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# A Comparison between Pixel Intensity and Texture Analysis based Damage Detection Techniques

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## Abstract

Imaging based damage detection techniques are increasingly being utilized alongside traditional visual inspection methods to provide owners/operators of infrastructure with an efficient source of quantitative information for ensuring their continued safe and economic operation. However, choosing a suitable damage detection technique that will provide a high level of quantitative information is often a timely and challenging prospect as there exists a wide array of algorithms currently available. These algorithms may be partitioned into one of two groups; pixel intensity based methods and texture analysis based methods. The algorithms in each group are naturally suited to different applications, depending largely on whether the damaged region under consideration is more separable from the background based on colour or on texture. This paper compares two algorithms, one from each category, which have previously been proposed in the domain of Infrastructure Maintenance Management (IMM). The algorithms are applied to a range of scenes featuring various forms of damage and their performance is investigated for best detection on the basis of performance coordinates in the Receiver Operating Characteristic (ROC) space. The general superiority of the pixel intensity based approach over the texture analysis based approach is demonstrated, in particular when considering High Dynamic Range (HDR) imagery.

**Keywords:** Image processing, damage detection, comparative study, texture analysis

## 1. Introduction

Regular inspections of structures are vital to ensure that they remain safe and fit for purpose. Currently, many structures are assessed using a regime of visual inspections. The levels of inspection cover a range of detail. It can be a cursory check, a principal inspection involving detailed examination of all surfaces, or special inspections where the employment of invasive, semi-invasive and non-invasive tests may become necessary. Most inspections still depend on visual observations and the quality of data collected largely depends on the ability of the inspectors to observe and objectively record details of damage. The approach is prone to considerations such as operator boredom, lapses in concentration, subjectivity, and fatigue, which contribute to the variability and reduced accuracy of visual inspections [1,2]. With this in mind, it is often desirable to incorporate a second, more objective and quantitative, source of information about the health condition of a structure. Non-Destructive Techniques (NDT) often provide the only method of obtaining such information.

The information obtained from the NDT may be fed into an Infrastructure Management System (IMS), which can help the decision makers to make more effective and informed judgments when allocating resources towards the correction of deficiencies and when choosing an appropriate future course of action. This aspect has attracted a growing interest in recent years as the importance of life cycle optimisation and the related financial benefits continue to be recognised [3,4]. For a well calibrated IMS, it is important that the input information is accurate and comprehensive. This requires selecting the most suitable NDT technique, which for a given application is not always readily apparent as a measure of the

onsite performance of an NDT technique remains a pertinent question in the majority of cases [6]. The choice of NDT will largely depend on the damage to be detected and will require an in-depth knowledge of the advantages and limitations associated with each option. Even NDTs which fall under the same category can produce markedly varying results. Unfortunately, many inspections proceed without a proper evaluation of all available options and as a result an inferior level of information is obtained.

In recent times, image processing based damage detection methods have been increasingly considered as a viable NDT option. This is due to a number of reasons. Image processing methods use inexpensive and readily available equipment (i.e. a standard digital camera), and they do not require the inspector to undertake extensive training. Furthermore, advances in camera technology mean that rich detailed imagery of damaged components can be acquired. Additionally, visual inspections almost always capture photographs to include in the inspection report to corroborate the inspector's comments; however, these photographs are rarely exploited to their fullest potential in either a qualitative or a quantitative fashion. The primary limitations image processing methods are the lack of penetration below the surface of the material and the requirement of good visibility and lighting conditions.

Applying damage detection algorithms to the photographs can locate and quantify visible mechanical damage on the surface of infrastructural elements with minimal human supervision. Physical properties of the identified damage, such as the size and shape characteristics, may be easily extracted with knowledge of a real world scale. The quantitative nature of the data obtained from image analysis is important and naturally lends itself to numerous applications. It is helpful for developing new damage models, or strengthening existing ones, which are used to forecast the rate of propagation of damage as the structure continues to operate.

