 doi:10.20944/preprints201808.0517.v1

Article

A Generic Adaptive Fractal Filtering Algorithm for Identifying Work Piece Defects on Multiple Surfaces

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Featured Application: Detecting workpiece's edge and surface defects in a noisy image.

Abstract: In addition to image filtering in the spatial and frequency domains, fractal characteristics induced algorithms offers considerable flexibility in the design and implementations of image processing solutions in areas such as image enhancement, image restoration, image data compression and spectrum of applications of practical interests. Facing up to a real-world problem of identifying workpiece surface defects, a generic adaptive fractal filtering algorithm is proposed, which shows advantages on the problems of target recognition, feature extraction and image denoising at multiple scales. First, we reveal the physical principles underlying between signal SNR and its representative fractal dimension indicative parameters, validating that the fractal dimension can be used to adaptively obtain the image features. Second, an adaptive fractal filtering algorithm (Abbreviated as AFFA) is proposed according to the identified correlation between the image fractal dimensions and the scales of objects, and it is verified by a benchmarking image processing case study. Third, by using the proposed fractal filtering algorithm, surface defects on a flange workpiece are identified. Compared to conventional image processing algorithms, the proposed algorithm shows superior computing simplicity and better performance Numerical analysis and engineering case studies show that the fractal dimension is eligible for deriving an adaptive filtering algorithm for diverse-scale object identification, and the proposed AFFA is feasible for general application in workpiece surface defect detection.

Keywords: Fractal dimension, surface defect identification, adaptive fractal filtering, edge extraction, image denoising.

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1. Introduction

Surface defects on metal components are commonly under careful manual inspection in mass production lines since they impact the normal operation of a mechanical system [1,2]. Compared to detection methods such as electromagnet magnetization, eddy current testing, or to other methods using instruments such as ultrasonic phased array, scanning microscope, thin film inductive microsensor, infrared interferometry [3-8], image-based surface defect identification takes advantages over its counterparts on accuracy, efficiency and noncontact measuring convenience.

However, it is still a challenge to inspect the defects using an automatic imaging system owing to miscellaneous patterns of the defects, low contrast between the defect and background, the existence of pseudo defects, as well as tiny workpiece surface defect detection problem such as small cracks and scratches are not easily identified by the conventional algorithms [9-12]. For surface defect identification application, Ke X. etal propose the methods include Scale Invariant Feature Transform

 doi:10.20944/preprints201808.0517.v1

(SIFT), Speeded Up Robust Features (SURF) and Local Binary Patterns (LBP) [13] and a novel non-symmetry and anti-packing model (NAM) was proposed in [14].

In addition to image filtering in the spatial and frequency domains, fractal characteristics induced algorithms offers considerable flexibility in the design and implementations of image processing solutions.

Chen Moon and Guo Hongyang [15] designed their experiments in which the input signal of the filter is divided into many frames containing the same number of sample points. The fractal dimension of each frame will be used to determine the control parameters of the filter corresponding to the frame. In other studies [16,17], the fractal dimension is used to effectively enhance the image contour in the filtering algorithm. In [18], the impact response signal of fiber grating is processed by fractal filter method. After fractal filtering, the signal purity of time domain impact energy signal is increased, and the signal clutter caused by external interference factors are eliminated [13].

Although these works are inspiring, the parameter tuning is cumbersome for achieving high-performance results and an adaptive algorithm is needed to compute the general and detailed information of an image and automatically derives the filtering parameters according to the object features.

The principal objective in this study is to simultaneously detect the work piece contour, segment its surfaces along edges, identify the defects and filter the high-frequency noises. The difficulties arise from the fact that all the sub-objectives do not abide by explicit patterns, herein under certain circumstances part of them are paradox in conventional image processing algorithms. To tackle this problem, an intuitive way is to mimic the attention mechanism during visual inspection by recognizing the features at different scales in turn. Fortunately, the fractal dimension lend itself to this computation. In this paper, a fractal dimension-based filtering algorithm is proposed by leveraging the full-image complexity, self-similarity and different scale characteristics to recognize the elements including the work piece contour, edges, defects, and noises. The proposed algorithm evaluates the individual scale and morphological features for each element and constructs an operator to associate the fractal dimension with image processing purposes. Hereby an adaptive digital image filer is designed to simultaneously enhance the object features and suppress the noises, which automatically identify the elements at different scale according to intrinsic metrics and exempts from artificially tuning the filtering parameters.

