Adaptive Edge Detection Algorithm Based on Grey Entropy Theory and Textural Features

ZHENG ZHEN, BINGTING ZHA, YOUSHI XUCHEN, HAILU YUAN, YANLIANG GAO, AND HE ZHANG
School of Mechanical Engineering, Nanjing University of Science and Technology, Nanjing 210094, China
Corresponding authors: Bingting Zha (zhabingting@163.com) and He Zhang (hezhangz@mail.njust.edu.cn)
This work was supported in part by the National Natural Science Foundation of China under Grant 51709147, in part by the Central University Special Funding for Basic Scientific Research under Grant 309171B8805, in part by the Postgraduate Research and Practice Innovation Program of Jiangsu Province under Grant KYCX19_0262, and in part by the Key Basic Research Projects of Basic Strengthening Plan under Grant 2017-JCJQ-ZD-004.

ABSTRACT The traditional edge detection method is altogether inaccurate, nonadaptive, and particularly ineffective on noisy images. This paper proposes a novel edge detection algorithm based on gray entropy theory and local texture features. In the $3 \times 3$ neighborhood window, 28 comparison sequences are constructed according to local texture features. The reference sequence is composed of the median of all elements in the $3 \times 3$ neighborhood window. A total of 28 gray relation degrees as obtained by gray relation analysis between the 28 comparison sequences and reference sequences, as well as 28 gray relation degrees, are analyzed by gray entropy theory to initially filter the image. Gray entropy analysis is then performed on the comparison sequences composed of 28 texture features and reference sequences composed of the central pixel points of the filtered image to determine the maximum gray entropy difference. A comparative threshold adaptive acquisition method is designed to separate gray entropy difference sequence elements and identify all edge points accordingly. The simulation results show that the proposed algorithm effectively achieves adaptive edge detection and has strong anti-noise capability. The results of this study may provide a workable reference for edge information detection in the field of artificial intelligence (e.g., image recognition, pattern recognition applications).

INDEX TERMS Image processing, image edge detection, gray relation analysis, gray entropy theory, textural feature analysis.

I. INTRODUCTION

The “edge” of an image is the region which shows the most dramatic shift in gray level [1]. This shift is reflected as a collection of pixels with different gray level “steps” or “roofs” by comparison against the rest of the image. There is a great deal of scholarly interest in image edges, and two traditional edge detection methods which currently exist. First is the integer pixel edge detection algorithm (based on Sobel, Roberts, Prewitt, Laplacian, LoG, Canny, and other similar methods), which yields generally inaccurate or resistant edge positioning results and has weak noise interference robustness [2]–[4]; it is aimed at the step edge, but the actual image encompasses mostly the edge of the slope, so the detection effect is generally poor. The most popular traditional integer edge detection operator is the Canny operator, which is based on non-maximum suppression and morphological continuity. Its edge detection effect is better than other traditional operators, but its anti-noise ability is still weak and it is susceptible to over-detection. The accuracy of the integer pixel edge detection operator can be improved by increasing the sampling frequency, however, the maximum sampling frequency is limited by the device conditions due to its cost and performance [5], [6].

Many scholars have attempted to mitigate the shortcomings of traditional edge detection operators. Rong et al. [7], for example, proposed an improved algorithm based on the Canny algorithm in 2014; this algorithm can be used to identify useful edge information and is more robust to noise than the traditional Canny operator. Shi et al. [8] proposed an improved algorithm with six templates at different directions based on the Sobel algorithm in 2016 which provides accurate and efficient localization while minimizing defect-edge noise disturbance.
The sub-pixel detection method first proposed by Hueckel can also drive edge positioning precision below one pixel without changing the device resulting in strong edge detection capability. There are three sub-pixel detection algorithms currently available. The first is based on the fitting sub-pixel edge detection algorithm, where the sub-pixel edge location is obtained by least square fitting the gray value of the hypothetical edge model. Nalwa et al. [9] proposed a sub-pixel edge detection algorithm base on Hyperbolic tangent fitting edge model; Ye et al. [10] proposed an algorithm to locate the position of a sub-pixel edge by two-dimensional Gaussian fitting edge model. Nalwa et al. [9] proposed an algorithm to locate the position of a sub-pixel edge by Bessel fitting edge model and Su et al. [11] proposed an algorithm to locate the position of a sub-pixel edge by parabolic fitting edge model. The fitting sub-pixel edge detection algorithm is robust to noise, but it is difficult to apply to real-time online detection because of its long calculation time. It is also difficult to obtain an accurate edge fitting model due to the inherent complexity of the edge.

Other methods are based on interpolation, where the position is determined by interpolating pixel values and gradients. These methods include Lagrange interpolation, Newton interpolation, and cubic spline interpolation. The noise immunity of these methods is not strong and it is difficult to design a suitable order of the interpolation function – when the order is low, the sub-pixel positioning accuracy may be insufficient; when the order is high, the system processing speed is low and the processing time is excessive [12], [13].