Most image processing based damage detection algorithms consist of segmentation followed by subsequent classification of the segmented regions. Ideally, the segmentation methodology should identify and accurately define all regions of interest in an image whilst minimizing the inclusion of extraneous regions. In reality, perfect segmentation is difficult to achieve given the inherent chromatic and luminous complexities encountered in natural scenes. Segmentation algorithms use either pixel intensity (colour) information or texture information to isolate similar regions in an image. The effectiveness of colour based segmentation algorithms and texture based segmentation algorithms will vary according to the surface and damage type under consideration as certain damages are more separable from the undamaged surface based on either their colour or texture attributes.

This paper evaluates and compares the performance of a pixel intensity based method [6] and a texture analysis based method [7] which have previously been proposed in the domain of IMM. Both methods are applied to four different scenes featuring various damage forms, lighting conditions, viewing angles, resolutions etc. Additionally, High Dynamic Range (HDR) imagery is adopted as a protocol, as proposed by [8], in an attempt to optimise the detection accuracy of each method.

The following section provides an overview of each of the detection techniques as well as providing a brief background to HDR. This section also details the performance evaluation process which is based on performance points plotted in the Receiver Operating Characteristic (ROC) space. Section 3 introduces the imagery used while Section 4 presents the results obtained from each method. Section 5 concludes the paper.

## 2. Methodology

A comparison study between two previously proposed image processing based damage detection methods has been conducted in this paper; a pixel intensity based segmentation method and a texture analysis based method. The comparison involves two steps. Firstly, each detection method is applied to the four Standard Dynamic Range (SDR) images and the corresponding HDR images. Secondly, the detection accuracy obtained from each method is calculated for each image and a comparison is then drawn. The detection methods are briefly described below.

### 2.1 Pixel Intensity based Segmentation Method

Pixel intensity based segmentation algorithms may be grouped into four major categories: thresholding, edge detection using gradient information, region growing, and hybrid methods [9]. The method used in this paper, known as REMPS (Regionally Enhanced Multi-Phase Segmentation), is a hybrid method which integrates three feature detection stages. The first stage involves the application of the Sobel edge detector on a pre-processed image in order to form closed geometries corresponding to objects in a scene. Statistical properties are then calculated for each closed geometry, which are used as the basis for the clustering based filtering phase. This phase retains closed geometries deemed to represent damaged regions. Finally, Support Vector Machines SVMs are used to identify pixels having intensity values characteristic of damaged zones. These pixels are then applied locally to the filtered closed geometries in order to improve the definition of the detected damaged regions. REMPS attempts to utilise the advantages of these three independent techniques most effectively and extract their mutual benefits. For instance, the robustness and generality of the Sobel edge detector serves as a natural precursor to the closed geometry clustering stage. This clustering stage performs well at classifying the presence of damage, however, it is only after the pixel supplementation stage that the shape and size characteristics of the retained closed geometries are sufficiently realised. A flowchart illustrating the order of the feature detection methods is presented in Figure 1(a).

### 2.2 Texture Analysis based Segmentation Method

Texture is an innate property of surfaces which, for human observers, texture may be qualified by terms such as fine, coarse, smooth, rippled, mottled, irregular, or lineated [10]. There are numerous ways to quantify texture; wavelet analysis, Laws' texture energy, First Order Statistics (FOS) and Grey Level Co-occurrence Matrix (GLCM). The texture analysis based segmentation method used in this paper combines both FOS and GLCM statistics. The texture dependent statistics, or texture measures, are calculated at every pixel in an image using a sliding window approach. Four statistics were derived from a GLCM; angular second moment, homogeneity, contrast and correlation, while a further six texture measures were calculated directly from the pixel intensity values from the original image. These were Shannon entropy, mean, variance, range, skewness and kurtosis. The 10 texture measures calculated at each pixel location form a feature vector. Non-linear SVM models are used to classify pixels as either damaged or undamaged based on the feature vector corresponding to that pixel. Two SVM classification models were considered; a Custom-Weighted Iterative (CWI) model and a 4-Dimensional Feature Space (4DFS) model in which the feature vectors were mapped to a four dimensional feature space. The 4DFS model was generally shown to

produce better segmentation results so this model was used for the purposes of this comparison. The method is illustrated in the following flowchart Figure 1(b).

