Multifractal Analysis of Blockboard X-Ray Images for the Defect Detection

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Abstract

Nowadays, nondestructive testing technology is a new subject that has gotten rapid development. X-ray nondestructive scanning technology has been applied to the detection of internal defects in blockboard for the purpose of obtaining prior information that can be used to arrive at better production quality. Since producers currently cannot see the inside of blockboard until its faces are revealed by cutting. Therefore, the recognition of internal defects has become gradually significant. The traditional Euclidean geometry is not proficient of describing different natural objects and phenomena. In contrast, fractal geometry and its multifractal extension are new implements which can be used for describing, processing and analyzing complex shapes and images. A method in blockboard X-ray image defect detection based on multifractal theory was applied in this paper. The Lipschitz–Hölder exponent α of image was computed first. Then its multifractal spectrum $f(\alpha)$ was calculated and different image points were classified by analysis of multifractal spectrum $\alpha - f(\alpha)$. Experimental results showed that the method based on multifractal theory was effective to detect defects in blockboard X-ray images. Due to the information of defect, the areas and boundaries was obtained accurately by this method. Hence, in this paper, a dependable method by applying multifractal theory in defect detection of blockboard X-ray images was provided.

Keywords: *Blockboard, X-ray Nondestructive Testing, Multifractal Analysis, Defect Detection, Image Processing*

1. Introduction

Blockboard is widely used material in many fields recently, such as the furniture-making and carpentry in general. It plays an important role in the production of our life. It is advanced man-made sheet by comprehensively using of timber resources, thought as an ideal substitute for natural high quality timber [1]. However, its physical-mechanical properties are largely unknown and the combination of wood components having very different thickness (strips and veneers) makes it difficult to precisely determine the bonding quality [2]. Because its major components are cemented with agglutinant, detecting bond quality, uniformity degree and situations of filler is necessary. Once the testing methods of blockboard were destructive, it led to large numbers of timber resources waste. But nowadays, a new nondestructive blockboard was proposed based on x-ray technology. This kind of testing method can detect specimen without damaging both the appearance and structure. Furthermore, the internal defects of objects can be detected accurately. Firstly, an x-ray machine is operated to pass through the sample blockboard. Then the image signal of the blockboard is transformed from x-ray camera into computer. And then the detected images are collected by applying image collection hardware and software of computer. Finally, the digital blockboard image is displayed on the screen.

After obtaining the blockboard image, the important stage in the detection of defects in blockboard images is image edge detection. While there are many edge detection algorithms, each algorithm can be categorized based on whether it uses discontinuities or similarities in the image data or whether it is a local or global operator [3].In the classical method of edge testing, boundary operators are constructed by gray gradient change of the image pixels in the neighborhood, such as gradient operator, Laplacian operator, Sobel operator, Marr operator, or Canny operator. But the disadvantage common to all operators listed above is that they are sensitive to fluctuation [4].

These methods are already widely used in the field of image analysis and processing, but in the real world, most two-dimensional graphics cannot be expressed in terms of simple states such as: triangle, square, circle, etc. Therefore, these features require more general mathematical objects for a successful

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description of levels beyond these simple states. Therefore, a theory of self-similarity is extended from fractals to multifractals.

For example, as a fundamental appellation of fractals theory, consider a 2-D gray scale image. To describe an object of the image, the box-counting method (basic method in calculating fractal dimension) is not appropriate since it gives only a relation between nonempty boxes and the box size, regardless of the signal level into the boxes [5]. Multifractal (also called multiscale fractal or complex fractal) methods [6] are usually used to express a singular probability distribution, which cannot be expressed by whole fractal dimension. This method determines the properties of a signal based on its local characteristics or it applies a spectrum function to generate the image growth trend and the characteristics of a fractal object in different layers. Then it studies the final global characteristics from local system characteristics. [7]

The purpose of multifractal analysis is to quantify the singular structure of measure, and to provide models of different scale power laws when dimension changes [8], specifically for irregular images, which are hard to model in processing and analysis. Fractal and multifractal methods have been successfully applied in many fields of geosciences [9]. They can provide valuable information on the statistical and geometrical properties of geological and geophysical variables. Furthermore, multifractal theory also has been successfully used in Analysis and processing of decayed log CT image. The results showed that multifractal theory was a more effective and more local method than classical method of edge testing. [7]. Thus, in this paper, the defect areas in blockboard X-ray images detecting method was selected based on multifractal theory.

