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# An Image Analysis Based Damage Classification Methodology

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ABSTRACT: Measurement of the extent of damage in a real structure is extremely important in terms of any maintenance strategy. However, this measurement often turns out to be difficult, time consuming and error – prone. The necessity of a simple, fast and relatively inexpensive damage monitoring system with reliable measurements is growing for quite sometime. The paper proposes a camera based image analysis technique to quantify and classify damage in structures at various levels of scale. The general method has been applied to corroded plate specimens in the laboratory with the aim to identify the affected areas on a steel pile due to pitting corrosion. The method depends on the contrast of the corroded region with respect to its surroundings, performs intelligent edge detection through image processing techniques and computes each affected and closed region to predict the total area of the affected part along with its spatial distribution on a two dimensional plane. Moreover the performance of the camera allows defining a detection threshold and the so-called probability of detection (PoD) and probability of false alarms (PFA). PoD are suggested as functions of the area of the pitting for the construction of Receiver-Operating-Characteristic (ROC) curves. The methodology can be used as a tool for the owners/managers of the structure for objectively quantifying and localising the extent of pitting corrosion, rather than providing information through a subjective visual assessment. Moreover, it allows introducing the probability of detection and probability of false alarms in the decision chain and in risk analysis. The method is shown to be robust, reliable, simple and inexpensive.

## 1 INTRODUCTION

Structural health monitoring and the detection of damages in structures have gained increasing importance in recent times. Successful detection of damage can be directly related to the epistemic uncertainty related to the deterioration of a structure and recommend appropriate proactive maintenance, rehabilitation strategies and optimized decision making policies as required by the engineers, owners, managers and the users from safety and serviceability aspects. Accurate non-destructive damage detection techniques help recommending proactive measures in terms of assessment and performance at any given condition of a structure. This paper considers a four level hierarchical framework proposed by Rytter (1993) comprising of the detection of the presence, location and extent of damage and the prediction of remaining service life of a structure. The paper proceeds to illustrate an image processing based damage detection technology including the first three levels of such a framework since the problem of predicting service life is dissociated from the remaining three levels both in scope and extent (Carneiro, 2000).

The problem of marine environment induced damage on steel piles has been considered and the harbour in St. Nazaire, located on the Atlantic coast of France has been considered to be the structure under consideration. The photographs of chloride induced corroded plates have been analysed using image processing techniques and the damage has been successfully described from both qualitative and quantitative aspects. The statistical properties of the spatial variation of the damage have been found. The probability of detection and the receiver operating characteristics (ROC) have been constructed. The method is observed to have a definite potential for use as an unmanned structural health monitoring tool.

## 2 DESCRIPTION OF THE PROBLEM

### 2.1 *The Benchmark Structure*

The benchmark structure is a wharf located at St. Nazaire, France and the general arrangement of the wharf is provided in Figure 1. This wharf belongs to the category of on piles wharfs. It is located in the

estuary of Loire river near between Nantes and Saint Nazaire towns and is a very important harbour on the Atlantic side of Franc.



Figure 1. Steel piles with Corrosion.

Being in the marine environment, the steel piles are susceptible to corrosion and hence the assessment of the structural health of such a structure is considered to be of great practical importance. In fact steel piles play two major roles - the first being a mechanical function and the second being a protection of reinforced concrete inside against corrosion, which is generally uniform. Submarine inspections and investigations of localized corrosion have been observed by divers in this regard. These damage conditions have been recorded on video tapes and reported as pictures on inspection report. The damages look like pitting in white metals, which is usually why the corrosion is referred to as 'pitting corrosion'. This type of corrosion is often a consequence of the defects in the metals that the structure is comprised of. In fact, these piles come sometimes from the rebus of the pipe-lines (non-conforming pieces).

The presence, the location and the distribution of the corroded regions are regarded to be vital information for the assessment of structural health at a certain condition. From standard inspection it is very hard to quantify these properties due to the harsh conditions and it brings about a considerable and unwanted increase of inspection time. An automatic video pictures processing after appropriate preprocessing of the material seems to be a good alternative once the errors on measurement have been quantified.