The third category of methods is moment-based, where moment information of the image is used to solve the edge parameters. The moments used for sub-pixel edge detection mainly include space, gray, Zernike, and Legend moments. The detection of sub-pixels by the moment method has proven effective, but there is currently no universally applicable technique. It is usually necessary to increase the template size to improve the edge positioning capability, but once there are complex edges inside the template, the edges will interfere with each other resulting in incorrect edge positioning [14]–[16].

Researchers have attempted to use other methods to obtain a balance between edge positioning and anti-noise ability. Neural network-based methods, for example, can provide accurate edge detections. However, they have long processing time, require difficult-to-obtain prior knowledge, readily converge to local minimum points, and do not have easily adjustable training parameters making them unsuitable for automatic edge detection [17], [18]. Wavelet transform-based methods yield the local features of a signal corresponding to different frequencies by decomposing the high and low frequencies of the image. The large-scale wavelet is used to remove the noise, and the small-scale wavelet is used to locate the edges; edge information is obtained by combining the results of each scale. The anti-noise ability of this method is strong, but multiple iterations are necessary when reconstructing the signal, so the processing speed is extremely slow [19]. Finally, mathematical morphology-based methods have the advantages of simple calculation and high positioning accuracy, but they obtain edges by combining morphological operators – this does not amplify the noise, but noise cannot be removed. Multi-scale methods are often used to make edge positioning more accurate, but once applied, produce coarse edges [20]–[22].

In 1982, Professor Deng founded the discipline of grey system theory to the analysis of uncertain systems with “small data and poor information”. After more than 30 years of vigorous development, grey system theory has been applied to economics, control, social, geological, ecological, military, and other fields of research [23]–[28]. Image edge information is processed by computer; the local information of the image to be processed is an uncertain system with said characteristics of “small data and poor information”, which makes grey system theory well applicable. Ma first used grey relation analysis (GRA) for image edge detection in 2003 [29], where the algorithm did reveal edge information accurately and with some anti-noise capability. Threshold-setting proves difficult, however, and the comprehensive relation coefficient is affected by any extreme point which appears in the relation sequence resulting in the over-detection of edges. Li proposed an effective edge detection algorithm based on GRA and validated it by simulation [30], but its anti-noise ability is still weak.

The grey relation degree obtained by the traditional grey relation model is equal to the arithmetic average of each relation coefficient. The local point relation value thus affects the entire grey relation sequence and reduces the individuality of any individual in the system resulting in a certain amount of information loss. Based on the theory of Shannon entropy, Professor Zhang established the grey relation entropy theory to reduce the influence of local points on the relation value of the overall system [31]. In 2010, Li successfully used grey entropy theory for pavement gap detection; this technique requires manual selection of the optimal threshold point, which is not suitable for subsequent auto-complete target recognition or image recognition [33].

A novel, adaptive edge detection algorithm based on grey entropy theory and textural features was designed in this study. The remainder of this paper is organized as follows. Section II introduces related work on grey relation analysis, grey entropy theory, and textural structure features. Section III presents an adaptive edge detection algorithm based on grey entropy theory and textural features. Section V discusses edge detection experiments on an original image and noise-containing image, including a performance comparison; limitations and potential approaches to improving the proposed algorithm are also discussed. Conclusions are given in Section V.

II. RELATED WORK
A. GREY RELATION ANALYSIS
GRA is an important branch of the grey theory system. It can be used to measure the similarity and proximity between two
grey systems [33]. Compared with traditional system analysis methods, its main advantages are:
1) The distribution model of the analysis object can be unknown;
2) The data of the analysis system can have a small sample data size;
3) When performing GRA on the system, it is not necessary to consider the internal connection of the system.

Many scholars have established relation models based on Deng’s relation analysis model and the point relation coefficient created by Professor Deng Julong (e.g., slope relation degree, B-type relation degree, T-type relation degree, geometric relation degree, absolute relation degree, relative relation degree, and comprehensive relevance degree). GRA works by judging the degree of relation between factors according to the geometric relationship of the series or the degree of similarity of the curves. If the shapes of the two curves are similar, the degree of association is large; otherwise, the degree of association is small. The degree of grey relation can be defined according to the distance in n-dimensional space [23], [34].

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

The proximity of the two curves in a finite discrete sequence can be judged by the degree of closeness of the slope on the corresponding curve segment of each point. As shown in Fig. 1, the proximity of the reference sequence and the comparison sequence can be determined by slope 1 and slope 2, respectively.