Basically, the core problem for detecting subtle defects in images is to identify and recognize the workpiece outlines, edges, surface defects, and noises with different spatial scales.

Taking flange image processing as an example, the workpieces, edges, surface defects and noises have different fractal dimensions. For these feature dimensions, adjusting the parameters in the fractal filter algorithm can achieve filtering or extracting the edges of the workpieces and surface defects.

The paper is organized as follows. Section 2 gives the definition of fractal dimension of signals and proves the fractal dimension is strongly related to the signal-to-noise ratio of signals. Section 3 gives the procedure of fractal filtering and shows the results of fractal filtering on two benchmark datasets. Section 4 shows the application of the AFFA in a work piece surface defect identification practice. Finally, a conclusion is drawn in section 5.

2. Fractal Dimension Relevant to Signal-to-noise Ratio

Fractal dimension is one of the intrinsic characteristics of signals. Through the mathematical calculation and derivation, the fractal dimension calculation method of one-dimensional or even multi-dimensional signals can be obtained. For solving the problem of whether the signal of a certain signal-to-noise ratio can be processed by using fractal dimension-based filtering, it is necessary to first demonstrate that there is a significant correlation between the fractal dimension and the signal-to-noise ratio of the signal.

2.1 Calculation of Fractal Dimension

In these studies, the definition of fractal dimension can be described as follows [13,14],

$$D^{(k)}(\Delta) = \sum_{j=1}^{n} |x_j - x_{j+1}| \quad (1)$$

$$D^{(k)}(2\Delta) = \sum_{j=1}^{n/2} (\max\{x_{2j-1}, x_{2j}, x_{2j+1}\} - \min\{x_{2j-1}, x_{2j}, x_{2j+1}\}) \quad (2)$$

$$N^{(k)}(\Delta) = D^{(k)}(\Delta)/\Delta \quad (3)$$

$$N^{(k)}(2\Delta) = D^{(k)}(2\Delta)/2\Delta \quad (4)$$

$$d_F{}^{(k)} = \frac{\log N^{(k)}(\Delta) - \log N^{(k)}(2\Delta)}{\log 2} = 1 + \log_2 \frac{D^{(k)}(\Delta)}{D^{(k)}(2\Delta)} \quad (5)$$

Where k means the sequence number of the frame in the entire signal. N means the number of discrete points in each frame. Δ is the side length of the grid used to calculate the fractal dimension.

2.2 Relationship between Signal-to-Noise Ratio and Fractal Dimension

Take sine signal as an example. B.U. Heerdun and Feng Han [14] process the signal without dividing it into frames. According to their settings, the input signal of the filter should be a combined signal of sine wave and random noise,

$$f(t) = \sin(t) + A * (\mathrm{rand}(1, \mathrm{length}) - 0.5) \quad (6)$$

The results show that fractal dimensions vary with signal-to-noise ratio of the input signal (Table 1). More specifically, the fractal dimension increases when the noise level rises which implies that the artificial thresholds in digital filter can be designed adaptively according to the fractal characteristics.

3. Image Processing Using Adaptive Fractal Filtering Algorithm（AFFA）

For identifying objects in an image, a fractal dimension is able to indicate the geometrical features at different scales. Intuitively the outline of object, the texture, the local abnormality, and the noise shows both diverse frequency-domain independence and scale variability. Meanwhile the fractal dimension is invariant to image translation and rotation. According to these characteristics, an adaptive fractal algorithm is proposed to deal with identifying objects with different scale and patterns in an image.

3.1 The design of Fractal Filter in Image Processing

Step one, convert a picture to a grayscale image if necessary. Then change every pixel into floating point number. Take every rows and columns of pixels as lines of one-dimensional data. Calculate their average fractal dimension (Using equation 1-5), which will be regarded as the fractal dimension of the whole image.

