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Application of New Multi-Scale Edge Fusion Algorithm in Structural Edge Extraction of Aluminum Foam

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ABSTRACT Accurate extraction of structural edge information of aluminum foam is an important method to study the complex structural properties of aluminum foam, but the conventional single-scale edge detection method is difficult to achieve complete extraction of structural edge information of aluminum foam. However, the multi-scale fusion edge detection method based on Gaussian smoothing also has some problems, such as strong edge diffusion, weak edge degradation, edge pixel movement and so on. In order to solve the shortcomings of the above methods, this paper proposes a multi-scale edge fusion algorithm based on texture suppression, which can extract the edge information of aluminum foam structure more accurately and completely. Firstly, preprocess the image. The illumination component of the image is extracted by the multi-scale fusion method, and the luminance of the image is corrected by the adaptive luminance correction method based on the two-dimensional gamma function. Secondly, construct multi-scale space. It is proposed to construct the guiding image of the guiding filtering by using the bilateral texture filtering and construct the multi-scale space by changing the scale factor of the guiding filtering. Both bilateral filtering and guided filtering have the function of suppressing the texture information of the image while maintaining the structural edge features of the image. Finally, extract edge seeds and fuse multi-scale edges. A new multi-scale image edge fusion algorithm is proposed, which uses seed edges as a medium to gradually merge multi-scale image edges. In order to extract the edge information of the foam aluminum cross-section structure more accurately and completely, the algorithm further optimizes the edge using gradient direction consistency and non-maximum suppression. In order to verify the feasibility of the proposed algorithm, this paper uses the dataset to test the proposed algorithm and a variety of existing algorithms, and compare the results of various algorithms by quantitative analysis. The experimental results show that the proposed algorithm is feasible and effective, and its performance is better than the comparison algorithm.

INDEX TERMS Multi-scale space, multi-scale image processing, multi-scale edge fusion, edge extraction, aluminum foam, seed edges.

I. INTRODUCTION

Aluminum foam is a structural foam material with complex internal structure, different pore size and irregular distribution. Due to its special structural characteristics, it has good mechanical properties. The study on the properties of aluminum foam structure has become another research hotspot in the field of foam metal [1], [2]. Therefore, accurate structural edge extraction is meaningful for studying the internal structural properties of aluminum foam.

Accurate extraction of structural edge information from the cross-section of aluminum foam is an important method to study the complex structural properties of aluminum foam. There are many edge detection algorithms, such as Roberts algorithm, Sobel algorithm, Prewitt algorithm, Canny algorithm, Log algorithm, etc. [3]. But these methods can only solve problems in specific situations, and no one method is suitable for all images. Different algorithms have different calculation methods, including local measurements, discrete

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convolution and pattern matching [4]. However, in the process of edge detection, almost all methods evaluate the neighborhood of the pixel of the image. When performing neighborhood-based evaluation, firstly need to define the size of the neighborhood range, that is, the number of pixels included in the neighborhood calculation, and the neighborhood size is the so-called scale. Some edge detection methods are based on fixed-size neighborhoods (such as FIRE [5] or Sobel method [6]). Other edge detection methods modify the neighborhood size according to the parameter values (such as Canny [7] or Marr-Hildreth method [8]). The size of the neighborhood determines the scope of the intensity changes. In this sense, it can be considered to be the scale at which the edge detection is performed. In general, fine scale is expected to provide spatially accurate results, but the result is particularly sensitive to noise [9]–[14]. However, it is commonly accepted that detections performed at larger scales are more robust against noise, textures and spurious edges, but tend to suffer from displacements of the edges from their actual position [15], [16]. Canny's research [7] has pointed out that the single-scale method could not be applied to extract the edge of texture-rich images. And he gives some advises such as using multi-scale edge fusion method to extract image edge information or selectively smoothing the image according to local features. Therefore, the existing single-scale edge detection method cannot meet the requirements of accurate extraction of edge information of images with rich texture information and complicated structure. As discussed above, the single-scale edge detection methods have a certain limitations. In order to solve the limitations of the single-scale edge detection methods, the multi-scale edge detection method is proposed. The so-called multi-scale edge detection method is to gradually extract the effective signal from coarse to fine by changing the signal processing scale. The edges of the image are extracted at different smoothing scales, and the extracted edges are fused to obtain the final edge of the image. So far, many studies have been done on multi-scale edge detection methods. Witkin [17] uses multi-scale edge detection and tracking techniques to study the effect of Gaussian filtering on the edges of the original signal. Bergholm [18] made further research on the basis of Witkin's research, and proposed a coarse-to-fine edge tracking method to fuse edges of different scales and extend the application of multi-scale methods from one-dimensional signals to two-dimensional signals. Lindeberg [15] studies the effect on image edges of scale change in Gaussian scale space. Goshtasby [19] states the significance of Gaussian scale space in image processing, and proposes a method to detect whether the interval between two consecutive scales is too large. This can help determine the scale separation of multi-scale space. Lopez-Molina *et al.* [4] introduce multi-scale edge detection based on the Sobel method and fine-to-coarse edge tracking. However, none of the above methods can solve the problem of degradation, diffusion, and movement of image edges caused by Gaussian filtering.

With the vigorous development of deep learning, a series of edge detection methods based on deep learning have recently been invented. Hwang *et al.* [20] considered contour detection as a per-pixel classification problem. Iandola *et al.* [21] employ DenseNet to extract a feature vector for each pixel, and then SVM classier was used to classify each pixel into the edge or non-edge class. Li *et al.* [22] proposed a complex model for unsupervised learning of edge detection. Yu *et al.* [23] propose a novel end-to-end deep semantic edge learning architecture based on ResNet and a new skip-layer architecture where category-wise edge activations at the top convolution layer share and are fused with the same set of bottom layer features. In order to improve the efficiency of edge detection, they propose a multi-label loss function to supervise fusion activation. Liu *et al.* [24] achieve state-of-the-art performance on several available datasets by using VGG16 network. The proposed network fully exploits multiscale and multilevel information of objects to perform the image-to-image prediction by combining all the meaningful convolutional features in a holistic manner. He *et al.* [25] propose a Bi-Directional Cascade Network (BDCN) structure, where an individual layer is supervised by labeled edges at its specific scale, rather than directly applying the same supervision to all CNN outputs. Furthermore, to enrich multi-scale representations learned by BDCN, they introduce a Scale Enhancement Module (SEM) which utilizes dilated convolution to generate multi-scale features, instead of using deeper CNNs or explicitly fusing multi-scale edge maps. The above-mentioned deep learning-based edge detection method has achieved recognition or classification performance beyond the existing algorithms in an application scenario that satisfies certain conditions. However, deep learning requires a large number of datasets for training, currently, there is no published datasets on aluminum foam, so it is impossible to train to generate a network model for structural edge detection of aluminum foam. If training is performed using other image datasets, the training generated network model may also be difficult to migrate to other applications. At present, due to lack of datasets on aluminum foam, there are certain difficulties in using the deep learning-based method to extract the structural edge features of aluminum foam.

In order to solve the above problems, this paper proposes a new multi-scale edge fusion algorithm. This method uses guided filtering to construct multi-scale space instead of Gaussian filtering. Unlike Gaussian filtering, guided filtering is a content-aware filtering method. It effectively preserves image edges and suppresses image noise and texture. This also fundamentally solves the problem of edge diffusion, edge degradation and edge shift from their actual position. Image quality is also an important factor in accurately extracting the edges of an image. Due to the influence of lighting conditions and surface roughness, strong texture information similar to structural edge information appears on the aluminum foam surface, which directly affects the detection accuracy and increases the difficulty of edge extraction. Therefore, it is necessary to preprocess the image before extracting the structural edge information of the aluminum foam.

In this paper the proposed method is divided into three parts. Firstly the proposed method extracts the illumination component of the image by multi-scale fusion method, and combines the illumination component with the two-dimensional gamma function to construct an adaptive luminance correction method; Secondly, it is proposed to construct a guided image of the guided filter function using a bilateral filtering function, and construct a multi-scale space by changing the scale factor of the guided filter function; Finally, in order to extract the complete and precise structural edge information of aluminum foam, this paper proposes a new multi-scale edge fusion algorithm based on seed edge. The quality of the seed edge directly affects the results of the experiment.

II. BASIC THEORY OF EDGE FUSION ALGORITHM BASED ON GAUSSIAN MULTI-SCALE SPACE

A. IMAGE PREPROCESS

There are many factors that affect the image quality of objects, such as the surface characteristics of the object and the varying environmental lighting conditions. Especially the unevenness of illumination directly increases the difficulty of edge detection. The main performance is that some areas are too bright, but some areas are too dark, which leads to some important details that cannot be highlighted or even concealed. This seriously affects the visual effect and application value of the image. In the field of feature extraction, the above problems are mainly manifested in the two aspects: First, in the darker areas of the image, the contrast between the features and the background is too small, which increases the difficulty of edge extraction; Second, image brightness intensity mutation may form a spurious edge in the image, which reduces the correctness of edge information extraction. This paper mainly study the structural characteristics of aluminum foam, and the quality of the image has a great influence on the extraction of the edge of the aluminum foam cross-section. Therefore, in order to eliminate the influence of image quality on the edge extraction, it is necessary to preprocess the image before extracting the structural edge of the aluminum foam.

This paper uses a simple illumination-reflection imaging model to correct the brightness of the image. According to the principle of the light reflection imaging model, the image is formed by the environmental light reflected by the object entering the imaging device. The basic theoretical model [26] can be described by equation (1).

$$f(x, y) = i(x, y)r(x, y) \tag{1}$$

Usually, a digital image can be seen as a two-dimensional function $f(x, y)$, and the value of the function is the brightness value of the image at the coordinate point (x, y). It consists of the product of the illumination component $i(x, y)$ incident in the scene and the reflection component $r(x, y)$ of the surface of the object.