2. X-ray blockboard nondestructive detection theory

In recent years, X-ray detection method has been widely applied in the field of nondestructive detection. Wood defects image was acquired first by an X-ray image system as the major application way using X-ray. Then, blockboard defects and other internal structure features were detected by subsequent evaluation methods.

X-ray is a kind of electromagnetic wave which has shorter wavelength than visible lights. It can penetrate a certain thick opaque body of blockboard. After penetrating the body, X-ray will be absorbed partly when it passes through the blockboard. The abilities of absorption are different between different types of areas in the blockboard. Therefore, after the X-ray has intensity as I_0, penetrating the substance has a thickness as T, the intensity of the X-ray is:

$$I = I_0 e^{-\mu T} \tag{1}$$

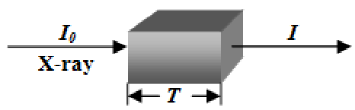

Figure 1. Attenuation Diagram of X-Ray Imaging Law.

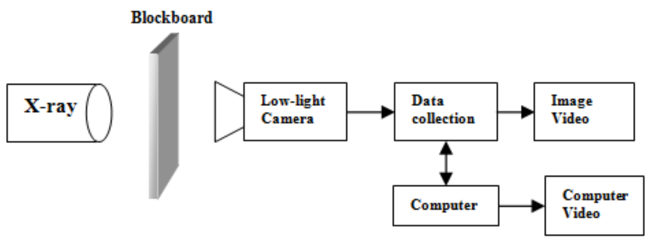

Figure 2. Blockboard X-Ray Nondestructive System.

The diagram of X-ray blockboard nondestructive detection imaging system is shown in Figure 2. The system used in our experiment is capable of producing blockboard defects images. The sample will be placed between the X-ray source and the image intensifier. The X-ray source gives off the X-ray which will be absorbed partly by the material when it penetrates the objects. Absorption quantity is related to the types and the density of blockboard defects. The attenuation of X-ray in the material reduces the energy, reflected in different degrees of activating the same image intensifier screen. The visual information of image intensifier is transmitted to a computer by a CCD camera. The digital signals transmitted by the A/D converter circuit from the simulation signals are deposited in the image storage system for the defects image detection.

3. Multifractal theory

3.1. Hausdorff dimension

The term fractal is used to describe geometrical objects or functions which are scale invariant, i.e. the part of object (or function) is similar to the whole (self-similarity) [10].Sets the properties of fractal geometry a power-law dependence on the scale and the power is the fractal dimension (or Hausdorff dimension). The dimension is denoted by D. Consider a set which is embedding in a (hyper) -volume in Euclidean space with maximal linear length L. The fractal dimension is usually calculated by covering the object with (hyper) -boxes of linear length $r \le L$, and counting the number $N(r)$ of boxes that contain points:

$$N(r) \propto r^{-D} \tag{2}$$

Hence, the fractal dimension D is obtained by evaluating:

$$D = -\lim_{r \to 0} \ln N(r) / \ln r \tag{3}$$

3.2. Lipschitz–hölder exponent

Multifractals are related to the statistical distribution of measures on a geometrical support: a line, a surface, a volume, or a fractal, for instance [10]. Multifractals are formed by an interlinked of fractal subsets with different scaling exponents.

Let us consider a set which is embedding in a (hyper) -volume in Euclidean space once again. And we divide the space into N parts; the i-th part has its own maximal linear length L_i . The probability of the fractal object appears in the i-th part is P_i , different area has different probability. P_i and L_i also obey the power-law:

$$P_i \propto L_i^{\alpha_i} \quad i = 1, 2, 3, \cdots, N \tag{4}$$

α_i is the local Lipschitz–Hölder exponent. Thus, the exponent α_i is obtained by evaluating:

$$\alpha_i = \lim_{L_i \to 0} \ln P_i / \ln L_i \tag{5}$$

In digital image processing field, the Lipschitz–Hölder exponent α_i is also called singularity index. The singularity index indicates the singularity characteristics of local image, which can be acquired as follows:

Firstly, we select a square r×r neighborhood $V_i(r)$ for the i-th part in the image (we divide the image into N parts, $i = 1, 2, 3, \cdots, N$). The neighborhood size i is correlated with the scale of target. In this situation, the linear length $L_i = r$, and we let the appearance-probability $P_i = \mu(V_i(r))$. $\mu(V)$ is the measure for V, it is a kind of algorithm that we can get a certain value P_i from the square r×r neighborhood $V_i(r)$.