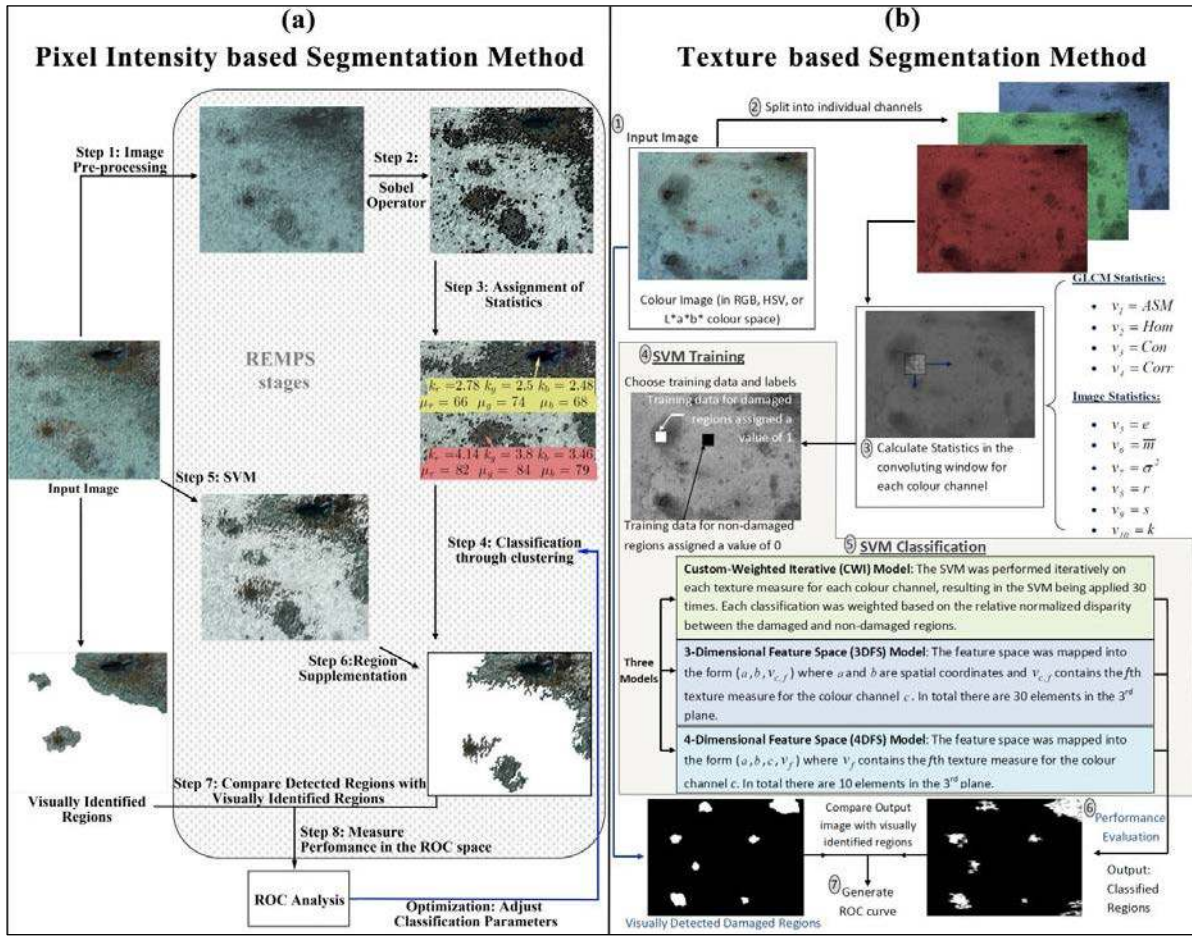


Figure 1. (a) Flowchart for the pixel intensity based segmentation method, and (b) flowchart for the texture analysis based segmentation method