In the illumination-reflection imaging model, the illumination component characterizes the low frequency characteristics of the image, while the reflection component characterizes the high frequency detail information of the image, which is related to the surface characteristics of the object. The preprocess of the image in this paper is mainly for the illumination component which stands mainly for low-frequency information of the image. The multi-scale fusion method can effectively compress the dynamic range and accurately estimate the illumination component of the scene [27]. The specific calculation method is as shown in equation (2)(3).

$$G(x, y) = \lambda \exp\left(-\frac{x^2 + y^2}{C^2}\right) \tag{2}$$

$$I(x, y) = \sum_{i=1}^{N} \omega_i \left[f(x, y) * G_i(x, y)\right] \tag{3}$$

where C is the scale factor; λ is the normalization constant which ensure that the function $G(x, y)$ satisfies the normalization condition $\int G(x, y)dxdy = 1$; $f(x, y)$ is the input image; $I(x, y)$ is the light component; ω_i is fusion coefficient, generally $\omega_i = 1/N$.

The value of the scale factor C of the equation (2) determines the range of the convolution kernel. The larger the value of C is, the higher the global characteristic of the extracted illumination component is. Well, the smaller the value of C is, the better the local characteristics of the extracted illumination component is.

The adaptive brightness correction method is constructed by combining the illumination component and the two-dimensional gamma function. The parameters of the two-dimensional gamma function are adaptively adjusted by the distribution characteristics of the illumination component to realize the adaptive correction of the image illumination intensity. The specific implementation is as shown in formula (4), formula (5), and formula (6).

$$O(x, y) = 255\left(\frac{f(x, y)}{255}\right)^{\gamma} \tag{4}$$

$$\gamma = \left(\frac{1}{2}\right)^{\frac{I(x,y)-m}{m}} \tag{5}$$

$$m = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I(x, y) \tag{6}$$

where $O(x, y)$ is the image after illumination equalization, γ is the adaptive adjustment factor, m is the average illumination intensity, $f(x, y)$ is the input image and the size is $M*N$.

B. CONSTRUCTION OF GAUSSIAN MULTI-SCALE SPACE

Any multi-scale image processing method samples the continuous space by different methods and obtains the image sequence to construct a multi-scale space. The most common way to generate such an image sequence is to apply filter functions with different scales to smooth the image. As the scale increases, part of the detail information of the image disappears and the image becomes more and more blurred. This process is similar to the focusing process of the human eye. In the field of image processing, using filter function to construct multi-scale image space is the mainstream method of multi-scale image processing. However, Gaussian functions are widely used in the field of image processing. Gaussian smoothing is a simple, non-content-aware image processing method. Using Gaussian filter function with different scales can constructe Gaussian multi-scale space. The input image $f(x, y)$ is smothed by the two-dimensional Gaussian kernel function sequence $G_\sigma(x, y)$ with standard deviation $\sigma = \{\sigma_1, \sigma_2, \sigma_3, \cdots, \sigma_{n-1}, \sigma_n\}$. The image $f(x, y)$ is mapped into Gaussian multi-scale space. This can obtain the multi-scale image sequence $I_\sigma = \left\{I_{\sigma_1}, I_{\sigma_2}, I_{\sigma_3}, \cdots, I_{\sigma_{(n-1)}}, I_{\sigma_n}\right\}$ in Gaussian multi-scale space, Where $I_\sigma(x, y) = G_\sigma^* f(x, y)$.

C. EDGE DETECTION ALGORITHM BASED ON GAUSSIAN MULTI-SCALE SPACE

The multi-scale edge detection algorithm based on Gaussian smoothing and edge tracking includes the following steps: (1) extracting a limited number of images from Gaussian multi-scale space to form an image sequence I_{σ_1}; (2) extracting edges of each image in I_{σ_1}; (3) extracting the final edge of the image by a coarse-to-fine edge tracking method.

Firstly, extracting image sequence I_{σ_1}. The finite images is extracted in the Gaussian multi-scale space to form the image sequence I_{σ_1}, $\forall\sigma^1 \subset \sigma, \exists I_{\sigma\_1} \subset I_\sigma$, where I_{σ_1} is the sequence of images that need to be extracted from the Gaussian multi-scale space. The standard deviation set $\sigma^1 = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$ of the Gaussian kernel function selected in this paper. Secondly, extracting the edge of the image sequence I_{σ_1}. Construct the gradient operator G_x, G_y. Where $G_x = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}$, $G_y = \begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix}$. Using G_x, G_y and the image in the image sequence I_{σ_1} perform a convolution operation to obtain gradient and gradient direction of the image; then, using the local maximum constraint and the hysteresis threshold obtain the edge $B_{\sigma i}$ of each image in the image sequence I_{σ_1}, where $i = 1, 2, 3, \cdots, 8, 9$. Lastly, tracking edges and extracting the image edge. If the point (x, y) in the image is an edge point, the point must meet the following conditions:

(c1) $(x, y) = (x_1, y_1)$, $\exists(x_1, y_1) \in B_{\sigma 1}$,

(c2) $B_{\sigma i}(x_i, y_i) = 1, \forall i \in \{1, 2, 3, \cdots, n\}$,

(c3) $d\left((x_i, y_i), (x_{i-1}, y_{i-1})\right) \leq T_{dist}, \forall i \in \{2, 3, \cdots, n\}$,

(c4) $\varphi\left(D_{\sigma i}(x_i, y_i), D\sigma_{(i-1)}(x_{i-1}, y_{i-1})\right) \leq T_{ang}, \forall i \in \{2, 3, \cdots, n\}$

where T_{dist} is the distance threshold, indicating the relationship between the edge positions of two adjacent images of the continuous image sequence, generally $T_{dist} = 1$; T_{ang} is the angle threshold, indicating the edge gradient direction between two adjacent images of the continuous image sequence relationship, generally $T_{ang} = \pi/8$.

When Gaussian kernel function is used to process images, as the scale σ increases, the image is continuously smoothed, and the image becomes more and more blurred, accompanied by the phenomenon of edge degradation, diffusion, and displacement. When σ increases to a certain extent, the weak edge information in the image will completely disappear. As a result, the image edge features extracted by the edge fusion algorithm based on Gaussian multi-scale space will be incomplete. It is commonly accepted that edge detection performed at larger scales are more robust against noise, textures and spurious edges, but tend to suffer from displacements of the edges from their actual position. Therefore, the size of the scale directly affects the accuracy of the edge position. In order to solve this problem, a new multi-scale edge fusion algorithm is proposed to extract the structural edge information of aluminum foam cross-section.

III. A NEW MULTI-SCALE EDGE FUSION ALGORITHM

This paper proposes a new multi-scale edge fusion algorithm. This method uses guided filtering to construct multi-scale space instead of Gaussian filtering. Unlike Gaussian filtering, guided filtering is a content-aware filtering method. It effectively preserves image edges and suppresses image noise and texture. This also fundamentally solves the problem of edge diffusion, edge degradation and edge shift from their actual position. The proposed algorithm can effectively solve the problems of the method based on Gaussian multi-scale space. The algorithm includes the following three steps: (1) preprocessing image (2) constructing guided image and multi-scale space (3)Proposing a new multi-scale image edge fusion algorithm based on the seed edge to extract the structural edge information of aluminum foam.

A. IMAGE PREPROCESS

In the second part of this paper, we have pointed out the factors that affect the image quality of the object, such as the surface characteristics of the object and the varying environmental lighting conditions. Especially the unevenness of illumination directly increases the difficulty of edge detection. The main performance is that some areas are too bright, but some areas are too dark, which leads to some important details that cannot be highlighted or even concealed. This seriously affects the visual effect and application value of the image. In the field of feature extraction, the above problems are mainly manifested in the two aspects: First, in the darker areas of the image, the contrast between the features and the background is too small, which increases the difficulty of edge extraction; Second, image brightness intensity mutation may form a spurious edge in the image, which reduces the correctness of edge information extraction. This paper mainly studies the structural information of aluminum foam, and the image quality has great influence on the edge information of aluminum foam. Therefore, in order to eliminate the influence of image quality on the edge extraction, it is necessary to preprocess the image before extracting the structural edge of the aluminum foam.

The image preprocessing method proposed in the second part above is still used in the improved algorithm. The method can adaptively correct the illumination component of the image, balance the brightness of the image and improve the image quality. It is beneficial to the following feature extraction. The image preprocessing method has been described in detail in the second part above. Here, the method will not be described again in this paper. Detailed calculation process refer to formula (1) (2) (3) (4) (5) (6).

B. BULIDING MULTI-SCALE IMAGE SPACE BASED ON GUIDED FILTERING

For an image with complex structure and rich texture information, the multi-scale edge fusion method is more suitable for extracting its edge than the single-scale edge extraction method. Gaussian functions are commonly used to construct multi-scale spaces. However, when Gaussian smoothing is used to process an image, it not only eliminates image noise, but also blurs the edges of the image, which causes degradation of the image edges. Therefore, this paper proposes a multi-scale space construction method based on guided filtering.

Firstly, Build a guided image. Guided image directly affects the result of guided filter processing. In order to better remove the noise and texture in the image and preserve the edge of the image as much as possible, this paper proposes a method based on bilateral texture filtering to build the guided image of the guide filtering. The method of the guided image construction will be described in detail below.