## 2.2 *Image Dependant Information*

Being an underwater structure, the measurement of the quantitative aspects of the corrosion is extremely difficult. However, information based on the photographs of the corroded regions are available. These photographs can be directly obtained from the piles or can be from the experimental plates attached to the piles or those corroded in a similar environment within the laboratory. The corroded plates can be untreated or chemically treated to accentuate the corroded region. A successful identification of the presence, location and the extent of damage using such photographs is required by any structural health monitoring scheme. Figure 2 shows an example of one of the treated plates. The corroded regions are observed to be in contrast with the background and this fact is considered to be the starting point behind damage detection from photographic information.

Even when the damage samples are available, both from the laboratory and from the structure, the quantification of the damage is manual and hence difficult and time consuming task. As a result such assessments are usually limited to accurate identification of the presence of damage. The information of the geometric properties of the damage is less reliable due to the presence of human factor and the time involved with such

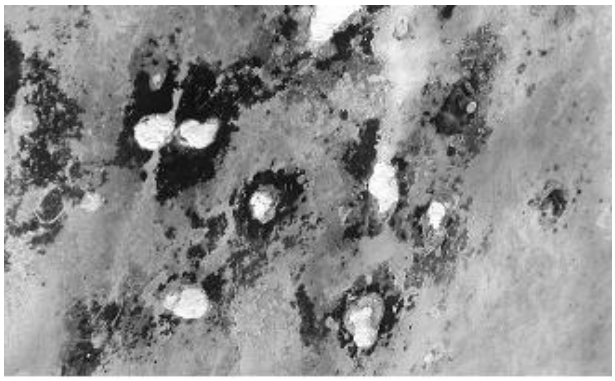


Figure 2. A Treated Specimen with Corrosion.

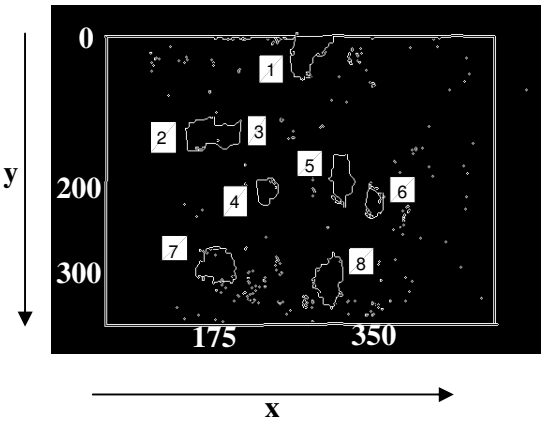



Figure 3. Detected Damage Regions in a Specimen.

analyses increase greatly even when the number of observations is moderate in size. All these problems necessitate the development of an image processing

based damage detection technique that is easy to handle, more accurate and less time consuming.

## 3 IMAGE PROCESSING BASED DAMAGE DETECTION

### 3.1 *Theoretical Background and Detection Scheme*

Applications of image processing have gained popularity very recently in the field of structural health monitoring. Patsias & Staszewski (2002) have illustrated the use of video camera based dynamic shape identification in conjunction with wavelet analysis. Similar image processing based damage descriptor for asphalt mix has been proposed by Hartman & Gilchrist (2004). Application of such video camera based work has also been seen to track the motion of a cable (Gehle & Masri, (1998)). Multiple cameras have been used to identify damages by using photogrammetric software by Benning et.al (2004). Open cracks in beams have been identified using wavelet analysis in conjunction with image processing by both static (Rucka & Wilde, (2006)) and dynamic (Pakrashi et.al, (2007)) deflected shapes.

The detection method in this paper is dependent on the fact that the damages present in the photograph are optically different from its surroundings in terms of colour, brightness and geometry. The object is to convert the coloured image to a binary image and identify the edges of the damaged regions successfully. A successful detection ensures that the coordinates of all the points lying at the edge of the closed geometry of the damages are available. By calibrating the pixel length of the photographs in the horizontal and the vertical direction against some pre-existing benchmark of distance in the real specimen or structure, the entire spatial geometry of the damaged regions are retrieved along with the possibility of post- processing to obtain the statistical measures of such geometry.