Then, by using formula (5), there is:

$$\alpha_i = \lim_{r \to 0} \ln \mu(V_i(r)) / \ln r \tag{6}$$

where $\alpha_i = \alpha(x_i, y_i)$, it expresses the partly singularity of a target image.

3.3. Sum measure

Through analyzing the results from processing some digital image, we finally choose the sum-measure for calculating the singularity index. By applying sum-measure, we can obtain the appearance-probability P_i from a square area $V_i(r)$.

In the square r×r neighborhood $V_i(r)$, $I_i(x,y)$ is the gray value of one point in the area $V_i(r)$. In real digital image, the size of every point is 1 pixel×1 pixel. We define the sum-measure:

$$P_i^{sum} = \mu_{sum}(V_i(r)) = \overline{I_i} / \sum_i^N \overline{I_i}\ , \quad \overline{I_i} = (\sum_{V_i} I_i(x,y)) / r^2 \tag{7}$$

$\overline{I_i}$ is the average gray value of all the pixel points in the $V_i(r)$ region. $\sum_i^N \overline{I_i}$ means the sum of all the $\overline{I_i}$ value in the target image. That is why we call this sort of measure the sum-measure.

Certainly, to calculate the appearance-probability, there are several other measures such as max-measure, min-measure, adaptive-measure, etc. In this paper, we just try to apply the sum-measure to analyze our blockboard X-ray images.

3.4. Multifractal spectrum

After using formula (6) and (7), we can get a series of singularity index α_i. The number of parts in which P_i has the same singularity index equals α_0 is given by:

$$N_{\alpha_0}(r) \propto r^{f(\alpha_0)} \tag{8}$$

Therefore, for a given α_0, as $r \to 0$, $f(\alpha_0)$ provide the dimension of the subset of the measure that has singularity index α_0. Then $f(\alpha)$ is called the multifractal spectrum of α .The multifractal spectrum offers a good description of the global point set α. In the processing of multifractal image analysis, based on the value of singularity index α and multifractal spectrum $f(\alpha)$ that is calculated from image, one classifies and processes each pixel of image by statistic and computer graphics theories. Thus, detection of the defect areas depends on not only local characteristics but the global image as well.

To obtain the $f(\alpha)$, it is appropriate to define a partition function:

$$\mathrm{X}_q(r) = \sum_i^N P_i^q(r) \tag{9}$$

The q parameter ($q \in R$) is called moment of order q. If the measure has a multifractal distribution, $\mathrm{X}_q(r)$ scale with r in the following way:

$$\mathrm{X}_q(r) \propto r^{\tau_q} \tag{10}$$

Where τ is the mass exponent or correlation exponent of order q. If we know the partition function (9), we can determine the $f(\alpha)$ function by evaluating τ_q:

$$\tau_q = \lim_{r \to 0} \ln \mathrm{X}_q(r) / \ln r \tag{11}$$

The variables $f(\alpha)$ and α are related to τ_q via the Legendre transform:

$$\alpha(q) = \frac{d\tau_q}{dq}\ , \ f(\alpha(q)) = q\alpha(q) - \tau_q \tag{12}$$

4. Multifractal analysis of blockboard x-ray images

We start to analyze blockboard X-ray image based on multifractal theory.

In multifractal theory, we select a square r×r neighborhood $V_i(r)$ for the i-th part in the image (we divide the image into N parts, $i = 1,2,3,\cdots,N$).And according to formula (6), for calculating the singularity index α , it demands the $r \to 0$, $N \to +\infty$. But in real digital images, the minimum r=1 (pixel). Hence, for getting the singularity index α precisely, we need to calculate several singularity indexes based on different value of r, such as r=2, 3, 4…, in the same location of the image, and then using regression analysis to predict the right singularity index α . When we select a value for r, the formula (6) changes to:

$$\alpha_i(r) = \frac{\ln \mu(V_i(r))}{\ln(r / N)} \quad r = 1,2,3,\cdots \tag{13}$$

In order to avoid the denominator of previous formula equals 0 when the r=1, we let it divided by a constant number N. This operation will change the value of α , but will not influence the distribution rule of α that we concern.

Pretreat the original image and then choose a kind of measure to obtain the appearance-probability $P_i = \mu(V_i(r))$ of this image. Certainly, in this paper, we apply the sum-measure.