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

![FIGURE 1. Spatial relationship between reference and comparison sequences.](image)

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

The proximity of the two curves in a finite discrete sequence can be judged by the degree of closeness of the slope on the corresponding curve segment of each point. As shown in Fig. 1, the proximity of the reference sequence and the comparison sequence can be determined by slope 1 and slope 2, respectively.

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

The proximity of the two curves in a finite discrete sequence can be judged by the degree of closeness of the slope on the corresponding curve segment of each point. As shown in Fig. 1, the proximity of the reference sequence and the comparison sequence can be determined by slope 1 and slope 2, respectively.

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

The proximity of the two curves in a finite discrete sequence can be judged by the degree of closeness of the slope on the corresponding curve segment of each point. As shown in Fig. 1, the proximity of the reference sequence and the comparison sequence can be determined by slope 1 and slope 2, respectively.

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

The proximity of the two curves in a finite discrete sequence can be judged by the degree of closeness of the slope on the corresponding curve segment of each point. As shown in Fig. 1, the proximity of the reference sequence and the comparison sequence can be determined by slope 1 and slope 2, respectively.

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

The proximity of the two curves in a finite discrete sequence can be judged by the degree of closeness of the slope on the corresponding curve segment of each point. As shown in Fig. 1, the proximity of the reference sequence and the comparison sequence can be determined by slope 1 and slope 2, respectively.

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

The proximity of the two curves in a finite discrete sequence can be judged by the degree of closeness of the slope on the corresponding curve segment of each point. As shown in Fig. 1, the proximity of the reference sequence and the comparison sequence can be determined by slope 1 and slope 2, respectively.

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

The proximity of the two curves in a finite discrete sequence can be judged by the degree of closeness of the slope on the corresponding curve segment of each point. As shown in Fig. 1, the proximity of the reference sequence and the comparison sequence can be determined by slope 1 and slope 2, respectively.

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

The proximity of the two curves in a finite discrete sequence can be judged by the degree of closeness of the slope on the corresponding curve segment of each point. As shown in Fig. 1, the proximity of the reference sequence and the comparison sequence can be determined by slope 1 and slope 2, respectively.

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

The proximity of the two curves in a finite discrete sequence can be judged by the degree of closeness of the slope on the corresponding curve segment of each point. As shown in Fig. 1, the proximity of the reference sequence and the comparison sequence can be determined by slope 1 and slope 2, respectively.

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

The proximity of the two curves in a finite discrete sequence can be judged by the degree of closeness of the slope on the corresponding curve segment of each point. As shown in Fig. 1, the proximity of the reference sequence and the comparison sequence can be determined by slope 1 and slope 2, respectively.

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

The proximity of the two curves in a finite discrete sequence can be judged by the degree of closeness of the slope on the corresponding curve segment of each point. As shown in Fig. 1, the proximity of the reference sequence and the comparison sequence can be determined by slope 1 and slope 2, respectively.

The geometric relation degree model reflects the closeness of the reference sequence and comparison sequence according to the proximity of each element in the sequence. The model not only satisfies the normality, whole, and symmetry properties of grey relation theorems, but also the parallel, uniform, parallel order-keeping, multiple order-keeping, and affine order-keeping properties [35].

The proximity of the two curves in a finite discrete sequence can be judged by the degree of closeness of the slope on the corresponding curve segment of each point. As shown in Fig. 1, the proximity of the reference sequence and the comparison sequence can be determined by slope 1 and slope 2, respectively.
\[ \sum_{k=1}^{n} p_h(k) = 1, \text{ which meets the requirements for normalization of grey entropy elements.} \]

C. TEXTURAL STRUCTURE FEATURE

The edge of the image is distributed in a place where the grey level changes drastically. Regardless of the grey value of each pixel of the image, we consider the 3×3 neighborhood window containing the central pixel to be the “system”. If there is an edge or any noise in the system, the internal gray value of the system fluctuates greatly (that is, the grey entropy value is small); if there is no edge or noise in the system, the grey value of the central pixel point and the 8 pixel points of the field are relatively close, the internal grey value fluctuation of the system is small, and the grey entropy value is large. We can judge whether there is an edge or noise point in the 3×3 neighborhood window by judging the grey entropy value [31], [36], [37]. The image edge information can be detected once the image noise is filtered out and an adaptive edge separation threshold is obtained.

As discussed above, the edge region shows the most dramatic change in grey level across the entire image. Traditional edge detection methods based on Sobel, Roberts, LoG, and other improved algorithms based on those operators by first-order or second-order differential operation amplify image noise as the noise in the image also belongs to the high-frequency variable category. In other words, traditional methods have poor noise resistance. The edge is structured, and the noise is not [38]–[40]. Therefore, the proposed image edge detection algorithm based on grey entropy theory and textural features is highly resistant to noise.