Step two, denote the image as $f(x_i, y_i)$ for each pixel, and an adaptive filtering operator a is constructed to represent the quantitative effect how the designated pixel affects its neighborhood and the whole image.

$$a = (m - d)^p \quad (7)$$

where d is the fractal dimension of a whole image and m, p are constants, According to Table 1, d generally varies from 1.10 to 1.50 and the item "m-d" should be comparable to d. In most cases, set m = 2.7 to fulfill the symmetry for d.

Table 1. Deterministic relationship between the fractal dimension and noise

A	d(Test 1)	d(Test 2)	d(Test 3)	Average d
0.02	1.1482	1.1490	1.1470	1.1481
0.05	1.3542	1.3411	1.3483	1.3479
0.10	1.4029	1.3992	1.3907	1.3976
0.30	1.4422	1.4300	1.4329	1.4350

 doi:10.20944/preprints201808.0517.v1

The purpose of constructing "*m-d*" is to let this term be monotonically decreasing during the span [1.10-1.50]. The corresponding physical meaning is that a lower SNR, stronger noise lead to a greater value of d, and a decrease when d increases which can be interpreted as the filter needs to take into more considerations of the overall information rather than the designated pixel. The value of p is used to magnify the variation of the term "*m-d*" to enhance its discrimination, making it more sensitive to the fractal dimension changes, and its empirical value of p is 6.

Accordingly, an adaptive fractal filter is designed as follows,

$$g(x_i, y_i) = af(x_i, y_i) + \frac{1-a}{3}[g(x_{i-1}, y_{i-1}) + g(x_i, y_{i-1}) + g(x_{i-1}, y_i)] \tag{8}$$

Step three, subtract the former image $f(x_i, y_i)$ from the processed image $g(x_i, y_i)$, then change it back to a grayscale image.

To show the procedure more clearly, generalize a flow diagram as in Figure.1.

3.2 Fractal Filtering Performance Benchmarking

Take the benchmark picture Lenna as the input and extract the edges of Lenna used the proposed AFFA. It's obvious that the edges are enhanced in the processing image 2(b) and reserve edges very clearly in the final image 2(c).

In general, the proposed algorithm is adaptive to image features of different scales, it can enhance the outlines to proper extent. This algorithm has a computational complexity of O(9N) (where N is the total number of pixels).

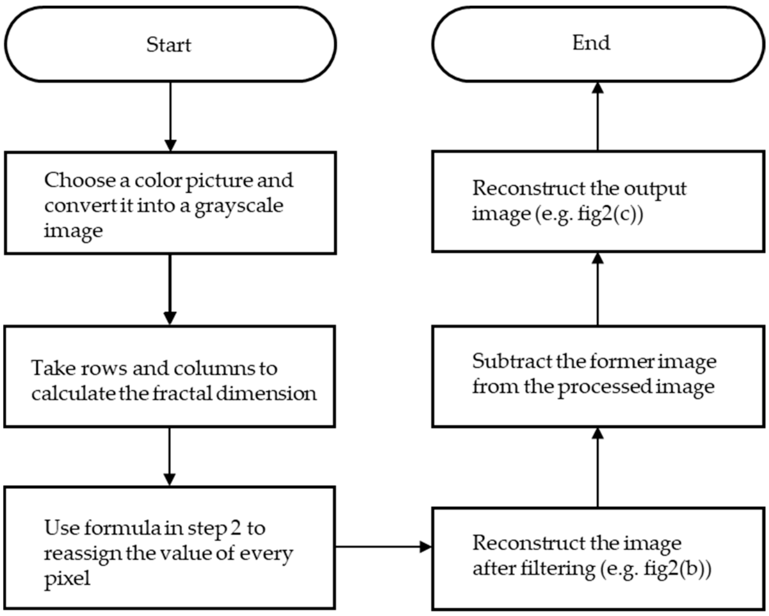


Figure 1. Flow chart of Fractal Filtering in Image Processing

(a) (b) (c)

Figure 2. set m=2.7, p=6. (a) is an original LENA image.

(b) is the image after step two. (c) is the final image.