The image used in the experiment is a blockboard X-ray image after pretreatment. (Figure 3). For example, to obtain α_1 , we calculate the $\alpha_1(1),\alpha_1(2),\alpha_1(3),\cdots,\alpha_1(6)$ from the image firstly:

Table 1. The values of $\alpha_1(r)$

r	**1**	**2**	**3**	**4**	**5**	**6**
$\alpha_1(r)$	1.0931	1.2294	1.3303	1.4114	1.4816	1.5441

By using regression analysis, we fit these data into a linear function:

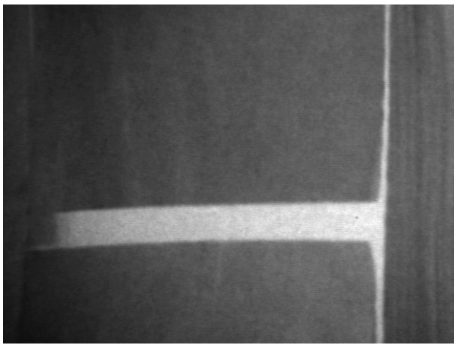

Figure 3. Blockboard X-Ray Image after Pretreatment

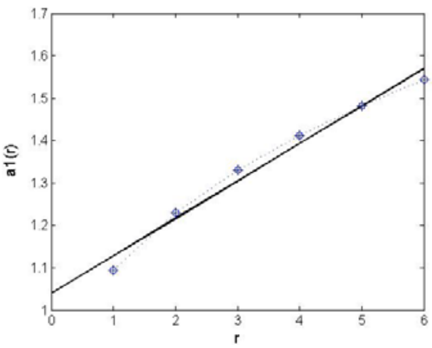

Figure 4. the Fitted Function

The fitted linear function that showed in Figure 4 is:

$$\alpha_1(r) = 0.0884 \times r + 1.0391 \tag{14}$$

Through the function, we can predict that: $\alpha_1(r \to 0) = 1.0391$. After applying this method to all the parts in this image, we will finally obtain the whole singularity indexes of it.

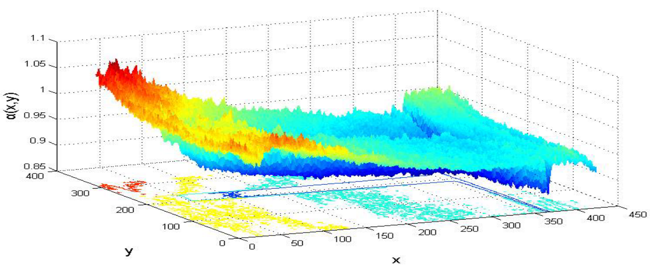

Figure 5. The Singularity Index α of Image

5. Multifractal spectrum in defect detection

Calculate multifractal spectrum $f(\alpha)$ of α via formula (12), and we set the $q \in [-10,10]$. During calculation of the multifractal spectrum in the image, we also encounter the problem that the minimum r=1, cannot pass to the limit 0. So we need to apply regression analysis again to predict the accurate results.

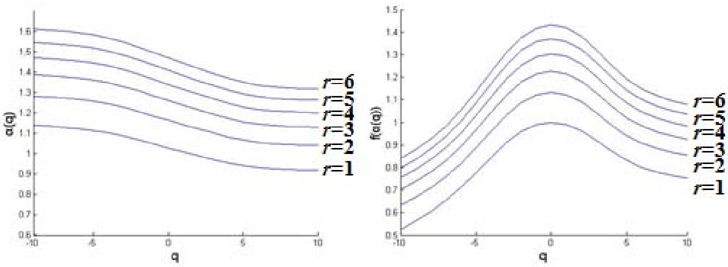

Figure 6. Q- α and Q- $f(\alpha)$ in Different R

The result is shown in Figure 8, which shows the multifractal spectrum distribution.

Value of $f(\alpha)$ gives global information about the image. For instance, points on the transitional region belong to the point set with $f(\alpha)$ close to 0.95. And based on multifractal theory and above analysis, some conclusions can be drawn as follows:

(1) $f(\alpha) \approx 0.9$ are transitional regions. The boundary of defect is enclosed as the contour line.

(2) $f(\alpha) > 0.9$ are some smooth areas. In Figure 9, they are in black.

(3) $f(\alpha) < 0.9$ are coarse or background areas, these areas occupy the most part of this image. Also, the defect areas are contained in it.

Edge points have not only geometry characteristics but also statistical characteristics: if a pixel is selected arbitrarily in an image, the point can be recognized by the probability of finding it[12].The multifractal spectrum α - $f(\alpha)$ provides us the distribution of this kind of probability. In some circumstances, the α also need to be given, because one value of $f(\alpha)$ could correspond to two α values.