To operate the proposed algorithm, take \( g(i,j) \) as the center pixel, select the shape of the possible distribution of the edge pixels in the 3×3 neighborhood window, and construct comparison sequences. The number of comparison sequences in the 3×3 neighborhood window is \( n = C_8^2 = 28 \). The 28 resulting cases, and comparison sequences constructed according to the 28 edge structures, are shown in Fig. 2.

III. ADAPTIVE EDGE DETECTION ALGORITHM DESIGN

A. IMAGE DENOISING

Noise has no local texture structure and is not continuous with the surrounding pixels, so it is possible to denoise the image before the edge is formally detected.

When the central pixel is noisy and the noise density is low, most pixels in the 3×3 neighborhood windows are non-noise points; fluctuations in the pixel grey values of most of the 28 comparison sequences can then be constructed according to the texture structures with small grey entropy values. If the fluctuations are very small, the grey entropy will instead be very large. The threshold value can be adjusted accordingly to determine whether the central pixel is a noise point. A median filter is imposed when it is a noise point, and the system remains unchanged if it is a non-noise point.

Peak signal-to-noise ratio (PSNR) is an objective measure of image distortion or noise level. A larger PSNR value between two images indicates that the two images are similar [41]–[46].

The 3×3 neighborhood window is obtained by taking \( f(i,j) \) as the central pixel. The median value of 9 grey pixels is obtained as follows:

\[
\begin{align*}
    m &= \text{median}(f(i-1,j-1), f(i-1,j), f(i-1,j+1), \ldots, f(i+1,j-1), f(i+1,j), f(i+1,j+1)) \\
    &= \frac{1}{28} \sum_{k=1}^{28} f(x_k) 
\end{align*}
\]

A reference sequence is constructed according to the median size: \( X_0 = \{x_0(1), x_0(2), \ldots, x_0(28)\} \) where \( m, m, m \).

The 1-time interval sequence of the slope formed by each point in the reference sequence \( X_0 \) and the central pixel is 0; the comparison sequence is constructed with the central pixel. Therefore, the 1-time interval sequence of the slope between the points in the reference sequence (i.e., the proximity of the neighborhood pixel to the center pixel) is:

\[
\Delta_m(k) = \frac{|x_m(k) - m|}{255} \quad (m = 1, 2, \ldots, 28; k = 1, 2, 3) \quad (7)
\]

According to the image relation model described above, the grey relation degree between the central pixel point and the neighboring pixel is:

\[
y_m'(k) = \frac{1}{1 + \Delta_m(k)} \quad (8)
\]

The grey entropy of the 3×3 neighborhood window according to Eq. (5) can be calculated as follows:

\[
H'_m(m) \triangleq \begin{cases} 
\sum_{k=1}^{28} p_h(m,k) \ln p_h(m,k) & p_h \neq 0 \\
0 & p_h = 0 
\end{cases} \quad (9)
\]
The grey entropy set \( \{ H'_m(m) \} m = 1, 2, \cdots, 28 \) is constructed according to Eq. (9) and the maximum grey entropy value \( H'_{\text{max}} \) in the grey entropy set is obtained. Set the threshold \( th' \) and compare \( H'_{\text{max}} \) and \( th' \) to determine whether it is a noise point under the following calibration rule:

\[
noise(i, j) = \begin{cases} 
1 & H'_{\text{max}} > th' \\
0 & H'_{\text{max}} \leq th'
\end{cases}
\]

(10)

Search for all noise points according to Eq. (10) and find the maximum grey value \( noise(i,j)_{\text{max}} \) and minimum grey value \( noise(i,j)_{\text{min}} \) among all the noise points. When the image edges are adaptively detected and the target is automatically recognized and classified, the manual threshold setting affects the automation process; it is necessary to let the system adaptively generate the optimal threshold \( th' \). A suitable search step size is set to find the PSNR of all equally spaced points between \( noise(i,j)_{\text{min}} \) and \( noise(i,j)_{\text{max}} \), and to identify the noise point with the largest PSNR. This noise point is set as the most suitable threshold \( th' \). Substitute the obtained \( th' \) into the noise calibration function (Eq. (10)) to obtain all the noise points, then apply the median filter upon noise-point judgment (or keep the pixel unchanged if it is a non-noise point).

\[
f'(i,j) = \begin{cases} 
 f(i, j) & H'_{\text{max}} > th' \\
 \text{median}(f(i+a, j+b)) & H'_{\text{max}} \leq th'
\end{cases}
\]

(11)

B. IMAGE EDGE DETECTION ALGORITHM

Construct a reference sequence with \( g(i, j) \) as the central pixel. The reference sequence as follows,

\[
X_0 = \{ x_0 (1), x_0 (2), x_0 (3) \} = \{ g(i, j), g(i, j), g(i, j) \}
\]