For the input image I, the mean image B of image I is calculated using a $k \times k$ box filter while $\Delta(\Omega_q)$ is calculated using a sliding window of $k \times k$.

$$\Delta(\Omega_q) = I_{\max}(\Omega_q) - I_{\min}(\Omega_q) \tag{7}$$

where $I_{max}(\Omega_q)$, $I_{\min}(\Omega_q)$ respectively represents the maximum and minimum values in the neighborhood Ω_q ; $\Delta(\Omega_q)$ represents the maximum difference value of the gray level in the neighborhood Ω_q. A large difference in the gray value of the image in the neighborhood Ω_q indicates that there is an image edge in the neighborhood Ω_q. However, the value of $\Delta(\Omega_q)$ is tend to suffer from the noise and strong texture of the image.

In order to solve the problem that texture structure information is stronger than edge information, the following amendments are made to formula (7).

$$|(\partial I)_r|_{r\in\Omega_q} = sqrt\left((\partial_x I)_r^2 + \left(\partial_y I\right)_r^2\right) \tag{8}$$

$$\mathrm{m}RTV\left(\Omega_q\right) = \Delta\left(\Omega_q\right)\frac{\max\limits_{r\in\Omega_q}|(\partial I)_r|}{\sum\limits_{r\in\Omega_q}|(\partial I)_r| + \varepsilon} \tag{9}$$

where $|(\partial I)_r|_{r\in\Omega_q}$ is the intensity gradient value at pixel r, ε is any small value, $\varepsilon = 10^9$ in this paper.

The value of mRTV is large in a window Ω_q containing edge information, and the value of mRTV is small in a window Ω_q containing texture information. This can promote the removal of strong texture information and the preservation of weak edge information. However, the mRTV value is susceptible to noise in the smooth region of the image, the guide image p can be determined at the point (x, y) by comparing the value of the mRTV in the neighborhood Ω_p and the neighborhood Ω_q , and both Ω_p and Ω_q contains the pixel (x, y). The specific calculation is as follows:

$$\alpha_p = 2\left(\frac{1}{1+\exp(-\beta(\mathrm{m}RTV(\Omega_p)-mRTV(\Omega_q)))}-0.5\right) \tag{10}$$

$$p = \alpha_p I_p + \left(1-\alpha_p\right) B_p \tag{11}$$

where $\alpha_p \in [0, 1]$ is an adaptive adjustment factor, in the smooth region and the texture region, the value of α_p is small, and in the region containing the edge, the value of α_p is large; β is an scale factor, which controls the conversion of edge regions to smooth or textured regions; p is the guide image.

Secondly, construct multi-scale image space based on guided filtering. Guided filtering effectively smoothes the image background and preserves edge features. Use the formula (12) to represent the guide filter function.

$$q = guidefilter(p, I, r, \varepsilon) \tag{12}$$

where r is the size of the filtering window, ε is the regularization parameter, p is the guiding image, I is the input image, q is the output image, and the images I, p are all predetermined. The guided filtering assumes that the output image has a linear correlation with the guided image in the local window ω_k. The linear relationship of the guided filtering hypothesis is as follows:

$$q(x, y) = a_k p(x, y) + b_k, \quad \forall (x, y) \in \omega_k \tag{13}$$

where a_k, b_k is the constant coefficient in ω_k. The core of the guided filtering is to calculate the optimal solution of the linear coefficient (a_k, b_k) which will reduce the difference between the input picture I and the output image q as much as possible. Use the formula (14) to represent the optimization function.

$$\mathrm{E}(a_k, b_k) = \sum_{(x,y)\in\omega_k}\left((a_k p(x, y)+b_k-I(x, y))^2+\varepsilon a_k^2\right) \tag{14}$$

where ε is the regularization parameter, which is used to avoid the value of a_k too large, and to maintain data stability.

In window ω_k, by minimizing the cost function(15), you can get the optimal value of (a_k, b_k). According to linear regression analysis, the optimal solution expression of a_k, b_k can be expressed as the formula (15).

$$a_k = \frac{\frac{1}{|\omega|}\sum\limits_{(x,y)\in\omega_k} I(x, y)\, p(x, y) - \mu_k\overline{p_k}}{\sigma_k^2+\varepsilon}, \quad b_k = \overline{p_k} - a_k\overline{\mu_k} \tag{15}$$

Bring formula (15) into formula (13) can get formula (16), and formula (16) has the same meaning as formula (13).

$$\mathrm{q}(\mathrm{x,y}) = \frac{1}{|\omega|}\sum_{k\in\omega_k}(a_k p(x, y) + b_k) = \overline{a_k} p(x, y) + \overline{b_k} \tag{16}$$

where ω_k is an window of guide image; μ_k is the mean value of window ω_k; $|\omega|$ is number of pixels; σ_k^2 represents the pixel variance.

The parameter ε is a basis for determining whether the region of image is smooth. When the local variance σ_k^2 is smaller than ε, the region is considered to be a smooth region, which does not have structural edge information , and the filtering process can be performed to smooth the image. When the local variance σ_k^2 is greater than ε, the image region is considered to be non-smooth area, which may contain structural edge information. So the area cannot be filtered by the filter function, and should be maintained.

Through the above analysis, a multi-scale space can be constructed by changing the value of the parameter ε" of the guide filter function. The projection mapping of the input image I at multi-scale $\varepsilon = \{\varepsilon_1, \varepsilon_2, \varepsilon_3, \cdots, \varepsilon_n\}$ is

$$I_\varepsilon = \left\{I_{\varepsilon_1}, I_{\varepsilon_2}, I_{\varepsilon_3}, \cdots, I_{\varepsilon_n}\right\} \tag{17}$$

where I_ε is the image set after multi-scale mapping, and I_{ε_n} represents the image corresponding to the scale ε_n.

C. A NEW MULTI-SCALE IMAGE EDGE FUSION ALGORITHM

Firstly, extracting edge seeds. The Sobel algorithm is used to extract the edges of the image. The gradient operator G_x, G_y is defined as follows:

$$G_x = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix} \quad G_y = \begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix}$$

Calculate the horizontal gradient I_x and the vertical gradient I_y,

$$\begin{aligned} I_x &= I * G_x \\ I_y &= I * G_y \end{aligned}$$

Calculate the normalized gradient Z,

$$Z = norm\left(\sqrt{(I_x^2 + I_y^2)}\right),$$

Calculate the gradient direction *theta*,

$$theta = \arctan t\left(\frac{I_y}{I_x}\right)$$

The local maximum of the gradient is calculated fro Z and *theta*, and the non-local maximum in Z is eliminated to obtain M. The threshold η_1 is set, and for any (x, y), if $M(x, y) < \eta_1$ is satisfied, then $M(x, y) = 0$. This step mainly eliminates false edges caused by noise.

According to the consistency of the gradient direction of adjacent edge points, the threshold η_2 is set. For any $theta(x, y)$, there is a point $theta(i, k)$ whose gradient is not 0 in the neighborhood. If $abs\left(\cos(theat(x, y) - theta(i, k))\right) > \eta_2$, then $M(x, y) = 0$. This step mainly eliminates singular points.

If for any (x, y), $\mathrm{M(x, y)} > 0, \mathrm{B(x, y)} = 1$, otherwise $\mathrm{B(x, y)} = 0$, the edge binary B of the image is extracted. Mark the connected domain of the edge in B, and calculate the length of the edge connected domain corresponding to each mark. The true edge is generally continuous, and the connected domain of the edge is longer. According to the length of the edge connected domain, the threshold η_3 is set, and eliminate edge classification with edge connected domain length less than η_3. This step mainly eliminates pseudo edges caused by detail textures. The edge extracted by the above steps is called the edge seed I_s. The edge is sparse and incomplete, but contains some of the edge points of all edge classifications.

Secondly, extracting the edges of the image sequence and applying a new method for multi-scale edge fusion. Suppose using n scales $\varepsilon = \{\varepsilon_1, \varepsilon_2, \varepsilon_3, \cdots, \varepsilon_n\}$ sample the continuous space and get the image sequence $I_n = \left\{I_{\varepsilon_1}, I_{\varepsilon_2}, I_{\varepsilon_3}, \cdots, I_{\varepsilon_n}\right\}$. Then use the canny algorithm to extract the edges B_ε of images in I_n, where $B_\varepsilon = \left\{B_{\varepsilon_1}, B_{\varepsilon_2}, B_{\varepsilon_3}, \cdots, B_{\varepsilon_n}\right\}$. After extracting the edges of I_n, fuse edges as follow method.

If the point (x,y) in the image is an edge point, the following conditions must be met:

(c1) $\mathrm{B}_{\varepsilon_1}(\mathrm{x,y}) = 1$;

(c2) Edge classification $D_0 \subset I_s, D_1 \subset B_{\varepsilon_1}, \cdots, D_n \subset B_{\varepsilon_n}$, and $(x, y) \in D_1$, $(D_1 \cap D_2) \neq \Phi$, $(D_2 \cap D_3) \neq \Phi$, $\cdots$, $(D_{n-1} \cap D_n) \neq \Phi$, $(D_n \cap D_0) \neq \Phi$, where Φ is Empty set. The specific edge fusion process is as follows: use a set Ω to represent a set of edge classification whose length is greater than 0 in seed edge I_s, where $\Omega = \{(i, j)\,|p(i, j) > 0,\ (i, j) \in I_s\}$, where $p(i, k)$ is the length of the edge classification containing points (i, k). $\forall(i, k) \in \Omega, \exists D = \left\{(i, k)\,|p(i, k) > 0,\ (i, k) \in B_{\varepsilon_n}\right\}$, when the sets Ω and D satisfy the following condition $\Omega \cap D \neq \Phi$,edge seed needs to be updated to be $I_s = I_s \cup D$. Then, traverse all points belonging to Ω for generating new seed edges I_s. Repeat the above steps and sequentially label $B_{\varepsilon_{n-1}} \cdots B_{\varepsilon_1}$ to obtain the edge image B. Specific algorithm flow chart is shown in Fig.1.

