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Cracks and Defects Detection Based on Image Segmentation

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Abstract: This paper is about finding the defects and cracks in a metal surface. Earlier the defects and cracks in metals detected using eddy currents and microwave methods. In automobile industry or steel industries, the detection of surface cracks are been detected based on a digital image and it is the key requirement in quality control system. Conventionally, humans were engaged for detecting defects but it was a time consuming task. So an inspection system based on image processing is needed to be introduced. The main objective of the paper is to design a system based on image processing to detect the defects and cracks in a metal object. By using image processing for crack detection, a better and efficient solution to crack detection can be done.

Key words: Image De-noising · Edge detection · Image threshold · Image morphology · Image segmentation

INTRODUCTION

The use of image processing in automation industry and metal based industries is at its peak in present scenario. In various steel and automobile based industries the key basic product used is metal. Basically metal defects or cracks may lead to a major incident in an industry. Thus a crack detection system based on eddy current analysis was introduced. But eddy current based crack detection is not accurate enough to give the exact analysis. This led to the evolution of a new subject called vision assistant method which has a large area of common interest and motivation with another subject known as pattern recognition. A major portion of information received by a human to manipulate for the detection task is visual. Similarly, the method of processing and detecting defects from visual information grabbed by digital computer is called digital image processing and scene analysis. The cracks and defects in a metal can lead to a major event that may be hazardous for environment. If a metal pipe has a small defect or crack is there then many hazardous gases may leak as well as much hot water or steam may also leak through the pipes. In such cases a highly advanced a efficient crack system is to be designed. A high definition camera will be installed in every part of the industry that will capture a video and then it will convert tat video frame into packets such as image for further processing methods. Different authors have recently applied image processing techniques aiming to characterize cracks [1]. Has given a method to detect the road distress analysis for finding defects and cracks. In that paper the algorithm of anisotropic diffusion for removing noise is used, histogram threshold for defining the pixel variations and snake model for refining the results. But for detecting cracks in metals it is required to smoothen the image as well as finding the objects so that there would not be any similar object detection except cracks. In that paper the method of histogram threshold is used because the values are alwas accurate and easy to find the threshold values in histogram format of the image. In [2] they have proposed a method for de-noising medical images. In other words they have given an algorithm which will be helpful for medical applications and bio-medical purposes. In [2] a novel-example based method for super-resolution and de-noising of medical images is designed. The main objective of paper [2] is to estimate a high resolution image from a single noisy low-resolution image, with the help of a given database template which will have a high and low resolution images. Both the images will be matched with the given input image and accordingly the output will be produced as per the requirement. But in this paper for detecting cracks it is not required to use a database of template for matching the resolution of reference images.

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Only the image threshold values and image segmentation will be the key processing required for finding the cracks. In [3] they have proposed a new decision-based adaptive filter that will remove high density noise from digital images. In [3] some advanced median filters and fuzzy based filters have been used for removing the high density noises. In this paper it is not much important to remove noise and improve image quality as by using the threshold values we can detect the cracks, furthermore, we have followed some references and finally used some image processing techniques such as edge detection, image morphology and image segmentation methods for detection of cracks.

Edge Detection: In a grayscale image, the edge is a local feature that, within a neighborhood, separates two regions. In this portion each of the gray-level of image is more or less uniform when compared to the other values on the two sides of the edge. So, an ideal edge has a step like cross-section. The processes of edge detection are broadly classified into two categories:

- Derivative approach
- Pattern fitting approach

In this paper we will not go upto the depth of image enhancement methods. Here, in this paper we have used wiener filter for removing the noise from the image. Image enhancement is done only to smoothing the images so as to get better results. Furthermore, in this paper we have used edge detection method so as to find the borders of gray level in an image. Both the approaches have advantages and disadvantages [4]. As Faugeras (1993) has rightly pointed out, these properties are self-contradictory in nature and a desired result is always a trade-off between them. Suppose the resultant $S(x)$ of a signal $S(x)$ perturbed by a sinusoidal noise is given by;

$$S(x) = s(x) + \eta \operatorname{Sin} (\omega x)$$

Taking derivative with respect to x,

$$S(x) = s(x) + \eta\omega \operatorname{Cos} (\omega x)$$

If η is small then $s(x)$ is close to $S(x)$; while, if ω is large, the noise can predominate the resultant signal especially when the derivative is of interest. Many edge detection algorithms incorporate some of these steps without mentioning them explicitly. One of the main reasons of this is that these steps are not always easy to distinguish mutually from one another. In this paper we have used Sobel operator for finding out the edges of image;

$$d_1 = \frac{1}{4}\left[\left(g_4 + 2g_5 + g_6\right) - \left(g_2 + 2g_1 + g_8\right)\right]$$

$$d_2 = \frac{1}{4}\left[\left(g_8 + 2g_7 + g_6\right) - \left(g_2 + 2g_3 + g_4\right)\right]$$