The 1-time interval sequence of the slope formed by each point in the reference sequence \( X'_0 \) and the central pixel is 0; the comparison sequence is constructed with the central pixel, so the 1-time interval sequence of the slope between the points in the reference sequence (i.e., the proximity of the neighborhood pixel to the center pixel) is:

\[
\Delta_m(k) = \frac{|x_m(k) - g(i, j)|}{255} \quad (m = 1, 2, \cdots, 28; k = 1, 2, 3)
\]

(12)

According to the image relation model proposed above, the grey relation between the central pixel and the neighborhood pixel is:

\[
y_m(k) = \frac{1}{1 + \Delta_m(k)}
\]

(13)

Calculate the grey entropy of the \( 3 \times 3 \) neighborhood window according to Eq. (5):

\[
H_X(m) = -\sum_{i=1}^{3} p_{h_m}(k) \ln p_{h_m}(k)
\]

(14)
the difference between the maximum grey entropy value and the minimum grey entropy value $\Delta H = H_{\text{max}} - H_{\text{min}}$.

Set the edge detection threshold point $th$ to divide the image into two parts: the background point and the edge point. When $\Delta H > th$, $g(i,j) = \text{edge}(i,j) = 1$, the image center pixel point $g(i,j)$ is determined to be an edge pixel point and is marked into the edge pixel matrix; when $\Delta H < th$, $g(i,j) = \text{edge}(i,j) = 0$, the image center pixel point $g(i,j)$ is determined to be a non-edge pixel point. The edge point calibration function is as follows:

$$
\text{edge}(i,j) = \begin{cases} 1 & \Delta H > th \\ 0 & \Delta H < th \end{cases} \quad (15)
$$

Calibrate each pixel in the image in turn. A matrix of edge pixel points with elements of edge $(i,j)$ are created. All edge pixel points are scaled to the matrix of edge pixel points, thereby revealing all edge features.

The edge detection algorithm must adaptively find the optimal threshold $th_p$ according to different images to allow the computer to automatically detect edges. The difference $\Delta H = H_{\text{max}} - H_{\text{min}}$ between $H_{\text{max}}$ and $H_{\text{min}}$ is determined according to the maximum grey entropy value $H_{\text{max}}$ and the minimum grey entropy value $H_{\text{min}}$. When the image has $MN$ pixel points, there are $MN$ grey entropy difference values. The grey entropy difference values are sorted in order from small to large to form a grey entropy difference sequence $\{\Delta H_i | i = 1, 2, \ldots, k, \ldots, MN\}$. Let $\Delta H_k = th$, then divide the grey entropy difference sequence into two parts: the background and the target with $k$ as the boundary. When $1 < i \leq k$, $\Delta H_i$ is the background element; when $k < i \leq l$, $\Delta H_i$ is the target element.

The proportion of each component is $q_i = \Delta H_i \left/ \sum_{i=1}^{k+1} \Delta H_i \right.$, the proportion of background elements is $Q_1 = \sum_{i=1}^{k} q_i$, and the proportion of target elements is $Q_2 = 1 - Q_1 = \sum_{i=k+1}^{l} q_i$. The average grey entropy difference of the background elements is $b_1 = \sum_{i=1}^{k} \Delta H_i \cdot q_i / Q_1$, the average grey entropy difference of the target element is $b_2 = \sum_{k+1}^{l} \Delta H_i \cdot q_i / Q_2$, and the average grey entropy difference of the entire grey entropy difference sequence is $b_G = \sum_{i=1}^{l} \Delta H_i \cdot q_i$.

Define the class square error as $\sigma_B^2 = Q_1(b_1 - b_G)^2 + Q_2(b_2 - b_G)^2$. When $\Delta b = b_2 - b_1$ is larger, the target elements are farther from the background elements. The edge detection effects are better, and the class square error is higher [47]–[49]. The class square error set $\{\sigma_B^2(i) | i = 1, 2, \ldots, k, \ldots, MN\}$ is established in order from small to large. There must be a maximum value $\max_{0 \leq k \leq l} \sigma_B^2(k)$ and an optimal threshold $th^*$ so that $\sigma_B^2(th^*) = \max_{0 \leq k \leq l} \sigma_B^2(k)$. The edge detection effects are optimal when $th_p = \Delta H(th^*)$.

The obtained optimal separation threshold $th_p$ is returned to the edge point calibration function (Eq. (15)) and all edge pixels are recalibrated to complete the edge detection work.

### C. ADAPTIVE EDGE DETECTION BASED ON GREY ENTROPY AND TEXTURAL FEATURES

When the number of whole image pixels is $M \times N$, the flow chart of the proposed algorithm is as shown in Fig. 3.