IV. RESULTS AND ANALYSIS

In order to verify the scientificity and effectiveness of the proposed new algorithm, this paper firstly uses the edge fusion method based on Gaussian multi-scale space to extract the structural edge of aluminum foam cross-section, and obtain the corresponding structural edge image. Secondly, use the algorithm proposed in this paper to extract the structural edge features of the aluminum foam cross-section, and obtain the corresponding structural edge image. Finally, by comparing the results of the above two methods, it is verified that the new algorithm proposed in this paper is feasible.

A. IMAGE PREPROCESSING

Figure. 2 shows the contrast before and after image preprocessing. Fig. 2(a) is the original image, and Fig. 2(b) is the preprocessed image. Comparing the red marks in Fig. 2(a) and Fig. 2(b), it can be seen that after preprocessing, the brightness of the image is more balanced, which can reduce the pseudo edges caused by the change of the light

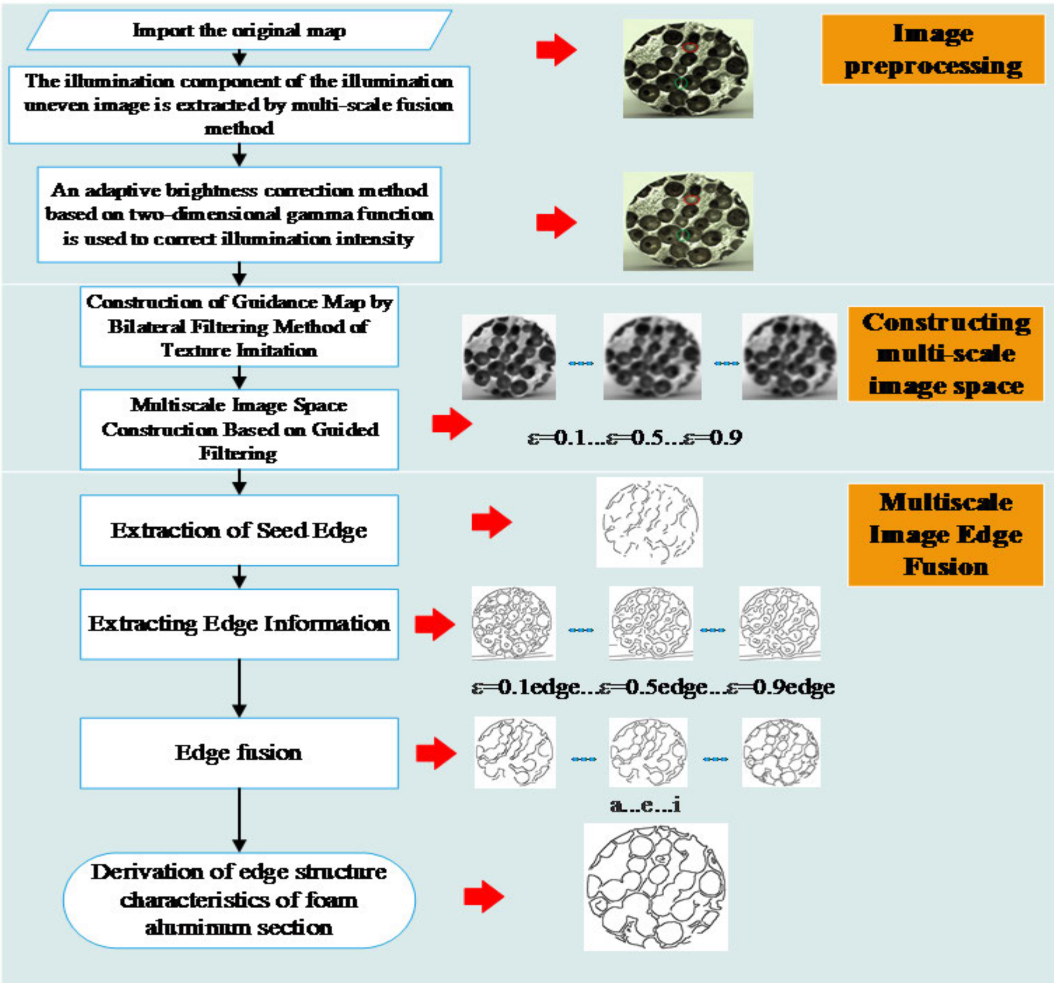
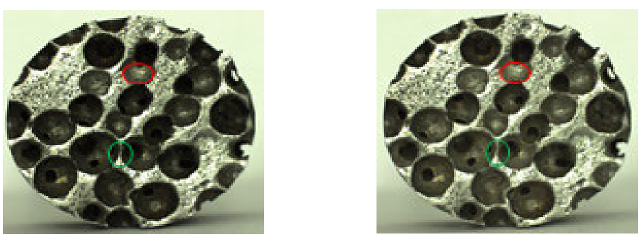


FIGURE 1. Algorithm flow chart.



(a) original image (b) preprocessed image

FIGURE 2. Comparison of original image and preprocessed image.

intensity. And comparing the green mark in Fig. 2(a) and figure. 2(b) shows that some weak edges of the image are enhanced after preprocessing.

B. BUILDING A MULTI-SCALE IMAGE SPACE

1) MULTISCALE IMAGE SPACE CONSTRUCTED BASED ON GAUSSIAN FUNCTION

First, construct a multi-scale space I_σ using Gaussian functions $G_\sigma(x, y)$, where $\sigma = \{\sigma_1, \sigma_2, \sigma_3, \cdots, \sigma_{n-1}, \sigma_n\}$, $I_\sigma = \{I_{\sigma_1}, I_{\sigma_2}, I_{\sigma_3}, \cdots, I_{\sigma(n-1)}, I_{\sigma_n}\}$. Second, extract images at specific scales σ^1 to form an image sequence $I_{\sigma\_1}, \forall\sigma^1 \subset \sigma, \exists I_{\sigma\_1} \subset I_\sigma$,where I_{σ_1} is the sequence of images that need to be extracted from the Gaussian multi-scale space. The standard deviation set $\sigma^1 = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$ of the Gaussian kernel function selected in this paper. The image sequence I_{σ_1} is obtained by using $G_\sigma(x, y)$ with the scale $\sigma^1 = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$ to smooth the image $I(x, y)$. The image sequence I_{σ_1} is shown in Figure 3.

As the scale continues to increase, the weak edges of the image continue to degenerate until disappear, which can be reflected in Fig. 3. And the strong edges of the image continue to spread, shift, and deform, which can be reflected in Fig.3.

2) CONSTRUCTING MULTI-SCALE IMAGE SPACE BASED ON GUIDED FILTERING METHOD

Firstly, constructe the guided image by using the bilateral texture filtering. As shown in Fig. 4(b), it can be seen from Fig. 4 that the detailed texture information of the guided image is degraded, the edge remains intact. Secondly, construct multi-scale space using guided filter function with the

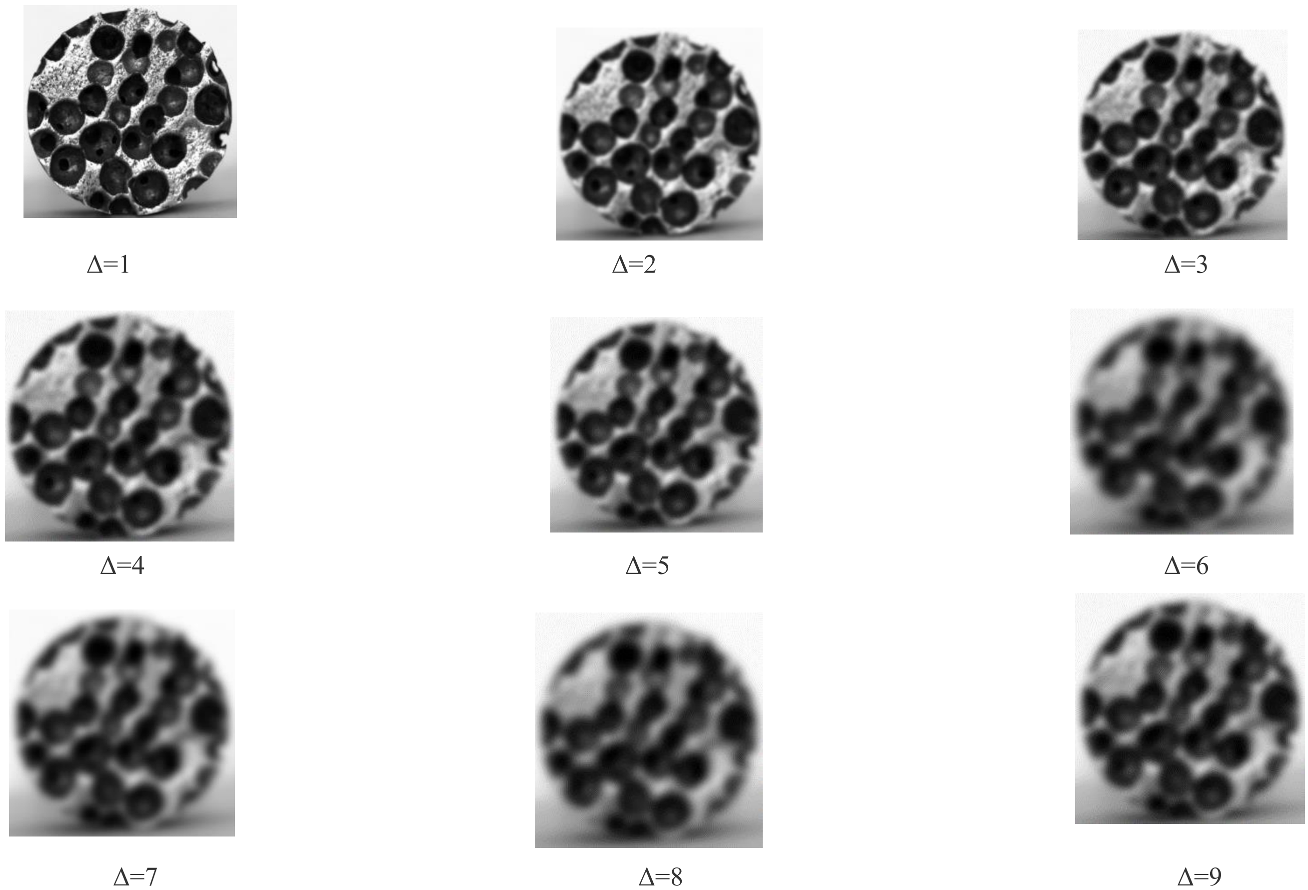


FIGURE 3. Gaussian multi-scale image space.