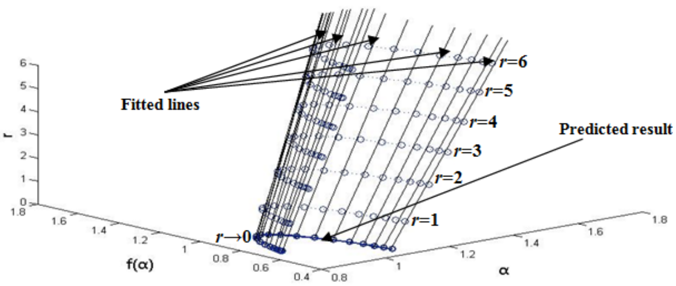

Figure 7. $\alpha - f(\alpha)$ in Different R

In order to detect the defects in X-ray images of blockboard, it is essential to get the information about the defect regions and edges. Therefore, we are more interested in the images of $f(\alpha) \approx 0.9$ and $f(\alpha) < 0.9$. Through analysis and processing the image based on multifractal theory, Fig 10-11 respectively show that the area and edge of the defect in blockboard X-ray images.

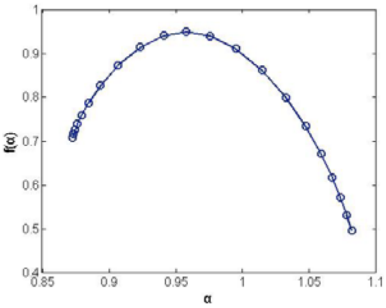

Figure 8. The Predicted Result of $\alpha - f(\alpha)$ in R→0

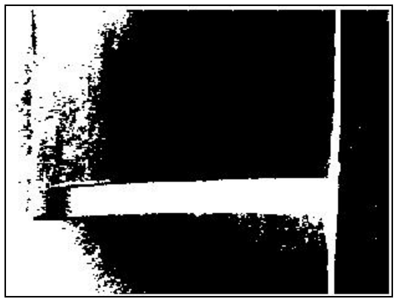

Figure 9. Image of $f(\alpha)$ >0.9

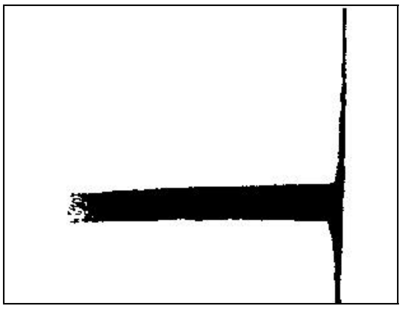

Figure 10. Image of $f(\alpha) < 0.9$ and $\alpha < 0.9$

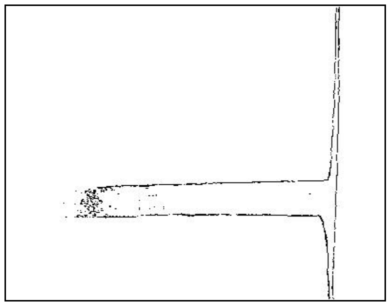

Figure 11. Image of $f(\alpha) \in (0.87, 0.91)$ and $\alpha < 0.92$

Figures 9–11 are the image details characterized by using different multifractal values of $f(\alpha)$ and α. Obviously, to Figure 11, if the appropriate multifractal spectrum thresholds $\alpha - f(\alpha)$ are selected, the precise edge can be detected by applying multifractal spectrum theory.

6. Conclusion

X-ray nondestructive technology was applied to the detection of internal defects in the blockboard for the purpose of obtaining prior information that can be used to arrive at better production quality. To be compared with other nondestructive testing, X-ray has advantages such as higher penetrability, higher resolution, fast testing speed and visible testing result etc. Multifractal theory was applied in the defect detection of blockboard X-ray images. In the experiment, we select the sum-measure to calculate the singularity index α (also Lipschitz–Hölder exponent). And in real digital images, regression analysis was used to estimate the ultimate value of α and $f(\alpha)$. After the calculation of the singularity index α of each point, the multifractal spectrum value $f(\alpha)$ can be calculated. From analysis of the multifractal spectrum $\alpha - f(\alpha)$, we can get the information of the defect regions and defect edges in the blockboard X-ray image. They are described by the points where ($f(\alpha) < 0.9$, $\alpha < 0.9$) and ($0.87 < f(\alpha) < 0.91$, $\alpha < 0.92$) in the image. The experimental result shown that the method based on multifractal theory was effective. Thus, a promising method based on multifractal spectrum in detecting defects of blockboard X-ray images is provided.

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