The MATLAB 7.0 image processing toolbox (MATLAB, 2006) has been employed for the proposed detection scheme. The saved image of the corroded plate is essentially a rectangular grid of pixels and the centre of a pixel occupies the integer co-ordinates in the grid so produced. The interior of each pixel can be further subdivided into a continuous spatial coordinate system by considering that the local origin for each pixel lies at the top left hand corner of the pixel, and not at the centre. Each pixel is associated with a vector of number describing its hue-saturation value.

The gray-level threshold of the image is computed by minimizing the interclass variances of the black and white pixels using Otsu's method using MATLAB 7.0 image processing toolbox. Pixels below the threshold assume a value zero and turn black, while the other pixels turn white. This enables to convert a complex matrix from the original image to a simpler binary black and white image.

This transformation is important when the feature of interest is in contrast with its surroundings in the image whereby the corroded regions in contrast to the background can be identified as closed geometries within the binary matrix so produced. The black and white binary images are converted by thresholding and the edges of the images are found using the Sobel method (Sarfraz, (2005)) incorporating the MATLAB 7.0 signal processing toolbox. The Sobel method scans a binary image and returns the approximation to the derivative of the two-dimensional data. The edges are returned as the points where the gradient of the image are locally maximum.

The efficiency of the detection lies in the contrast of the damage region with respect to its surroundings and the ability of the analyzing system to identify such contrasts within a closed geometry. Since ferric ions, in the presence of water, oxygen and/or organic and inorganic acids in the marine environment tend to form coloured products, the discolouration due to corrosion is usually common. This fact has been observed by Tsushima et.al (1997) in conjunction with basic image processing methodology.

Although the depth of the damage region and hence the extent of damage cannot be identified using such image processing methodology directly for certain limit states, the localisation and the spatial statistical information yielded from the analysis immediately enables the end user to minimize the maintenance region and prioritize the regions according to the importance within the framework of an existing maintenance plan. This has a direct and a positive effect in terms of efficient investment of the maintenance budget and the decision making policy of the structure in the long run.

An example of a successful image processing based damage region detection as proposed in the paper is given in Figure 3, where Figure 2 has been successfully analyzed to isolate eight major closed damaged areas of irregular geometry with precision. Some spurious features are also identified due to the environmental noise but are insignificant with respect to the damaged regions. Sometimes, a visual idea about the spurious features can be helpful to preprocess the picture to make the computational effort of the pattern recognition scheme easier and the scanning region comparatively smaller.

### 3.2 *Statistical Information*

Once the closed geometries and their co-ordinates are identified within the photograph, various

statistical properties of the geometries can be found. The centroids, the areas within each identified object and the major and minor axes of each of the objects have been computed in this study as an example using the MATLAB image processing toolbox. The summary of the information is provided in Table 1 where the spatial variability and the extent of the damage regions have been quantified. Any other photograph produces such results and can be related to the actual length scale by choosing a pre-existing benchmark.

It is also important to note that the objects labeled 2 and 3 in Figure 3 are considered to be a single object while processing and hence the combined geometric property of the system has been rendered instead of their individual statistics. This is due to the fact that in the real specimen the damages are in fact physically connected. However, by a proper control on preprocessing, lighting and camera resolution these two geometric regions can be separate incorporating some additional effort.

The information provided by Table 3 can also act as a tool for the relative ranking of the damaged locations within the structure. For this particular case the total area of damage has been found to be approximately 5.7% of the total area under consideration. The unit of length in Table 1 is in pixels and that of area is in square pixels. The terms Xbar and Ybar represent the coordinates of the centroid of each labeled damaged region in horizontal and vertical direction respectively. With the information on the successful detections and false alarms available, the receiver operating characteristics can be constructed.