4. Workpiece Surface Defect Identification with AFFA

As a detachable workpiece, the flange is widely used in the connection between the shaft end, the pipe end and the equipment. The surface quality directly determines the mechanical strength and sealing characteristics of the joint. The flange surface defects will cause equipment failure and device failure. The flange production involves 7 kinds of machining processes, forming 14 profiles, which are easy to cause plenty of surface flaws on each type of surface, and the inferior rate is nearly 10%. Flange manufacturers use visual inspection to monitor product quality, work intensity is high, detection efficiency is low, and accuracy is difficult to guarantee. The use of AFFA to process flange images is the first step to detect flange defects.

4.1 Flange surface imaging and processing with AFFA

Take two flange images as example, the defects on the surface and edges of flanges are apparent. Before applying AFFA, images are selected and cut. In the algorithm, it's set to save the images after filtering, which are enhanced on edges (figure3. b, e), and images after subtraction, which are the conclusive results (figure3, c, f). Finally, it can export a process result (figure4). Usually the defects end white dots on the surface.

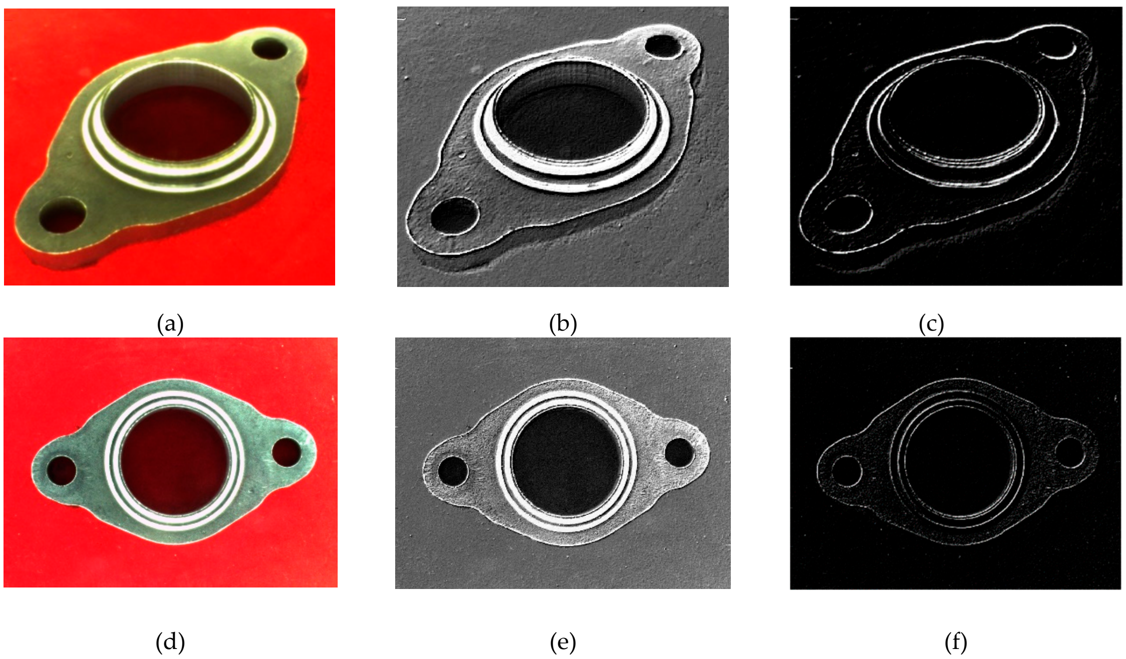


Figure 3. Flange surface image processing by setting m=2.6, p=6.