### 2.3 High Dynamic Range (HDR)

HDR is a set of techniques that allow a greater dynamic range of luminance values between the brightest and darkest regions of an image than standard digital images. SDR images can typically only accommodate a very limited range bracket of the full tonal spectrum in a real world scene. Therefore, a dynamic range bracket would have to be chosen in the knowledge that all luminance values outside the range would not be represented correctly. The broad principle behind HDR imagery is that multiple SDR images of the same scene, each taken at a different exposure, and thus capturing a different range bracket of the tonal spectrum, may be merged to form one HDR image that has a wider dynamic range [11]. Combining SDR images can be done using various merging algorithms [12].

The usefulness of HDR imagery as an imaging protocol may be observed in Figure 2 which depicts the pixel intensity values plotted along a profile line for a normally exposed SDR image and the corresponding HDR image (the SDR and HDR images in question are from Figure 4 (1) and (5) respectively). It may be observed that HDR image exhibits an increased tonal range compared to the SDR image, thus offering an altogether superior information content.

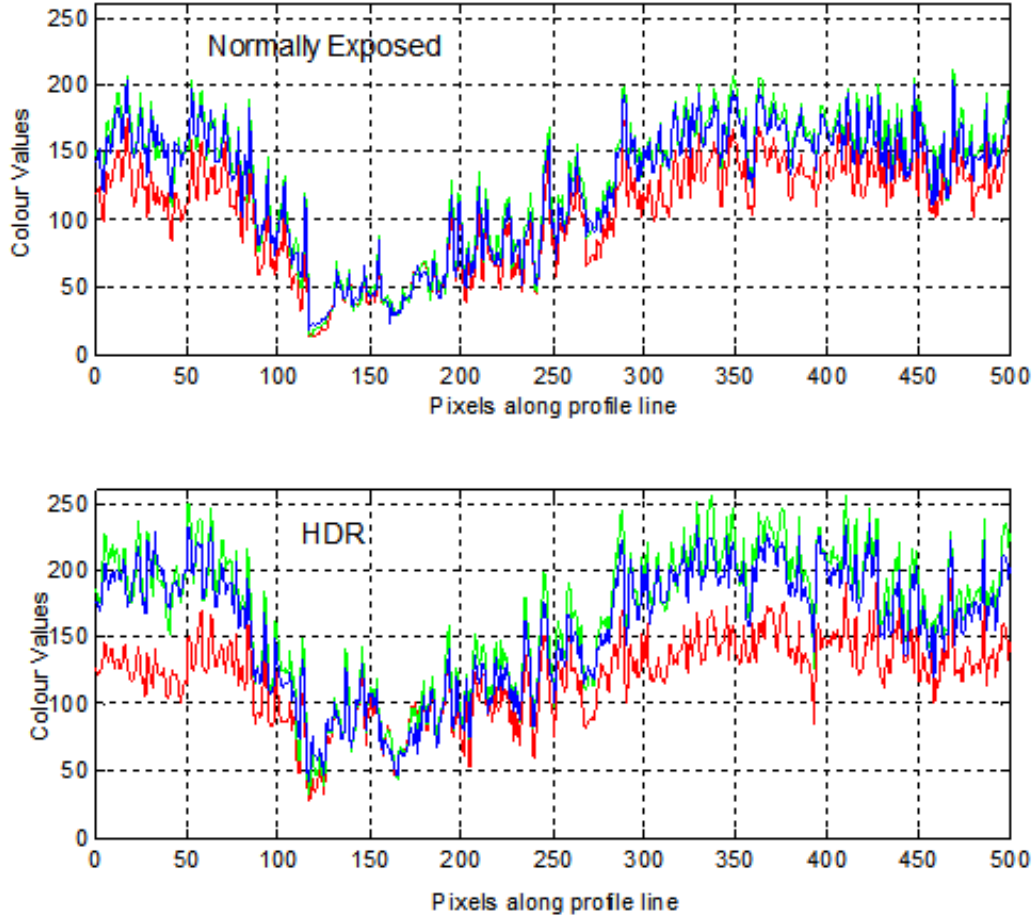


Figure 2. The increased tonal range during damage detection for an HDR image as compared to an SDR image with normal