Table 1. Spatial Variability of the Identified Locations of Damage.

| Damage No. | Xbar | Ybar | Major Axis | Minor Axis | Area | % Area |
|---|---|---|---|---|---|---|
| 1 | 273 | 56 | 51 | 36 | 1151 | 0.9 |
| 2 &3 | 173 | 139 | 66 | 34 | 1597 | 1.25 |
| 4 | 232 | 200 | 30 | 24 | 539 | 0.42 |
| 5 | 311 | 186 | 56 | 24 | 985 | 0.77 |
| 6 | 346 | 212 | 34.5 | 20.3 | 494 | 0.38 |
| 7 | 178 | 280 | 44 | 39.4 | 1272 | 0.99 |
| 8 | 298 | 295 | 54 | 31.2 | 1240 | 0.97 |

## 4 PROBABILISTIC STUDY ON IMAGE PROCESSING BASED DAMAGE DETECTION AND CALIBRATION

### 4.1 *Inspection results modeling: theoretical basic concepts.*

Inspection by video processing is not perfect when considering on site video recording: luminosity, distinctness and contrast are not known and are neither uniform on a given picture and from a picture to another. Moreover, for the quality of image the most difficult part is the decision on the actual existence of what seems to be a defect.

It has thus become a common practice to model the detection reliability in terms of the probability of detection (PoD), the probability of false alarms (PFA) and the Receiver Operating Characteristic (ROC) curves. The most common concept which characterizes inspection tool performance is the probability of detection. The PoD and the PFA depends on the following quantities of interest - the maximum size of the defect and the area of the defect. Here for simplicity, let us consider the area of the pitting. Let $A_d$ be the minimal pitting area, under which it is assumed that no detection is done. Parameter $A_d$ is called detection threshold in the following. Thus, the probability of detection is defined as:

$$\mathrm{PoD}(A) = \mathrm{P}(A \geq A_d) \qquad (1)$$

where $A$ is the measured area. $A_d$ is a deterministic parameter or a random variable. This definition implies that PoD is a monotonic increasing function. To complete this concept, the probability of false alarm has been introduced. It is the probability to defect a non-existing defect. For a given range of defects $A_i$, the curve that joints the points of coordinates (PFA, PoD($A_i$)) is called Receiver Operating Characteristic (ROC) curves (Arques (1982), Fücsök et al. (2000)). Such a curve is plotted on figure 4.

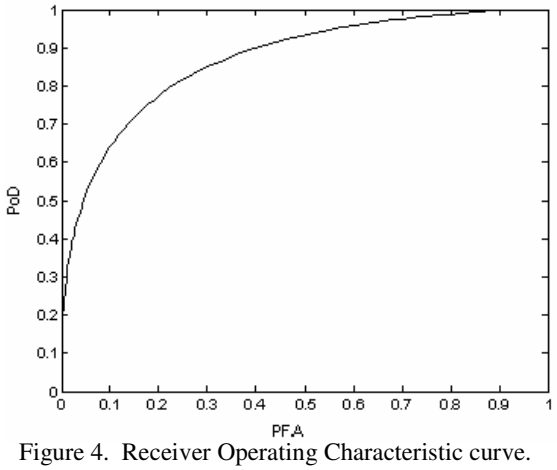


Figure 4. Receiver Operating Characteristic curve.

In view to introduce these concepts into practicable decision schemes, recent works have been carried out (Faber & Sorensen (1999), Rouhan and Schoefs (2000) and (2003)).

4.2 *Statistical modelling of inspection results.*

Knowing the probability density functions (pdf) of the signal and noise and that of the noise alone, the computation of PoD and PFA comes easily. It is reminded in Rouhan & Schoefs (2003). There is actually no way to obtain the pdf of the signal and the signal and noise together for image processing in harsh conditions where many factors affect the inspection results. One way of modelling such parameters is to analyse the probabilistic structure of the inspection results and to provide a model consequently. The I.C.O.N project has been dedicated to the inter-calibration of the N.D.T tools with the appropriate checks done on-the-spot in recent times for this purpose. A statistical analysis had been made there from a set of tests which consider

- Various node typologies
- Several inspection conditions (basin, sea)
- Several inspector teams coming from several countries.

These considerations are reminded in Rouhan & Schoefs (2003) and allow distinguishing between whether a crack or a group of cracks has been detected.

Here the problem is similar and conforms to such probabilistic information structure, especially in the case where two pitting areas are very close. We assume in the following that every detecting defect has a proper and identifiable shape. For the purpose of successful calibration, let us consider n(c*)* tests within a range *c* ( $c = \left\{ A \in \Re^{+} \middle| \; A \in \left[ A_c ; A_{c+1} \right] \right\}$ ) of the real pitting area.