The gradient $g'(r, c)$ at pixel (r, c) is obtained by a point operator 0_p applying on d_i ($i = 1,2$). Because of the nature of point operator by a point operator, d_1 and d_2 in the above equations can be defined interchangeably without affecting the value of $g'(r, c)$. Note that among these operators, the ordinary operator is not symmetric [5]. Prewitt operator can detect diagonal edges better than that by Sobel operator; while Sobel operator is superior to Prewitt operator in detecting vertical edges. Effect of noise is reduced in case of Prewitt and Sobel operators by inherent averaging of neighboring pixels. Therefore, to achieve the desired result, gradient operators are usually preceded by noise cleaning [6]. Below figures are showing the results for edge detection of image after using Imaq Threshold VI in labVIEW. Fig. 1 showing the reference image and Fig. 2 is showing edgels of the image that is used for defining the pixel values and edges. The image pixel variations are used for finding the defects of an image. In this paper image of same dimensions as that of the gray-level image taken as reference. Fig. 2. showing the edges of image after applying Imaq Threshold VI to it. Fig. 2. below shows the edgels of the image before using image morphology and image segmentation. In this paper finding the edges is a key requirement because the edges of image are showing the variation in pixels [7]. If pixel value is greater than threshold value than it is a crack pixel orelse it is a non-crack pixel. In such way the variation of pixel values will detect the cracks and defects.

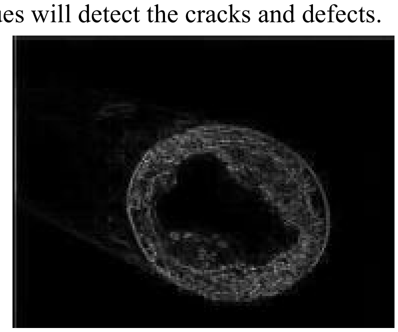

Fig. 1: The image showing after sobel operator edge detection

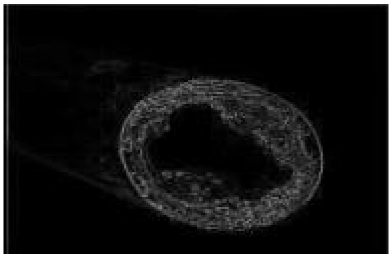

Fig. 2: Image after using Prewitt operator edge detection

Image Threshold: Basically, the threshold value or threshold can be explained as the relation, $t = t(r, c, p(r, c))$, where $p(r, c)$ is the feature value at the pixel (r, c). In case of gray-level threshold $p(r, c) = g(r, c)$ for all (r, c) inside image domain, If value of t depends on the feature $p(r, c)$ of image only, it is called *local threshold*, if the value of t depends on the value of pixel position (r, c) as well as on the feature $p(r, c)$ at that pixel [8], it is called *dynamic threshold*, otherwise it is *global* or *position-independent threshold.* In this paper we have used histogram threshold technique so as to get the threshold value of the grayscale image which will be required to find the segmentation of image. Our aim is to segment an image $g(r, c)$ of size $M \times N$ that contains, say, two types of regions. Secondly, the method is also valid for features other than gray-level. Let us denote graylevel histogram of the image as n_i for $i = 0,1,2,.....L - 1$.

$$\sum_{i=0}^{L-1} n_i = MN$$

Threshold can be selected by using data and information measured gray-level histogram of the image. There is a method called p-tile method suggested by Doyle (1962). Suppose gray-level pixels belonging to R_2-type regions are, in general, greater than that of R_1 and the number of pixels contained in R_2-type region is p% of total number pixels present in the image. Therefore, threshold t should be such that

$$\sum_{i=t+1}^{L-1} n_i = \frac{pMN}{100}$$

The problem with this method is that it cannot be applied to unknown class of images, i.e. where p is not known a priori. In this paper we have used Imaq threshold VI and got the results shown in Fig. 3 and Fig. 4. This method selects the threshold corresponding to the bottom of valley between the two peaks of the histogram. This method needs the histogram to be bimodal. Since the image contains two distinct regions, R_1 and R_2 [9], the gray-level histogram n_i, contains two distinct peaks or modes at z=k and z=l corresponding to gray-levels of pixels belonging to those regions. Ideally, the gray-levels between k and l should not occur frequently in the image. Thus we expect a deep valley at, say z=m between the peaks giving the histogram a bimodal shape. Now the bimodality of the histogram may be measured as follows [Chanda (1988)]. Suppose s_1 and s_2 are magnitudes of slopes of lines joining bottom of valley and each of the peaks, i.e.

$$s_1 = \left| \frac{n_k - n_m}{k - m} \right|$$

$$s_2 = \left| \frac{n_l - n_m}{l - m} \right|$$

Therefore, the histogram is said to,

- Be bimodal if $s_1 > t_{si}$ and $s_2 > t_{sl}$, or
- Have peak and shoulder if $s_1 > t_{sl}$ and $s_2 < = t_{sl}$, or vice versa, or
- Be flat if $s_1 < = t_{sl}$ and $s_2 < = t_{sl}$.

