuating deformations, which can produce micro-cracks or even total rupture of the material after a sufficiently large number of fluctuations. Fatigue can also be described as a progressive fail which occurs due to crack propagation until they reach an unstable size. For this reason, we should put attention to the materials used in the bone cement and also to its applications, particularly if it implies repeated and fluctuating forces. Fatigue causes failures because of the simultaneous action of cyclic and strain (tension) stress, as well as plastic deformation.

The goal of the analysis of the growth of (micro) cracks, is to understand the mechanisms of the beginning and growing of cracks governing early stages of serious damage in bone cement, which are manufactures with monomers of amino group in a matrix of methyl methacrylate.

In this work we deal with the early detection of micro cracks on the surface of bone cements, while they are under fatigue tests, in order to characterize the material and design better and more resistant materials according to where they would be applied.

We use a microscope and a conventional camera in order to obtain some images, which are analyzed to detect crack clusters, identify crack paths, and to count the number of cracks in the image.

2 Detection of Cracks

We can deal with crack detection by means of several approaches; for example, we can use probabilistic or stochastic theory [3,4], continuous models [5] or deterministic Markov processes [6]. However all of them deal only with crack detection and does not analyze the growth of the crack, which needs to follow the crack paths during time.

Some characteristics of the cracks are their color and their width; cracks have a darker color than plastic deformations, scratches and grain boundaries. Therefore the threshold calculated assure that only cracks are detected, also cracks are wider than grain boundaries so if a grain boundary is detected as a crack, the difference can be observed as it would be a discontinuous line (dotted line).

The method presented in this paper allows the analysis of crack growing or crack evolution due to its ability to get not only the crack clusters, but also the number and lengths of paths in the image. Figure 1 shows the general scheme of the method.

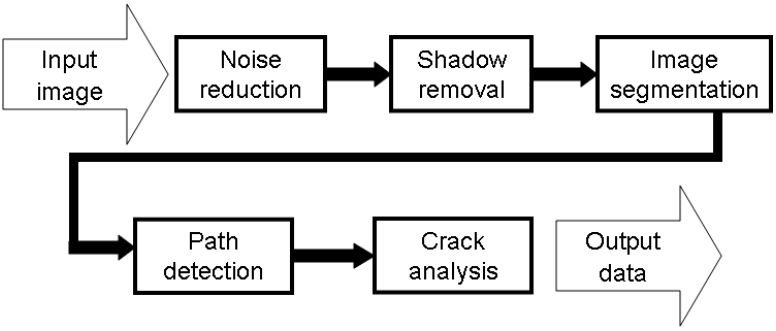

Fig. 1. General scheme of the method

A low pass frequency filter is used for noise reduction/elimination (Gaussian low pass filter), together with a median filter for elimination of salt and pepper noise (if it is present). Once the noise on the image has been reduced, it could be applied a method to reduce some effect on the boundaries of the images; this effect is called *shadow*. The shadows can result in erroneous detection of cracks on the boundaries of the image. To eliminate shadows, a histogram smoothed by a Gaussian kernel with bandwidth B can be used to calculate a threshold, and pixels with gray values over the thresholds are changed for such value.

After the stage of preprocessing the image, we need to classify the image pixel into regions; that is, we segment the image (assign every pixel to a particular segment). Given a pixel, we can determine if it belongs to a segment or to other one by comparing its gray value with a threshold. The threshold value in step 2 is calculated in such a way that the resulting value can minimize the variance of every segment, and at the same time maximize the variance between segments [7]; that is, we compute the ratio between the two variances and choose as the threshold the value which maximizes that ratio. The weighted within-class variance is given by Eq. (1), while the the class variances are given by Eq. (2), the class probabilities are given by Eq. (3) and the means are given by Eq. (4). $P(i)$ is the probability of the gray value i.