## 2.4 Performance Evaluation

The performance of each method is evaluated through the use of performance points in the Receiver Operating Characteristic (ROC) space. The ROC space allows for a convenient means for characterising and comparing the performance of NDTs in various conditions [13] and has been recently expanded to image detection [14]. For any NDT, the Detection Rate (*DR*) along with the accompanying Misclassification Rate (*MCR*), or alternatively known as Probability of Detection (*PoD*) and Probability of False Alarm (*PFA*) in the field of probability space and decision theory, are determined by comparing the corroded regions detected with a visually segmented image, which acts as the control. The *DR* and *MCR* are represented as a percentage between 0% and 100%. Each (*MCR, DR*) pair formed a coordinate in the ROC space.

There are a few measures for comparing segmentation performance [15]. In this paper, a measure of the performance was attained through the use of the  $\alpha$ - $\delta$  method [16,17]. This method relies on calculating the angle,  $\alpha$ , and the Euclidean distance,  $\delta$ , between the best performance point, defined as an ideal NDT with 100% detection and 0% misclassification rates and represented in the ROC space with coordinates (0,1) and the considered point to give a measure of the performance of the considered point. As this paper is not devoted to risk analysis where the shape to the ROC acts as a key factor, only the delta,  $\delta$ , parameter is required. A low value for  $\delta$  is indicative of a strong performing technique.



### 3. Data Analysis

The pixel intensity and texture based segmentation methods were applied to four images featuring various forms of damage on the surface of infrastructural elements. In order to provide a more meaningful comparison, the images were chosen to reflect a broad range of surfaces, damage forms, viewing angles, lighting conditions and image resolutions as shown in Figure 3. The sample images in the figure depict, (1) pitting corrosion on metal sheet piling in marine conditions, (2) marine growth on the surface of underwater steel pile wharf, (3) corroded metal sheeting, and (4) an exposed concrete bridge deck through wear of pavement surfacing. The HDR images are also displayed (5 - 8). It is readily apparent that the HDR images offer more detail than their SDR counterparts.