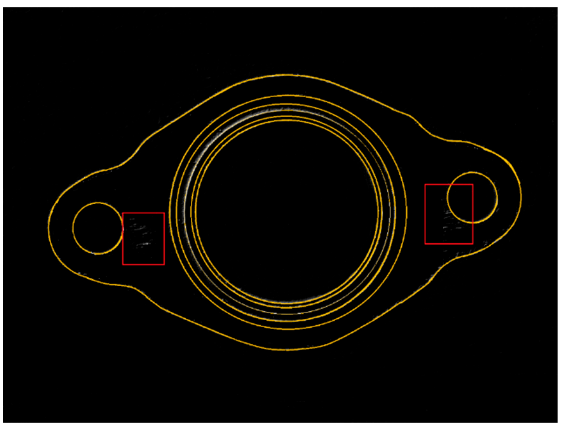
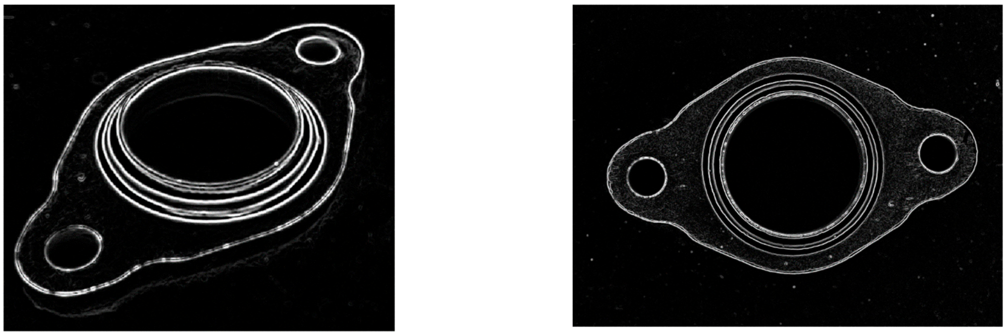


Figure 4. Process result



(a) (b)

Figure 5. Flange image processed by traditional algorithm.

Table 2. UIQI of images processed by AFFA and Gauss filtering

	AFFA	Gauss	Scoring Difference*
Fig3 (c) & Fig5 (a)	0.0406	0.0362	12.15%
Fig3 (f) & Fig5 (b)	0.0356	0.0322	10.55%

*Scoring Difference = (Score of AFFA-Score of Gauss)/Score of AFFA

4.2 Comparison against Gaussian Filtering & Canny Edge Extraction Algorithm

To reflect the enhancement of AFFA compare to the traditional filtering algorithm, combine Gaussian filtering algorithm with Canny operator to achieve the same goal that AFFA did.

Take an example of flange surface image process. It's obvious that the results are obscure and full of noise. Furthermore, it takes average 2.65 seconds using the traditional algorithm to process one image, comparing to 1.63 seconds by AFFA.

To compare the results of the two algorithms more objectively, a universal image quality index (UIQI) is adopted, which is independent of the contents and types of the image under test [19,20]. The observation condition or the quality measurement method of the individual observer has a strong ability to reflect the loss of real information, so the UIQI quality index is selected to reflect the quality of the processed image. The greater the value of the UIQI index, the higher the quality of the processed image. Table 2 shows the scores of AFFA and Gauss filtering results for flanges with different view angle.

For both cases, AFFA outperforms classic Gauss filtering algorithm by more than 10%, which validates the adaptability of the proposed AFFA from computational complexity and accuracy perspectives.

5. Conclusions

In this paper, a generic adaptive signal filtering algorithm is proposed, which automatically profiles the elements with different scale and morphological features according to the fractal dimension induced operator. In dealing with a work piece surface defect identification problem, the proposed algorithm preserves the image contour, edges while eliminates the noises, showing a superior performance and computational simplicity over conventional algorithms.

Inspired by human cognitive nature, the proposed AFFA can be applied to more extensive applications. Although to an engineering end the proposed adaptive fractal filter is approximately equal to a low-pass image filter in this paper, it stands to reason that by altering the structure in Equation (8), the AFFA will be equivalent to low-pass, band-pass, or high-pass digital filter in its result, which implies its feasibility and scalability in the digital signal processing field.

 doi:10.20944/preprints201808.0517.v1

Author Contributions: L.G. conceived the fundamental idea and derived basic mathematical frame, C.H. Lin and Z.M. conducted mathematical modeling and article writing. K.L. and Z.M. also completed the software development. X. S. and X. L. finished the algorithm experimental verification. C.L. Liu supervised the whole project.

Acknowledgments: The help of Yi Ju and Yuan Wei, in samples collection and software development is gratefully acknowledged.

Funding: This study was supported by the Natural Scientific Foundation of China under Grant NO.11202125 and the Scientific Plan Project of Shanghai Science and Technology Committee under Grant NO. 16391903102.

Conflicts of Interest: The authors declare no conflict of interest.

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