The following numbers are defined:

- $n_b(c)$ as the number of existing corroded regions which are detected.
- $n_f(c)$ as the number of non-existing pitting areas which are detected ;
- $n_n(c)$ number of existing corroded regions which are not detected.
- $n_r(c)$ as the number of healthy areas where no pitting areas have been detected.

As the number of detected pitting areas can exceed number of existing pitting areas, the corresponding ratio is not a probability. Two sets of probabilities (eq. (2) and (3)) are defined. The first one concerns correct detections:

$$P_b(c) = \left\{ p_b(c), p_r(c) \right\} \text{ with } \begin{cases} p_b(c) = \dfrac{n_b(c)}{n_b(c) + n_n(c)} = \dfrac{n_b(c)}{n_1(c)} \\ p_r(c) = \dfrac{n_r(c)}{n_f(c) + n_r(c)} = \dfrac{n_r(c)}{n_2(c)} \end{cases} \quad (2)$$

The second one deals with false detections:

$$P_f(c) = \left\{ p_f(c), p_n(c) \right\} \text{ with } \begin{cases} p_f(c) = \dfrac{n_f(c)}{n_2(c)} \\ p_n(c) = \dfrac{n_n(c)}{n_1(c)} \end{cases} \quad (3)$$

According to these definitions, $P_f(c)$ can be considered as PFA and $P_b(c)$ as PoD. This leads to obtain discrete PoD values according to the range defined and construct a whole ROC curve by modifying the image processing for a given range of defects.

An application of such a case is provided in the current problem and the results are provided in Figure 5. The ROC of the current detection condition is constructed. With the increase of resolution, the PoD detection increases, but so does the PFA. On the other hand with poor resolution characteristics within the image, both PoD and PFA are considerably low. It is only at some intermediate level of resolution is the optimized value obtained where a high PoD corresponds to a minimum of PFA. The effects of high and low resolutions are earmarked within the figure. Two alternative hypothetical curves in dotted lines are employed to emphasize the effects of the presence of other factors within the same methodology like lighting, nature of damage, etc.

The hypothetical ROC curves illustrate the uncertainties associated with the measuring conditions (which are variable) like luminosity, contrast, noise etc. and emphasize the shift of the efficiency achieved using the proposed NDT tool due to such uncertainties. It can be observed from Figure 5 that there may be possible cases where the ROC can be unsatisfactory due to the quality of the measured data itself and such situations can be identified by considering an envelope of ROC due to various conditions through existing data or simulations close to the chief governing conditions due to the change of the major affecting parameters. The efficiency and the robustness of the methodology are thus illustrated within the structural health monitoring framework in this regard.

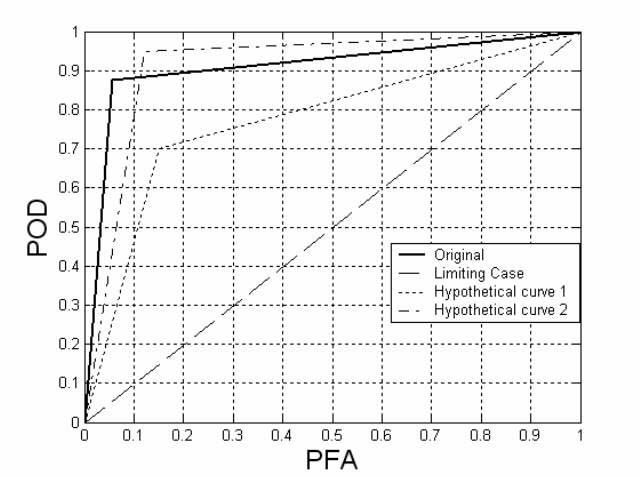



Figure 5ROC Curves for the Current Problem.

## 5 CONCLUSIONS

An image analysis based damage detection and calibration scheme has been introduced in this paper along with an investigation on the uncertainties related to such detection process. A study on the identification of corrosion in an experimental plate has been performed and the existence, location and the extent of the damage locations have been successfully identified. The damage classification methodology is seen to be independent of the damage process and the material affected. The ROC of the damage classification methodology in obtained. This general detection scheme is simple, computationally inexpensive and shows a definite potential to be used as an unmanned structural health monitoring system.

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