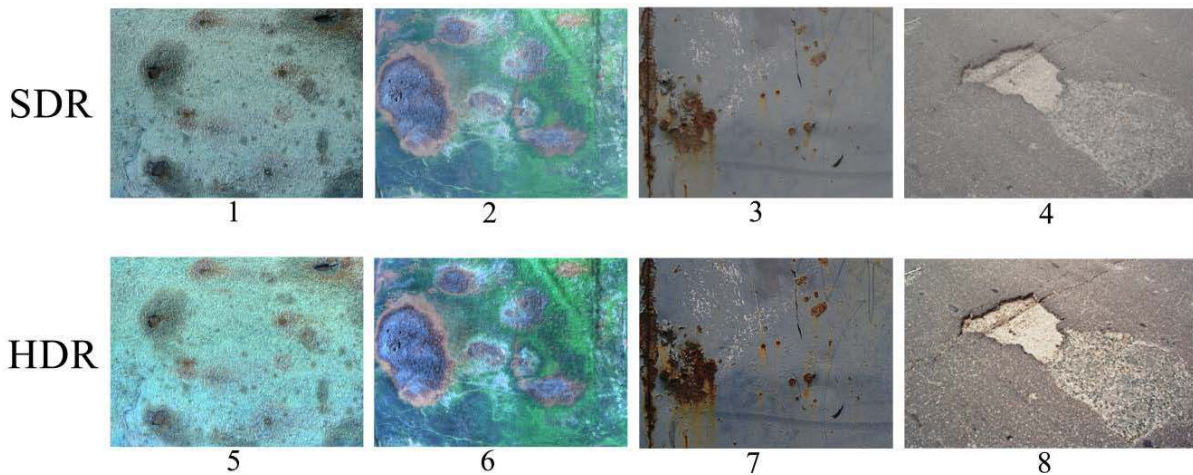


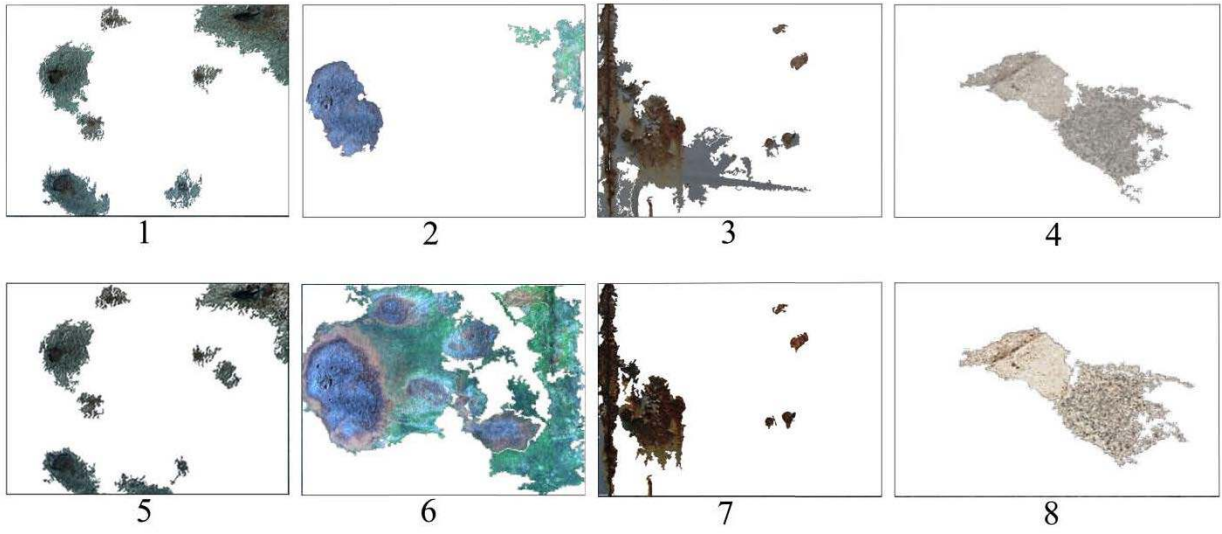
Figure 3. SDR images of various forms of damage (1 - 4), and the corresponding HDR images (5 - 8)

The next section presents the results obtained from each detection method performed on these images.

### 4. Results

Both detection methods required two SVM parameters as input parameters which ultimately had an influence on the detection accuracy. In order to achieve a fair comparison, a parameter search was performed according to the method outlined in each paper to find sufficiently optimized parameters. Following this optimization procedure, the methods were applied to each image in Figure 3 resulting in the detected regions shown in Figure 4. Their performance levels are summarized in Table 1 and the corresponding performance points are plotted in the ROC space in Figure 5.