### IV. EXPERIMENTAL RESULTS

We compared the proposed algorithm against other operators and improved algorithms based on those traditional operators. The limitations and potential approaches to improving the proposed algorithm are also discussed.
A. ACTUAL IMAGE EDGE DETECTION

To verify the edge detection effects of the proposed algorithm, we compared it against state-of-the-art methods including the Canny operator, improved Canny algorithm proposed by Rong et al. [7], morphological method proposed by Fu and Jiang [21], Zernike moment method proposed by Peng et al. [15], improved Sobel operator proposed by Shi et al. [8], and the traditional GRA (threshold value $k = 0.1$) proposed by...
Li et al. [30]. The results are shown in Figs. 5-7. Figure 5 shows the detection results of various methods on the Lena image, Fig. 6 the results on the Rice image, and Fig. 7 the results on the Cameraman image.

For simple images (Rice), edges were detected successfully by various methods and especially LI+GRA. Some missing detections did occur; for example, the edge of the rice grain in the lower right corner of Figs. 5(b)-(d) and 5(f) is missing and many discontinuous edges are visible in Figs. 5(c) and 5(e). For complex images (Lena and Cameraman), as shown in Figs. 4(e) and 6(e), PENG+Moment detected most of the edges but some discontinuous edges appeared. As shown in Figs. 4(b)-(f), 6(b)-(f), and 6(g), the Canny, RONG+Canny, FU+Morphology, PENG+Moment, SHI+Sobel, and LI+GRA methods all detected unneeded background areas. Lena’s mouth edge was also missed (Fig. 4(g)) and a coarse edge appeared (Figs. 4(d), 4(g), 5(d), 5(g), 6(f), and 6(g)). As shown in Figs. 4(h)-6(h), the proposed algorithm accurately detected most edges and had better edge continuity than the other methods. Moreover, there was no edge over-detection though some edges were detected as coarse edges.

Berkeley Segmentation Data Set (BSDS500) is a well-known boundary detection benchmark which contains 100 test images with human-labeled “ground truth” boundaries [50]. Fig. 7 shows the edges detected by various methods on this set. In order to objectively evaluate which edge detection algorithm is better, we utilized parameters such as intersection over union, true positive rate, false positive rate, recall, and precision for the sake of comparison [50]–[54].

The evaluation standard of intersection over union (IoU) was used to measure the correlation between the “ground truth” boundaries and compute-detected edges. A higher correlation produces a higher IoU value. Fig. 8 shows the IoUs obtained by various methods with “ground truth” boundaries on BSDS500.

The receiver operating characteristic (ROC) standard is judged by plotting the true positive rate (TPR) against the false positive rate (FPR) to identify the tradeoff between sensitivity and specificity. The closer the point follows the left-hand border and the top border of the ROC space, the more accurate the test; while the closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test. Fig. 9 shows the ROCs obtained by various methods on BSDS500.

The F-Measure evaluation standard is the weighted harmonic average precision and recall, i.e., a combination of those two measures. When F-Measure is higher, the edge detection method is more effective [51]. Fig. 10 shows the precision and recall evaluation results of various methods on BSDS500.

As shown in Fig. 8, the IoU obtained by the proposed algorithm is higher than that obtained by other methods on the BSDS500. As shown in Fig. 9, the points obtained by the proposed algorithm are closer to the left-hand border and the top border of the ROC space than other methods. According to Fig. 10 and Fig. 11, the precision and recall as well as the F-measure \( F = 2 \cdot \frac{\text{Recall} \cdot \text{Precision}}{\text{Recall} + \text{Precision}} \) of the proposed method are also higher than that of other methods. In summary, for images that are not polluted by
noise, the detection effect of the proposed algorithm is altogether better than other edge detection methods we tested.

B. NOISE IMAGE EDGE DETECTION

Imperfections in the imaging system, transmission media, and other factors may contaminate the acquired digital images with noise. Salt and pepper noise exerts the most significant damage on image quality among all types of noise. Noisy images must be carefully processed for any effective pattern recognition, computer vision, image analysis, or image recognition application to function properly.
We added 0.02-level salt and pepper noise to the digital image used in Section IV(A) and again tested the proposed algorithm by comparison against the other edge detection methods mentioned in Section IV(A); the edge detection results by various methods are shown in Fig. 12.

As shown in Figs. 12(c) and 12(f)-(g), FU+Morphology, SHI+Sobel, and LI+GRA methods were overwhelmed by noise. As shown in Figs. 12(e), PENG+Moment detected most of the edges but they were mainly discontinuous. As shown in Figs. 12(c) and 12(h), the proposed algorithm and RONG+Canny accurately detected most edges with good continuity. By comparison between Fig. 7(h) and Fig. 12(h), the proposed algorithm processed noisy and noiseless images similarly – in other words, it has excellent anti-noise ability.