where, t_{sl} is a pre-defined threshold and the values of s_1 and s_2 depend on the number of pixels in the image. So, before computing they n_i may be normalized with respect to M N. Finally, the strength of the bimodality may be measured as, $s_b = s_1 s_2$. After giving a range for threshold value we a resultant image. Based on the given range of threshold values the image edges vary. It is shown in the below Fig. 3 and Fig. 4 there are two different kinds of images with two different threshold ranges. It shows that as the threshold range is increased the image becomes sharper and it is easy to detect the edges and objects present in the image [10]. So based on the thresholding of image it will be easy to segment the image for further process of crack detection.

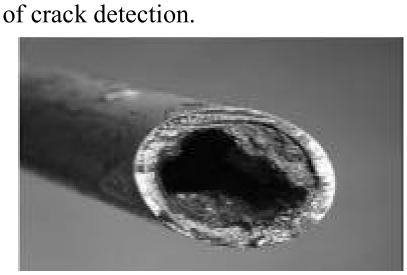

Fig. 3: This image is showing th`e gray-level image

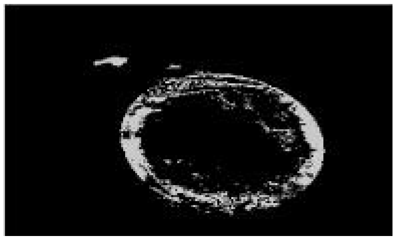

Fig. 4: Above image is showing the resultant image after giving a variable threshold value

Image Segmentation and Morphology: Gray-level image segmentation techniques discussed so far may be extended to colour image segmentation by taking care of colour information at each pixel in an appropriate manner. However, the extension may not be always straightforward from scalar to vector formed by the color triplet or even to each component of the vector, since the colur is the combined effect of the intensity or brightness, the hue, i.e. the main property exhibiting colour and the purity or saturation. These qualities of colour are distributed over three different colour planes i.e. red, green and blue; whereas an individual colour plane, say, red plane alone of a colour image represents the variation of intensity of light at a particular frequency of visible spectrumover the image domain. Basically an image shows the result of segmentation by thresholding the intensity of any plane let it be red plane. Note that since segmentation is done based only on red intensity, hue and saturation information is ignored. As a result bright gray and white regions where the intensity of red component is high are also mapped to red regions. However, if we separate out gray shades by sime means, then applying simple thresholdin on red plane we could segment out red dominated regions. Suppose we consider a pixel to have in gray shade if its saturation is low, i.e.

$$1-\frac{3\min\{R,G,B\}}{R+G+B}<TH_w$$

So taking $TH_w = 0.1$, i.e. labeling pixels with saturation less than 10% as gray pixels and thrsholding the red intensity produces the output. It should be remembered that each of the dominant colours (red, green, blue) and their various shades stands out when corresponding component of the colour triplet is maximum. That means for determining hue of the colours the ratio of R, G and B is important, not their absolute intensities. So to segment a colour image based on dominant primary colour, we may simply label its pixels by identifying the maximum among the colour components. However, before determining the dominant colour it is necessary to test whether the pixel belongs to gray shaded region. As a result, different regions are segmented out based on the dominant primary colours.

Results and Analysis: In this paper we have applied Gaussian filter noise in the images for observations and experimental purpose. To improve and enhance the quality of the degraded images restoration and filtering methods are been used. When there is no information about the degradation process is available the quality of an image may be improved for specific applications by some process called enhancement. Furthermore, the enhanced and improved quality images are been processed to find the edges using edge detection method. In this paper we have used Sobel operator to find the edges of the image. The results are shown in below figures Fig. 5 and Fig. 6.

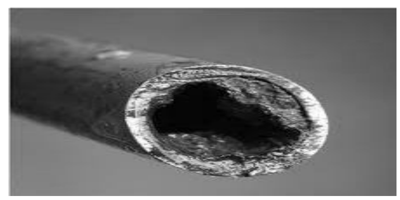

Fig. 5: The resultant image after erosion

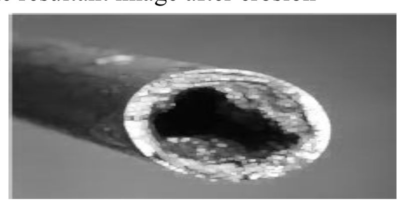

Fig. 6: This image is showing results after Dilation

Conclusion and Future Works: Based on the above results and analysis we come to know that wiener filter shows a good result in removing noise from the images. Pixel values and brightness is shown in the histograms of the images so that it will be useful to find the edge detection and segmentation. By using histogram threshold technique we found that the threshold value for the reference image is (185). In future the image segmentation and detection of cracks based on the threshold value will be processed and found.

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