$$\sigma_w^2(t) = q_1(t)\sigma_1^2(t) + q_2(t)\sigma_2^2(t) \tag{1}$$

$$\sigma_1^2(t) = \sum_{i=1}^{t} [i - \mu_1(t)]^2 \frac{P(i)}{q_1(t)} \qquad \sigma_2^2(t) = \sum_{i=t+1}^{I} [i - \mu_2(t)]^2 \frac{P(i)}{q_2(t)} \tag{2}$$

$$q_1(t) = \sum_{i=1}^{t} P(i) \qquad q_2(t) = \sum_{i=t+1}^{I} P(i) \tag{3}$$

$$\mu_1(t) = \sum_{i=1}^{t} \frac{iP(i)}{q_1(t)} \qquad \mu_2(t) = \sum_{i=t+1}^{I} \frac{iP(i)}{q_2(t)} \tag{4}$$

Once we have the segmentation, the crack clusters are detected as neighbor pixels with values under certain threshold; such pixels are considered as vertex of a directed graph. The adjacency of two vertex is determined with the adjacency of the pixels: if they are horizontal or vertical neighbors, they are connected with an arrow of length 1; if they are diagonal neighbors, they are connected with an arrow of length $sqrt(2)$ (see fig. 2). Then, the arrow lengths are modified adding a factor equal to the difference in gray values of the adjacent vertex (connected pixels). Finally, a method to find minimum length paths is used in order to build the paths in each crack cluster (considering that the cracks are associated with the darkest gray values of the pixels).

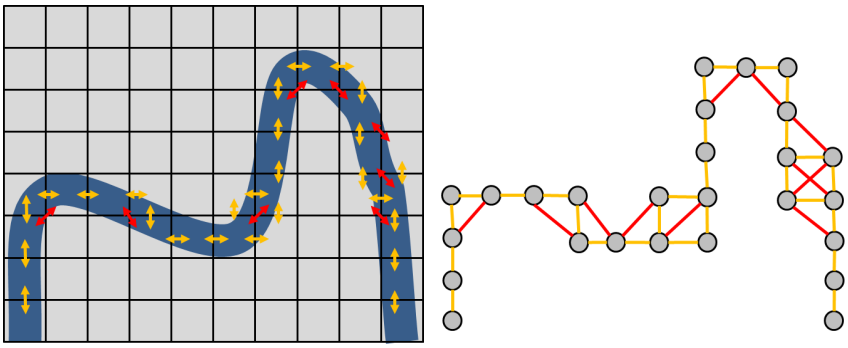

Fig. 2. Graph creation example. Supose there is a curve (crack pixels) like the blue one in the rigth image. The length of arrows is first assigned according to adjacency (yellow arrows are of length 1, while red arrows are of length $sqrt(2)$).

3 Experimental Results

Figure 3 shows an original image of a section of the surface of the material subject to strain efforts (obtained with a microscope with 200x of amplification), as well as the detected cracks. The threshold used in this case for the shadow elimination was 132 (gray value), which was obtained as the maximum increment of the blurred histogram of the image, with a bandwidth of $B = 30$. The number of cracks detected is 762, and the length of the longest crack is 179.41 pixels.

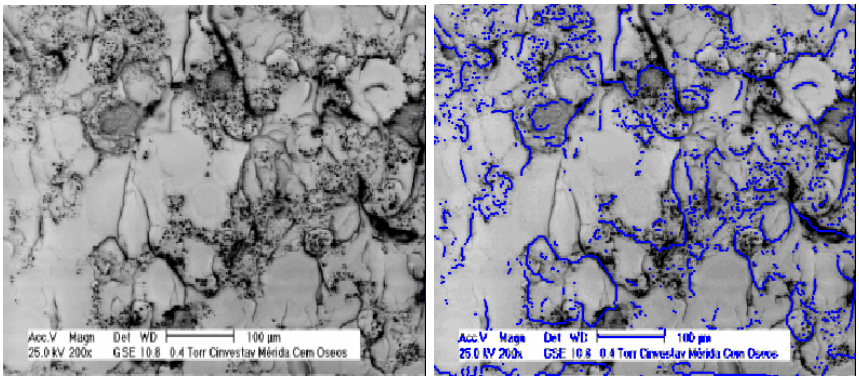

Fig. 3. Crack detection in a section of the surface of the material subject to assay under strain. a) Original image; b) Cracks detected (blue pixels).