### Pixel Intensity based Segmentation Method



### Texture based Segmentation Method

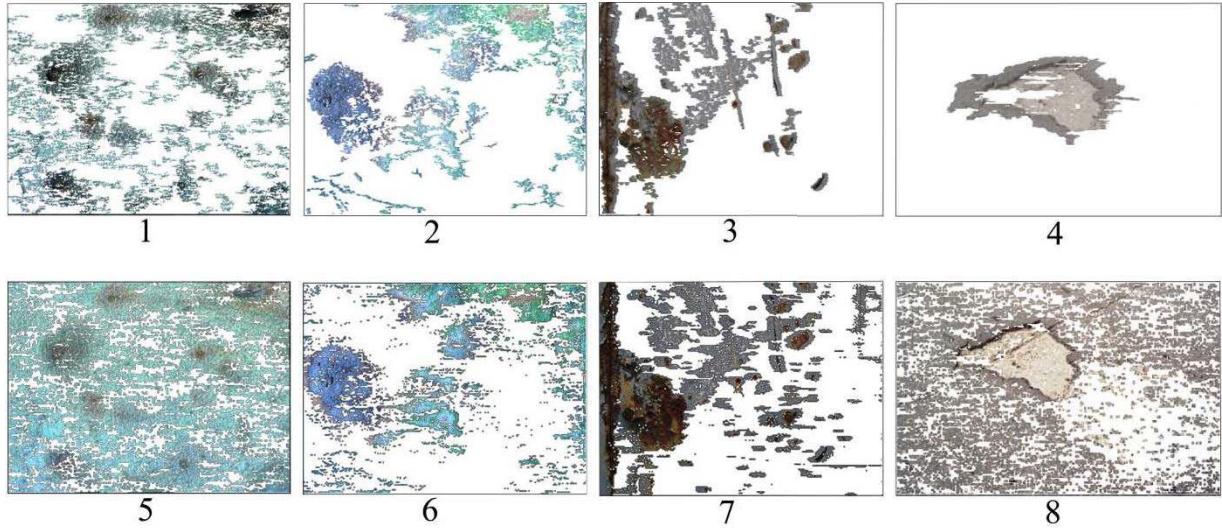


Figure 3. Detected regions for the pixel intensity and texture analysis based segmentation methods

**Table 1. Detection accuracy of the pixel intensity and texture analysis methods**

<i>Sample Image</i>	<i>Pixel Intensity based Segmentation</i>			<i>Texture based Segmentation</i>		
	<i>DR</i>	<i>MCR</i>	$\delta$	<i>DR</i>	<i>MCR</i>	$\delta$
(1) Pitting Corrosion - SDR	84%	8%	0.18	78%	32%	0.39
(2) Marine Growth - SDR	64%	8%	0.37	64%	29%	0.46
(3) Corroded Metal - SDR	98%	16%	0.16	96%	24%	0.24
(4) Exposed Deck - SDR	93%	10%	0.12	52%	10%	0.49
(5) Pitting Corrosion - HDR	85%	7%	0.17	75%	43%	0.50
(6) Marine Growth - HDR	96%	47%	0.47	69%	21%	0.37
(7) Corroded Metal - HDR	97%	7%	0.08	99%	31%	0.31
(8) Exposed Deck - HDR	93%	10%	0.12	78%	29%	0.36