We also obtained the IoU curve (Fig. 13), ROC point distribution (Fig. 14), and F-Measure curve (Fig. 15) \((F = 2 \cdot \text{Recall} \cdot \text{Precision}/(\text{Recall} + \text{Precision}))\) of the proposed algorithm, RONG+Canny, and PENG+Moment for the sake of comparison. As shown in Fig. 13, the proposed algorithm has a higher IoU overall on the BSDR500 than RONG+Canny and PENG+Moment; as shown in Fig. 10, it also has closer points to the left-hand border and top border of the ROC space than RONG+Canny and PENG+Moment; Its F-measure values are also consistently higher (Fig. 15). These results suggest that for images that are polluted by noise, the proposed algorithm outperforms the other edge detection methods we tested.

C. FUTURE RESEARCH

As discussed in Section IV-A, image processing grows increasingly complex if some edges are detected as coarse edges. It is necessary to refine the edges, such as by mathematical morphology, to ensure a smooth and effective process. Existing edge refinement methods have a better effect on coarse edges – for example, the parallel thinning algorithm established by Holt in 1987 [55]. M. Kang already improved Holt’s edge refinement method, in fact, to minimize its computational load in a 2018 study [2].

As shown in Fig. 13(h), under the condition of 0.02 salt and pepper noise, the noise in some pictures is not completely filtered. In the future, the preprocessing work of filtering should be improved. Fortunately, some excellent filters are designed, such as the MST-filtering, which can give a connected and undirected graph with minimum weight. Bao proposed a new efficient edge-preserving filter based on MST in 2014 [50], what impressed us is that the proposed filter can smooth out high-contrast details while preserving major edges. Therefore, we consider the combination of the edge algorithm proposed in this paper and MST-filtering in the future to perform the edge detection of images with high noise pollution.

In this study, the 28 edge structures which we used were fairly time-consuming to calculate. The optimal threshold-setting method also centers on the maximum value among the class square error set \(\{\sigma^2_B(i) | i = 1, 2, \cdots, k, \cdots, l\}\), but every class square error \(\sigma^2_B(i)\) needs to be calculated by running a loop; this requires a fairly lengthy processing time. In the future, selecting appropriate textural features and deploying appropriate optimal threshold acquisition methods can reduce the time and labor of the proposed method.

V. CONCLUSION

A new image edge detection method based on grey entropy theory and edge structure features was proposed in this paper. The method utilizes grey entropy theory to characterize the internal energy fluctuation of the system to identify pixel points, noise pixels, and edge pixels in the image. Edges are effectively assigned textural structure characteristics while the algorithm maintains excellent anti-noise capability. Edges are detected automatically under an adaptive comparison threshold: once the appropriate threshold is given, the system can perform edge detection on any grayscale image.

We conducted a series of simulations to find that the proposed algorithm has excellent overall edge detection and
anti-noise ability. It also realizes automatic edge detection of images with varying complexity and can provide references for image recognition or pattern recognition. However, it imposes a coarse edge condition on the edge which necessitates subsequent edge refinement processing according to the actual image situation at hand.

REFERENCES

[1] W. Gao, X. Zhang, L. Yang, and H. Liu, “An improved Sobel edge detection,” in Proc. Int. Conf. Comput. Sci. Inf. Technol., Chengdu, China, Jul. 2010, pp. 67–71.

[2] M. Kang, Q. Xu, and B. Wang, “A rovers’ adaptive edge detection method,” J. Xi’an Jiaotong Univ., vol. 42, no. 10, pp. 1240–1244, 2008.

[3] J. Canny, “A computational approach to edge detection,” IEEE Trans. Pattern Anal. Mach. Intell., vol. PAMI-8, no. 6, pp. 679–698, Nov. 1986.

[4] X. Wang, “Laplacian operator-based edge detectors,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 29, no. 5, pp. 886–890, May 2007.

[5] L. Yuan and X. Xu, “Adaptive image edge detection algorithm based on canny operator,” in Proc. Int. Conf. Adv. Inf. Technol. Sensor Array., Harbin, China, Aug. 2015, pp. 28–31.

[6] Q. Xu, S. Varadarajan, C. Chakrabarti, and L. J. Karam, “A distributed canny edge detector: Algorithm and FPGA implementation,” IEEE Trans. Image Process., vol. 23, no. 7, pp. 2944–2960, Jul. 2014.

[7] W. B. Rong, Z. Li, W. Zhang, and L. Sun, “An improved CANNY edge detection algorithm,” in Proc. IEEE Int. Conf. Mechatron. Automat., Tianjin, China, Aug. 2014, pp. 577–582.

[8] T. Shi, J.-Y. Kong, X.-D. Wang, Z. Liu, and G. Zheng, “Improved Sobel algorithm for defect detection of rail surfaces with enhanced efficiency and accuracy,” J. Central South Univ., vol. 23, no. 11, pp. 2867–2875, 2016.