Figure 4 shows the results with different bandwidth for the Gaussian filter. According to our experiments, the best value for the bandwidth of the Gaussian kernel used is $B = 35$, because in average it produces a threshold which allows a better identification of the cracks in the images.

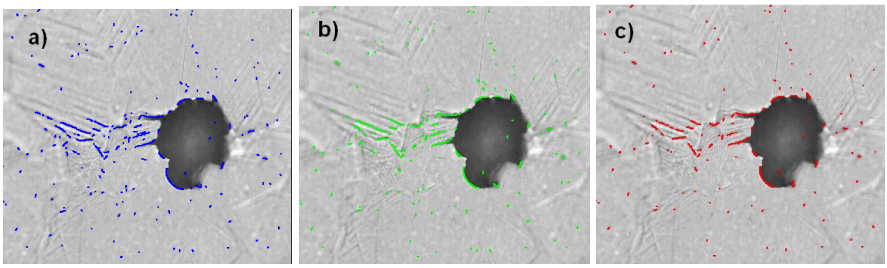

Fig. 4. Results obtained using different bandwidth for the Gaussian kernel used in filtering. Bandwidth: a) 30, b) 35, c) 40.

The method was applied to a set of 200 images (some of bone cement and others of steel). Two methods for removing the shadows in the images were applied. The first one applies an exponential decreasing value to the pixels of the border of an image if their mean gray level value is 10 units greater than the mean gray level value of the inner pixels of the image (this method is called shadow removal). The second one is the median filter. Figure 4 shows the number and size of the cracks detected (given in pixels) for a set of 40 images, comparing the results using the shadow removal method and using a median filter. According to the results, the median filter gives more accurate detection of cracks, in comparison with the crack detection using the shadow remove method instead; on average, if the shadow remove method is applied, fewer cracks are detected than

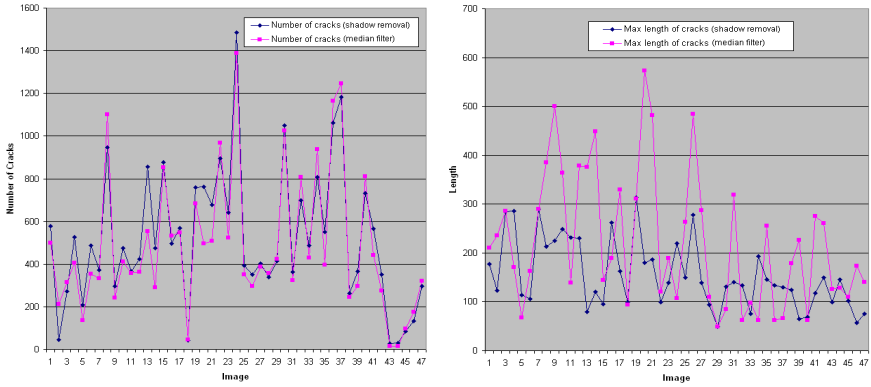

Fig. 5. Results obtained with some bone cement images. Observe that the number of cracks is bigger with the median filter, and the lengths are bigger with shadow remove (because some cracks are joined together).

using the median filter but that is because that method sometimes erroneously joins two or more cracks and because of that larger cracks are detected too.

Figure 6 shows why the median filter was the best option, you can observe than the median filter almost detect the complete hole in the middle of the image while shadow remove joins one crack at the left of the image with the crack at the bottom creating a big crack that goes through the hole. Using the median filter a threshold of 84 was calculated, 133 cracks were detected and the length of the largest cracks detected was 56.698. Using shadow remove a threshold of 158 was calculated, 155 were detected and the length of the largest crack detected was 173.509.