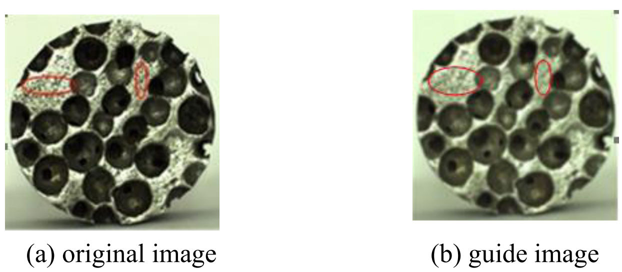


FIGURE 4. Comparison of original image and guide image.

regularization parameter $\varepsilon = \{0.1, 0.2, ..., 0.9\}$. the multi-scale image sequence is shown in figure. 5.

It is known that Gaussian filtering is a non-difference smoothing process for images. As the standard deviation increases, the image becomes more and more blurred, and the edges of the image are diffused and moved. At the same time, some weak edges in the image have completely degraded. However, guided filtering is a content-aware image processing method. Different processing methods are applied to different regions of the image, wherein the unimportant regions are smoothed, and the most important regions such as regions or edges of interest, remain unchanged, which can effectively maintain the edges of the image and suppress the diffusion and degradation of image edges.

As shown in Figure 5, when the scale factor is increased from 0.1 to 0.5, the texture suppression in the image is continuously enhanced, but the edges of the image are still clearly visible. When the scale factor is increased from 0.6 to 0.9, the image does not change significantly. This means that when the texture information in the image is filtered out, the edge information of the image will not be affected although the scale is increased.

C. MULTI-SCALE EDGE FUSION ALGORITHM FOR EXTRACTING THE EDGE OF FOAM ALUMINUM CROSS-SECTION

this paper use two kinds of Multi-scale edge fusion algorithm to extract the edge of aluminum foam cross-section. The first method is the edge fusion algorithm based on Gaussian Multi-scale Space, and the second is the new algorithm proposed in this paper, which is constructed by the guided filter function with different scale factors.

1) EDGE FUSION ALGORITHM BASED ON GAUSSIAN MULTI-SCALE SPACE

$B_\sigma = \left\{B_{\sigma_1}, B_{\sigma_2}, B_{\sigma_3}, B_{\sigma_4}, B_{\sigma_5}, B_{\sigma_6}, B_{\sigma_7},, B_{\varepsilon_8}, B_{\varepsilon_9}\right\}$ is the final acquired edge image sequence. It is shown in Fig. 6. From the figure, the following result can be got that as the scale factor continues to increase, the edges of the image are severely

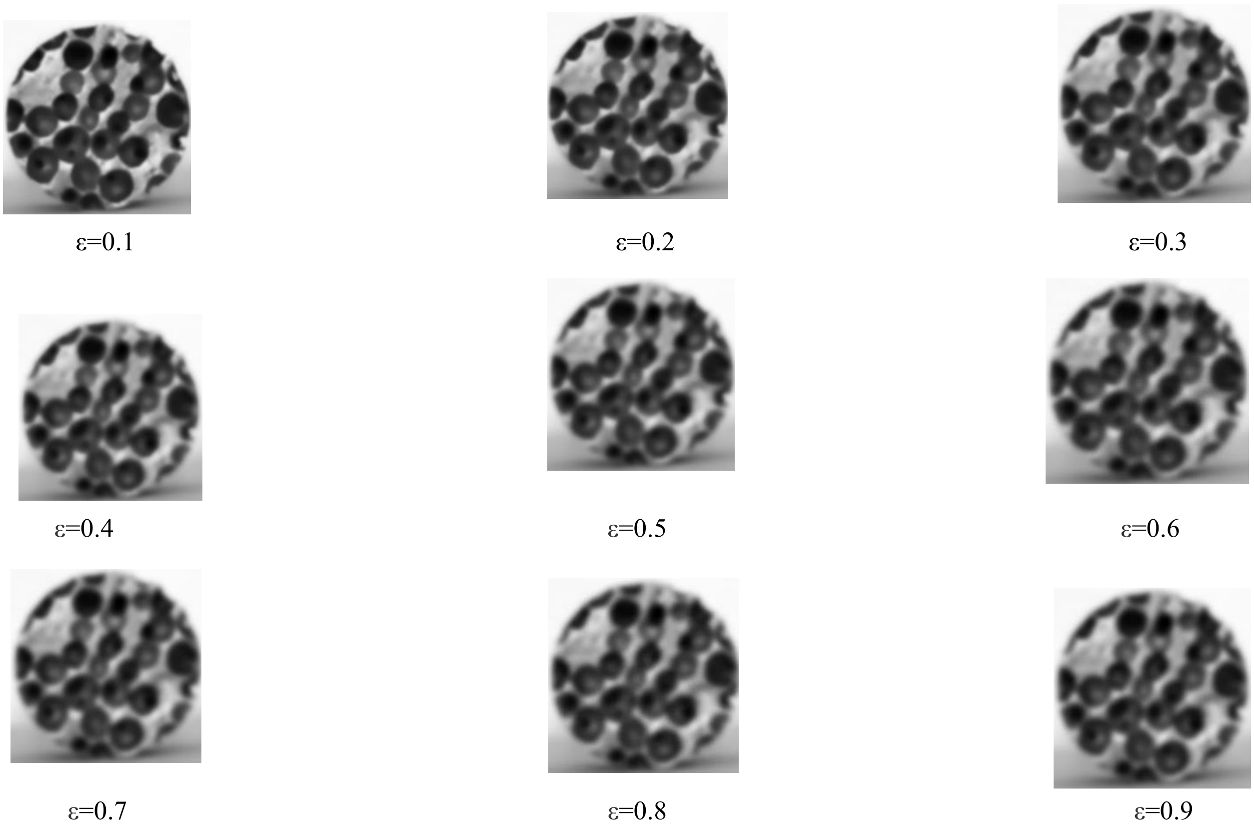


FIGURE 5. Building a multi-scale space based on the guided filtering method.

deformed and degraded, and some of the weak edges have completely disappeared.

Use the coarse-to-fine edge tracking method to track the edge information of the image sequence and extract the edge information of aluminum foam cross-section structure. The result is shown in Figure 7.

2) MULTI-SCALE EDGE FUSION ALGORITHM PROPOSED IN THIS PAPER

Extracting the edge seed is an important step in the method proposed in this paper. The quality of the edge seed directly affects the result of edge extraction. Fig.8 shows the results of extracting the edge seed, which is sparse and incomplete, but contains some of the edge points of all edge classifications.

Figure. 9 shows the result of extracting edges of multi-scale image sequence. As shown in Fig. 9, with the increase of the scale, structural edges of the image remains good.

Edge fusion is the most important step in the algorithm proposed in this paper. Fig.10 show the process of edge fusion. The final result is shown in Fig. 11.

It is known from Fig. 7(a) that the structural edge features of the aluminum foam cross-section extracted by the edge fusion algorithm based on Gaussian multi-scale space are incomplete and inaccurate, and some of the weak edges have completely degraded. Compared with the structural edge of the aluminum foam extracted by the edge fusion algorithm based on Gaussian multi-scale space, the edge of the aluminum foam cross-section extracted by the proposed algorithm in this paper is more complete and more accurate. As shown in Fig.11, compared with the original image, the edge feature extraction is more complete, and the weak edge degradation is less. In order to further verify the effectiveness of the proposed method, we will make a quantitative analysis of the method in the following sections, and compare the proposed method with some existing edge detection methods.