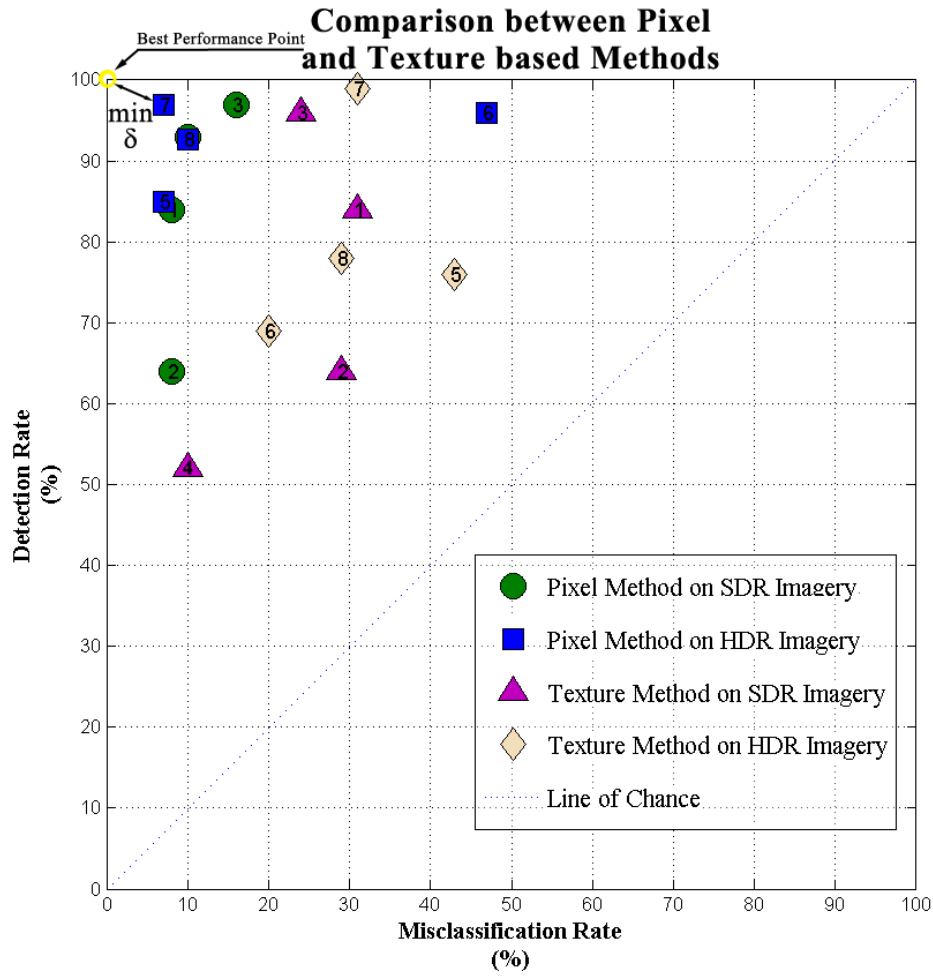


Figure 4. Comparison of detection methods through the use of performance points in the ROC space

#### 4.1 Discussion

It may be noted from the detected regions in Figure 4 that the pixel intensity based method was quite successful for the majority of cases with the exception of the marine growth image. The poor detection results for this image may be explained by the fact that the damaged regions throughout the image were not characterized by one single colour. Instead they took on numerous contrasting shades which often overlapped with the non-damaged background. Generally however, this method proved effective at locating the presence of damage as well as accurately defining the shape and size of damaged regions.

The texture based method was not as effective in terms of detection accuracy as the pixel intensity based method. The only case where it was on a par with the pixel intensity method was for the image of the marine growth. It also suffered from detecting many small spurious regions unlike the pixel intensity based method which a ‘cleaner’ and more homogenous detection.

Analysis of the  $\delta$  values in Table 1 reveals that HDR imagery does indeed improve the accuracy of the pixel intensity based method. Texture based segmentation on the other hand did not appear to benefit from the use of HDR as on two occasions, the best detection results emerged when using SDR images while on the other two occasions, HDR images provided

better results. This suggests that adopting a HDR protocol is not especially relevant when using texture analysis as a detection method.

Furthermore, the aspect of computational time may be an important factor for some, especially in cases where a large batch of images are required to be processed. It was found that the colour based segmentation method had a superior computational efficiency over the texture based algorithm, which is due to the fact that texture must be calculated by considering a collection of neighbouring pixels around each pixel while colour based segmentation techniques typically need only consider each pixel intensity value independently.

## **5. Conclusion**

This paper presents a comparison between two image based damage detection methods. This study was necessitated by the vast array of damage detection methods currently available, which makes choosing an appropriate method a timely and daunting prospect. This paper gauges the effectiveness of two contrasting approaches, thereby providing an insight into the expected performance levels that can be attained by anybody who is considering incorporating an image processing technique in their inspection routine. The two methods were based on detection via pixel intensity (colour) information and detection via texture information. While both of these methods are not necessarily reflective of all pixel intensity and texture analysis based methods currently available, the comparison does serve to underline how each approach may typically respond, especially when the damage type is known beforehand.

The main forms of surface damage encountered on ageing infrastructural elements (corrosion, leaching, etc.) are often characterised to a greater extent by the change in colour from the undamaged surface than by a change in texture. With this in mind, it is not surprising that the pixel intensity based method demonstrated a higher degree of success for the majority of the cases explored in this paper. Texture based segmentation fared worse at isolating damage, so it may be can be classified as suitable for specific applications such as marine growth where the damaged regions do not share a distinct colour but are characterised more so by their rougher texture than the surroundings.

The presented results indicate that improvements can be made to the detection accuracy of the pixel intensity based method by adopting a HDR protocol. The texture analysis based method however did not experience any noticeable gain by using HDR.

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