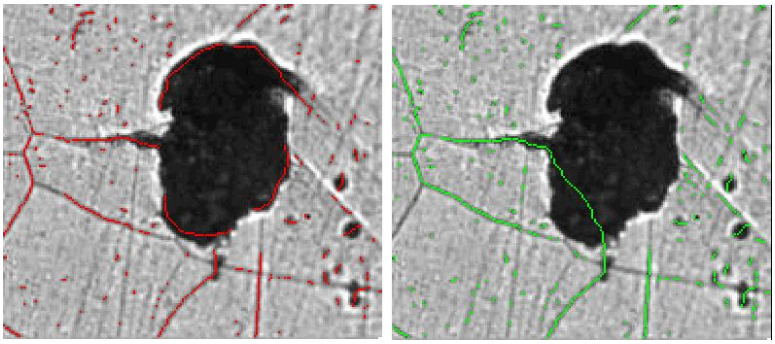

Fig. 6. Left: results using the median filter for removing the shadows (the cracks detected are in red color). Rigth: results using the method *shadow remove*, that is exponential decreasing gray value assignment (the cracks detected are in green color).

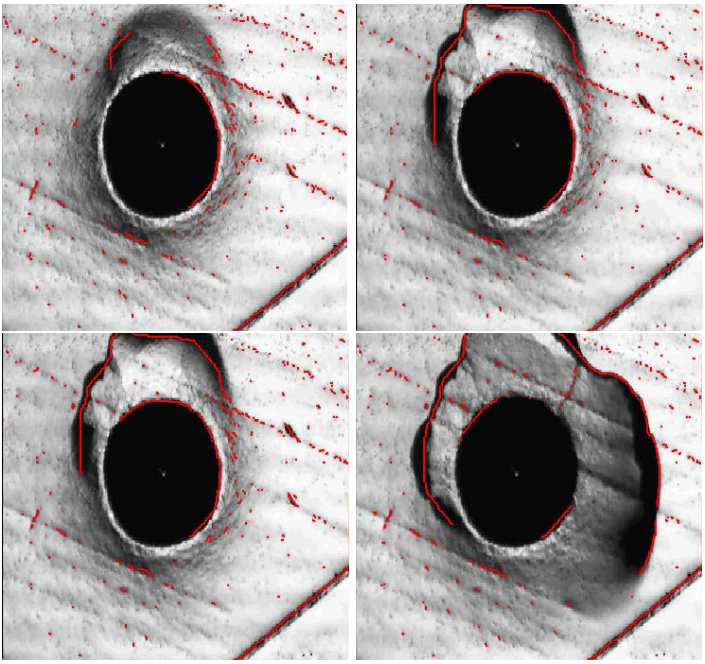

Fig. 7. Evolution of micro cracks detected in steel assay images

Figure 7 shows the detection of cracks in a steel assay subject to strain efforts; the method is applied to the set of images taken from the video of the microscope, and we can track the evolution of the cracks.

4 Conclusion

The method described can detect micro cracks in images of materials like bone cement under fatigue efforts. To accomplish such task several steps are needed, from image denoising to crack path calculation. The noise reduction and the shadow elimination, are of particular importance because otherwise, misclassification of pixels occurs.

The method presented has some limitations. One of them is that it cannot detect cracks in the form of trees because the crack are detected as one continuous line, and some cracks can be erroneously detected at the begging of the cracking process because the cracks are not dark enough yet.

Even that in about 93% of the images analized we were able to eliminate shadows correctly, there are some cases where different cracks are detected as one crack (they are erroneously joined), and other cases where one crack is divided into two cracks. We are analyzing how can we improve the accuracy of the method when detecting cracks by improving the removing of the shadows.

Another thing to work on, is that grain boundaries are sometimes confused with cracks; however this can be easily identified because the cracks are small in length, have a darker gray value and are thicker than grain boundaries; that is, visually the boundaries can be observed like a discontinuous crack (like a dotted line).

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