V. MEASURING THE PERFORMANCE OF AN EDGE DETECTOR

In the field of image processing, edges are features of object boundaries, so edge detection plays a crucial role in image processing. In order to accurately and completely extract the structural edge information of the image, many edge detection methods are designed. Each method obtains different segmentation results and different segmentation quality. How to evaluate the performance of the edge detection algorithm becomes a very critical issue. The paper adopts the evaluation method of confusion matrix-based assessments. The confusion matrix remains a cornerstone in boundary detection evaluation methods. The evaluation method that makes the comparison between the edge image generated by an edge detection method which is taken as candidate edge image and

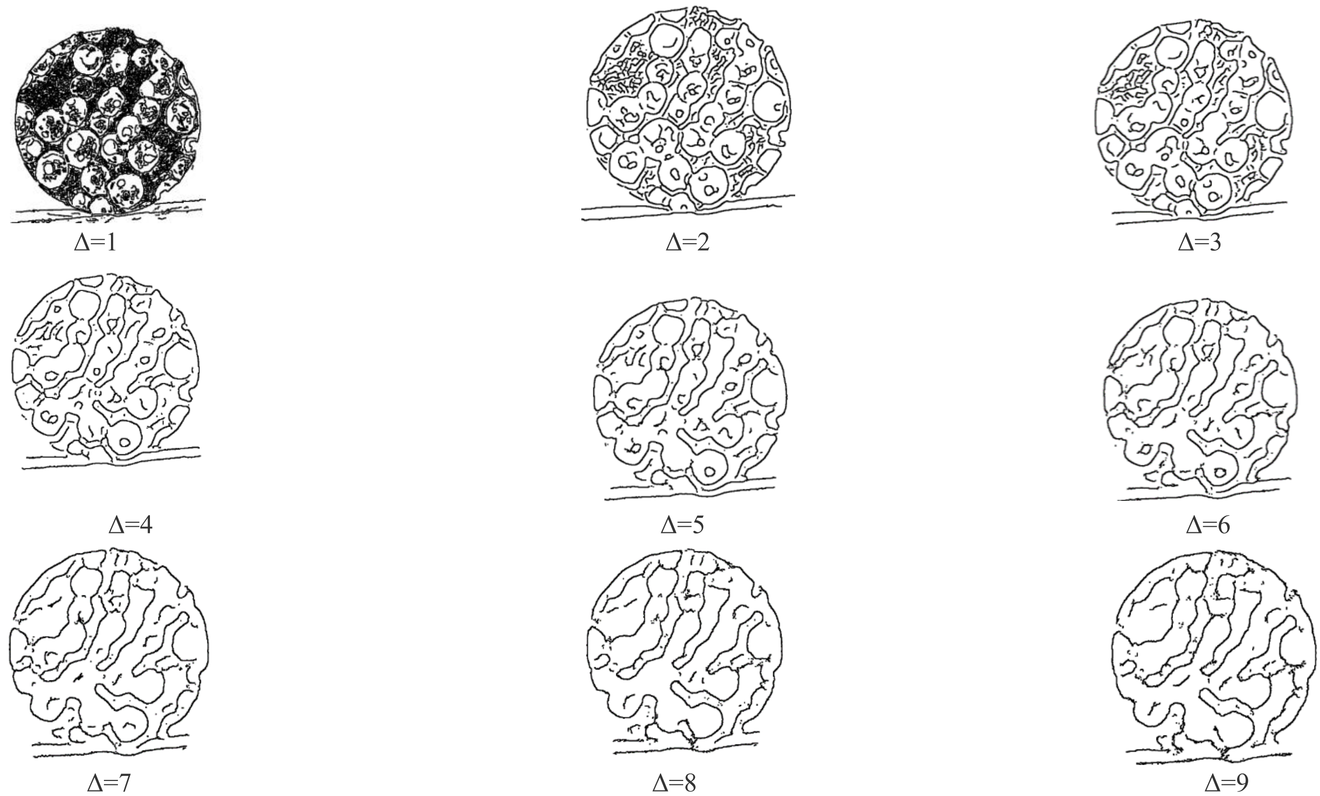


FIGURE 6. Edge in Gaussian multi-scale space.

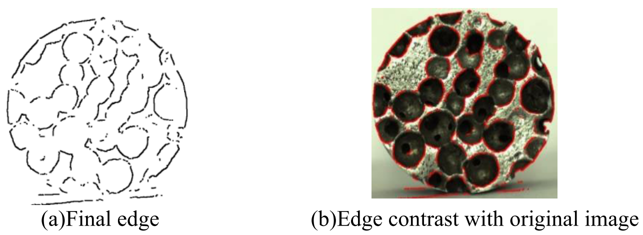


FIGURE 7. Comparison of the edge feature map of foam aluminum section extracted from Gaussian multi-scale spatial edge fusion algorithm and the original image.

FIGURE 8. Edge seed.

that generated by a human which is taken as ground truth. The confusion matrix divides the points in the image into four categories, true positive (TP), true negative (TN), false positive (FP) and false negative (FN) [28]. All the points of the detected edges create a set B1, and the actual edge points create a set B2. Use the following formula to describe the relationship between sets TP, TN, FP, FN, B1 and B2.

$$\forall (x, y) \in TP, \quad (x, y) \in B_1 \cap B_2 \tag{18}$$

$$\forall (x, y) \in TN, \quad (x, y) \notin B_1 \cup B_2 \tag{19}$$

$$\forall (x, y) \in FP, \quad (x, y) \in B_1 \ and \ (x, y) \notin B_2 \tag{20}$$

$$\forall (x, y) \in FN, \quad (x, y) \notin B_1 \ and \ (x, y) \in B_2 \tag{21}$$

In the process of quantitative analysis, the Cost Scaling Assignment (CSA) algorithm [29] is employed to perform a pixel-to-pixel matching between B1 and B2. For each detected edge pixel in B1, if it matches any of the ground truth edge pixels in B2 within a spatial tolerance distance, this detected edge pixel is considered as a true positive detection pixel(TP); otherwise, it is considered as a false positive detection pixel(FP). For each true edge pixel in the ground truth edge map, if it is matched by a detected edge pixel in B1 within a spatial tolerance distance, this ground truth edge pixel is counted as a matched ground truth pixel(TP); otherwise, it is counted as an unmatched ground truth pixel(FN). These matched ground truth pixels and unmatched ground truth pixels in the ground truth map(s) compose the aggregate matched ground truth pixels and aggregate unmatched ground truth pixels, respectively [29]. In this way, the precision(PREC) and recall(REC) are computed by:

$$PREC = TP/(TP + FP) \tag{22}$$

$$REC = TP/(TP + FN) \tag{23}$$

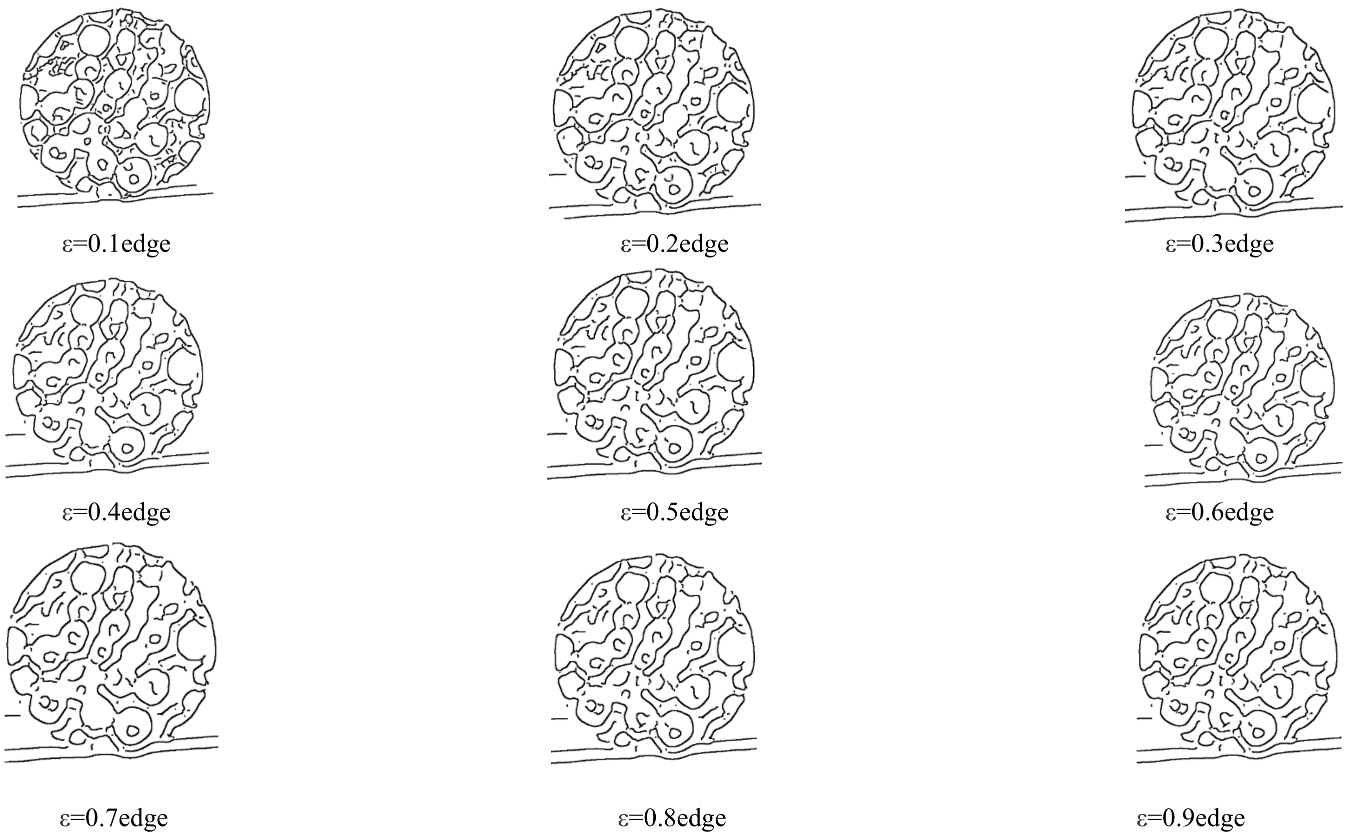


FIGURE 9. Multi-scale edge image extracted by the method of this paper.

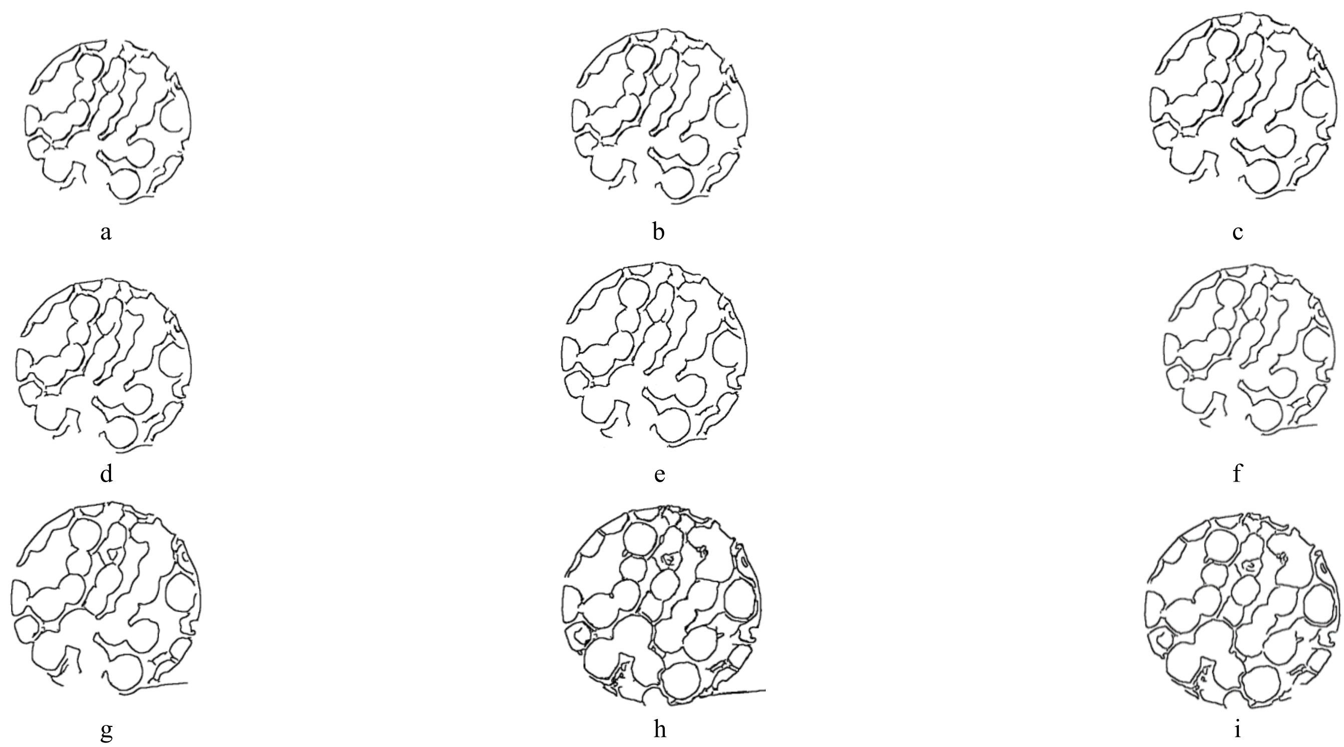


FIGURE 10. Edge fusion process.

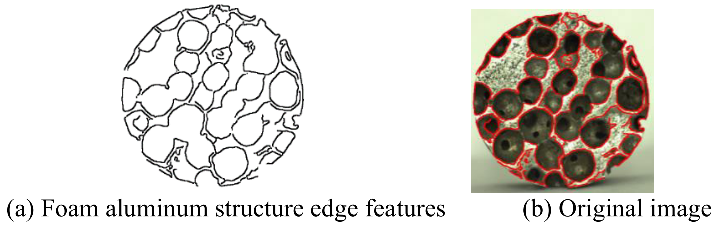


FIGURE 11. Comparison between the final result with the original image.

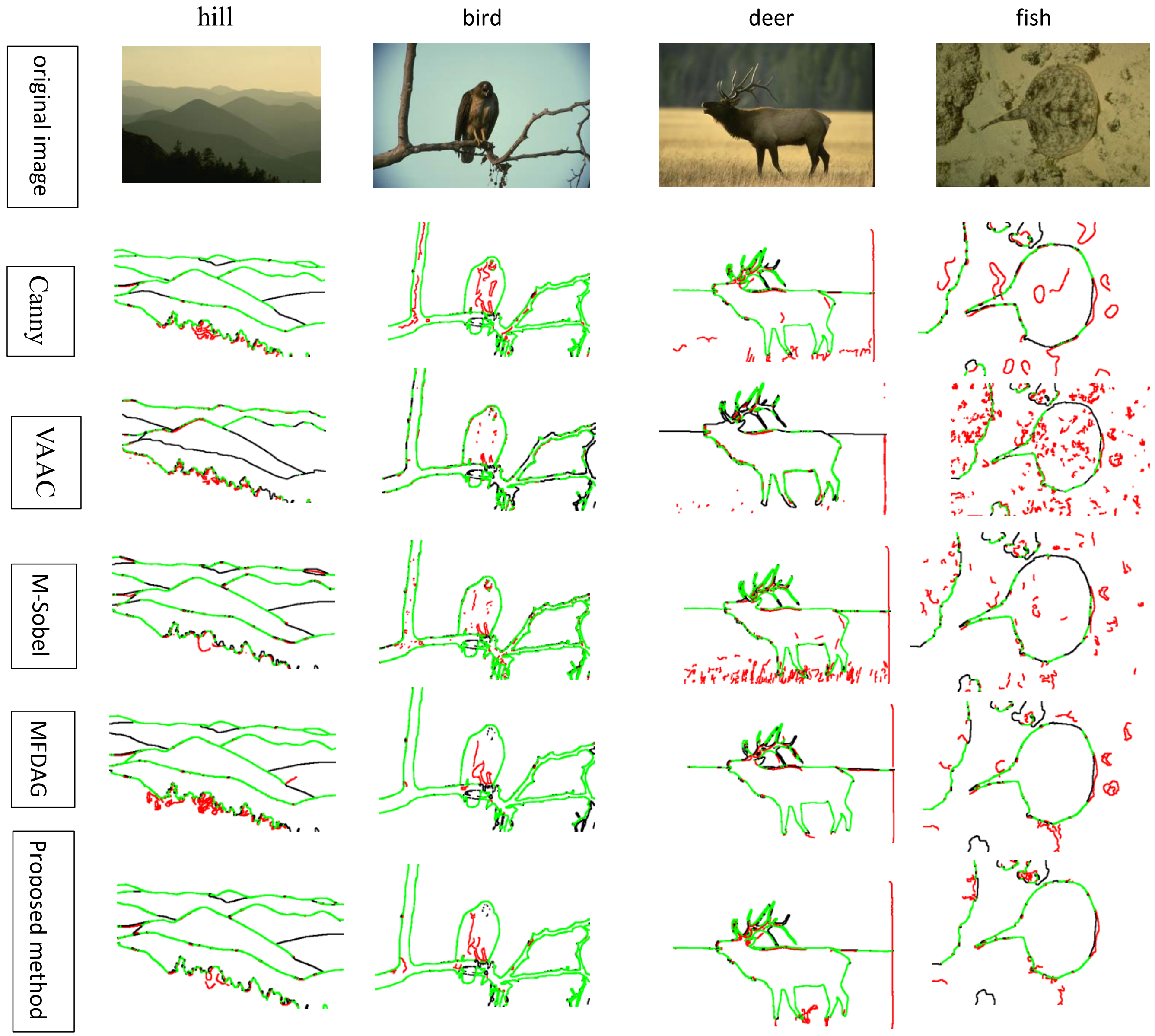


FIGURE 12. Results of detection obtained by different methods on the BSDS500 dataset. green pixels represent true positive detection pixels (TP), red ones stand for false positive detection pixels (FP) and black ones denote unmatched ground truth pixels (FN).

where TP, FP, FN are the numbers of true positive detection pixels, false positive detection pixels, aggregate unmatched ground truth pixels, respectively.

The PREC and REC measures illustrate specific aspects of the problem. However, in order to compare the performance we need some scalar evaluation of the overall quality of an

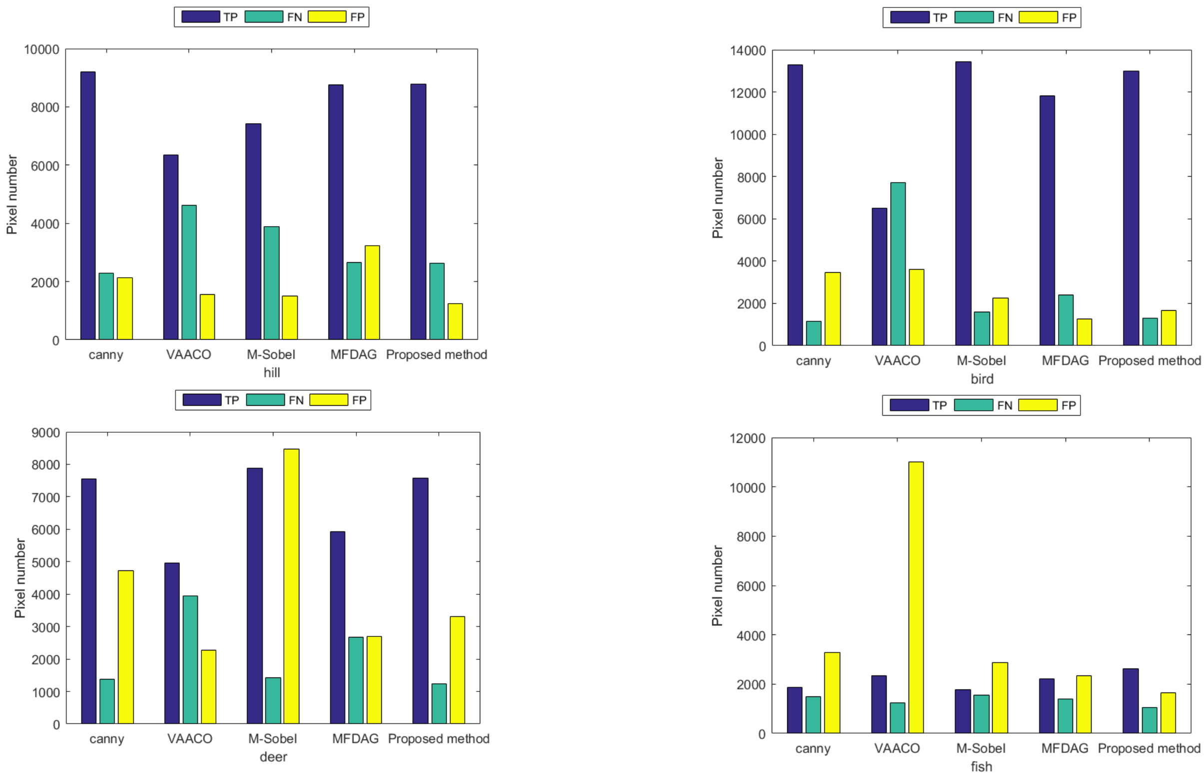


FIGURE 13. Type distribution of detection result by different methods. The height of the blue cylinder represents the quantity of true positive detection pixels (TP), The height of green one represents the quantity of unmatched ground truth pixels (FN). The height of yellow one represents the quantity of false positive detection pixels (FP).

edge image. We use the F-measure [30], defined as

$$F_\alpha = (PREC * REC) / (\alpha * PREC + (1-\alpha)\, REC) \quad (24)$$

where α is a value modulating the relative impact of the PREC and REC values. In this work we adhere to the commonly used $F_{0.5}$ [4]. In this way, we evaluate three different facets of the problem: the accuracy (using PREC), the fallout (using REC) and the overall quality (using $F_{0.5}$).

VI. RESULTS ON THE BSDS500 DATASET

Since there is no established dataset of aluminum foam, this paper cannot directly use the aluminum foam structure edge information for quantitative analysis. Therefore, this paper uses Berkeley's public dataset(BSDS) to verify the feasibility of the proposed algorithm and quantitative analysis of the algorithm. The feasibility of using public dataset verification algorithms is more convincing. The images in the BSDS have a resolution of 481*321 pixels. In addition, each of them comes together with 5–10 hand-made segmentations. Since those segmentations are provided in the shape of region boundaries, we use them as ground truth for the quantification of the quality of the edge detection results. In order to make the evaluation more convincing, we compare our method with several competing methods, including the Canny method [31], Image Edge Detection method Using Variation-Adaptive Ant Colony Optimization (VAACO) [32], multiscale edge detection method based on Gaussian smoothing (M-Sobel) [33], multiscale Edge Detection Using First-Order Derivative of Anisotropic Gaussian Kernels (MFDAG) [34]. In this paper, four types of images are used in the experiment, weak contrast images(hill), strong contrast images(bird), weak texture images(deer), strong texture images(fish). The edges of these four types of images contain all the types of aluminum foam cross-section structure edge information. Therefore, it is effective to use the image in the dataset (BSDS) to verify the feasibility of the proposed algorithm. The experimental results are shown in Figure 12.

Four types of images are used in the experiment, weak contrast images(hill), strong contrast images(bird), weak texture images(deer), strong texture images(fish). Experimental results shown in Fig. 12 show that the proposed method in this paper is feasible and effective. The proposed method can not only suppress the texture information of the image, but also extract the complete image edge information. Compared to other methods, our method produces more real edges while showing fewer false edges. The types analysis results of the detected edge point are shown in Fig. 13. The analysis results show that compared with other methods, the edge points detected by the proposed method contain more real edge points, and fewer real points are missed. Quantitative analysis results are shown in Fig. 14. Compared with other methods, the overall evaluation value $F_{0.5}$ of our

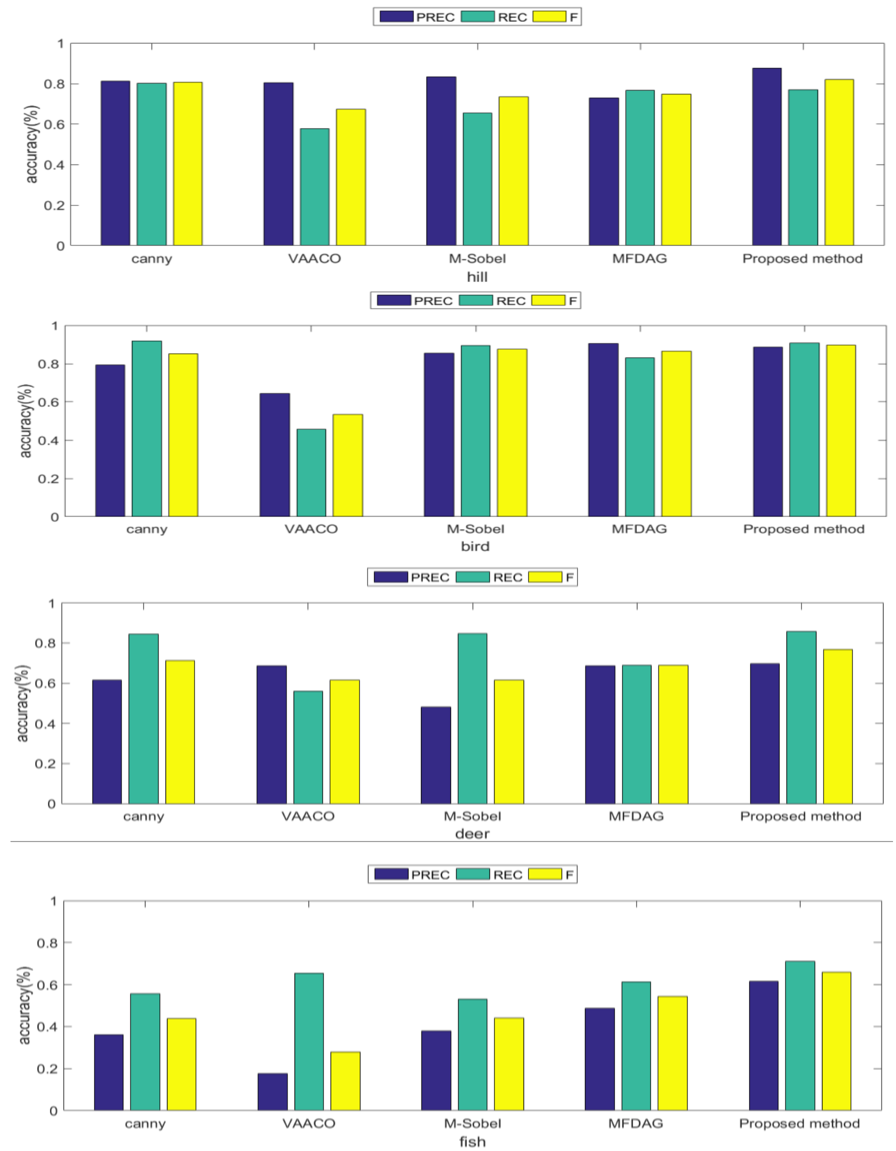


FIGURE 14. Evaluation result. The height of the blue cylinder represents the detection precision (PREC). The height of the green one represents the recall(REC). The height of the yellow one represents the overall quality(F).

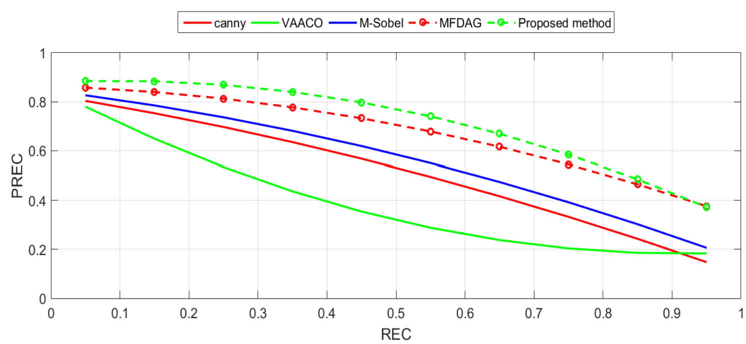


FIGURE 15. PR curves of different methods obtained on the BSDS500 dataset.

method is higher than other methods. This indicates that the detection method of this article is more efficient and more effective.

To further illustrate the advantages of the method described herein, we further evaluate our method on the BSDS500 dataset and also compare our method with other methods including Canny, VAACO, M-Sobel, MFDAG . The obtained precision–recall (PR) curves in Fig. 15. the PR curve of the proposed method is farther from the origin than for the competing methods, which shows that the method is better than other comparison methods [35]–[37]

VII. CONCLUSION

This paper mainly studies the structural edge extraction method of aluminum foam cross-section. It emphatically analyse the problems of the edge fusion method based on Gaussian multi-scale space in extracting the edge of the aluminum foam cross-section. The problem is mainly manifested in two aspects. Firstly, the edge information extracted is incomplete due to the degradation of image edge caused by Gaussian smoothing. Secondly, the edge of the image is moved due to Gaussian smoothing, resulting in inaccurate edge position extraction. In order to solve the above problems, a new edge multi-scale edge fusion algorithm is proposed to extract the edge information of the aluminum foam cross-section. This method provides a new idea for accurately extracting the edge information of aluminum foam cross-sections based on guided filtering with texture suppression characteristics.

In this paper, compared with edge fusion algorithm based on Gaussian multi-scale space, the extracted edge of aluminum foam cross-section by the proposed new algorithm is more complete and more precise. By comparing the extracted edges with the original image, it shows that the proposed method in this paper is feasible and effective. The experimental results show that the proposed algorithm effectively solves the problem of extracting the edge of aluminum foam cross-section by the edge fusion algorithm based on Gaussian multi-scale space.

In order to further analyze the performance of the proposed algorithm, this paper uses the common data set (BSDS500) to verify the proposed algorithm and make quantitative analysis of the proposed algorithm. It is also compared to a variety of existing algorithms. The experimental results show that the proposed algorithm is feasible and effective, However, this method still has certain shortcomings. For example, a small portion of the texture information is not removed, resulting in a certain error in the extracted edge structure feature information.

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