[9] V. S. Narula and T. O. Binford, “On detecting edges,” IEEE Trans. Pattern Anal. Mach. Intell., vol. PAMI-8, no. 6, pp. 699–714, Nov. 1986.

[10] J. Ye, G. Fu, and U. P. Poudel, “High-accuracy edge detection with blurred edge mode,” Image Vis. Comput., vol. 23, no. 5, pp. 453–467, 2005.

[11] C.-Y. Su, L.-A. Yu, and N.-K. Chen, “Effective subpixel edge detection for LED probes,” in Proc. IEEE Int. Conf. Syst., Man, Cybern., Budapest, Hungary, Oct. 2017, pp. 379–382.

[12] I. Overington and P. Greenway, “Practical first-difference edge detection with subpixel accuracy,” Image Vis. Comput., vol. 5, no. 3, pp. 217–224, 1987.

[13] K. Jensen and D. Anastassiou, “Subpixel edge localization and the interpolation of still images,” IEEE Trans. Image Process., vol. 4, no. 3, pp. 285–295, Mar. 1995.

[14] S. Ghosal and R. Mehrotra, “Orthogonal moment operators for subpixel edge detection,” Pattern Recognit., vol. 26, no. 2, pp. 295–306, 1993.

[15] S. Peng, W. Su, X. Hu, C. Liu, Y. Wu, and H. Nan, “Subpixel edge detection based on edge gradient directional interpolation and Zernike moment,” in Proc. Int. Conf. Comput. Sci. Softw. Eng., May 2018, pp. 106–116.

[16] Y. Li, J. Huo, M. Yang, and G. Zhang, “Algorithm of locating the sphere center imaging point based on novel edge model and Zernike moments for vision measurement,” J. Mod. Opt., vol. 66, no. 2, pp. 218–227, 2019.

[17] P. J. Terry and D. Vu, “Edge detection using neural networks,” in Proc. Asilomar Conf. Signals, Syst., Pacific Grove, CA, USA, Nov. 1993, pp. 391–395.

[18] Z. Zhang, Y. Liu, T. Liu, Y. Li, and W. Ye, “Edge detection algorithm of a symmetric difference kernel SAR image based on the GAN network model,” Symmetry, vol. 11, no. 4, p. 557, 2019.

[19] S. Mallat and W. L. Hwang, “Singularity detection and processing with wavelets,” IEEE Trans. Inf. Theory, vol. 38, no. 2, pp. 617–643, Mar. 1992.

[20] L. Vincent, “Morphological grayscale reconstruction in image analysis: Applications and efficient algorithms,” IEEE Trans. Image Process., vol. 2, no. 2, pp. 176–201, Apr. 1993.

[21] X. G. Fu and H. Jiang, “A multi-scale morphological algorithm for AFM micrograph edge detection,” in Proc. Int. Conf. Ind. Technol. Manage. Sci., Tianjin, China, vol. 34, Mar. 2015, pp. 942–945.

[22] X. Wang, X. Zhang, and R. Guo, “An adaptive edge detection algorithm based on gray-scale morphology,” in Proc. Int. Conf. Meas., Inf. Control, Harbin, China, Aug. 2013, pp. 1251–1254.

[23] J. L. Deng, “Grey information space,” J. Grey Syst., vol. 1, no. 2, pp. 103–117, 1985.
[48] H. Moon, R. Chellappa, and A. Rosenfeld, “Optimal edge-based shape detection,” IEEE Trans. Image Process., vol. 11, no. 11, pp. 1209–1226, Nov. 2002.

[49] J. Cao, L. Chen, M. Wang, and Y. Tian, “Implementing a parallel image edge detection algorithm based on the Otsu-canny operator on the Hadoop platform,” Comput. Intell. Neurosci., vol. 2018, May 2018, Art. no. 3598284.

[50] L. Bao, Y. Song, Q. Yang, H. Yuan, and G. Wang, “Tree filtering: Efficient structure-preserving smoothing with a minimum spanning tree,” IEEE Trans. Image Process., vol. 23, no. 2, pp. 555–569, Feb. 2014.

[51] P. Arbelaez, M. Maire, C. Fowlkes, and J. Malik, “Contour detection and hierarchical image segmentation,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, no. 5, pp. 898–916, May 2010.

[52] M. Borsotti, P. Campadelli, and R. Schettini, “Quantitative evaluation of color image segmentation results,” Pattern Recognit. Lett., vol. 19, no. 8, pp. 741–747, 1998.

[53] F. Ge, S. Wang, and T. Liu, “Image-segmentation evaluation from the perspective of salient object extraction,” in Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., New York, NY, USA, vol. 1, Jun. 2006, pp. 1146–1153.

[54] H. Zhang, J. E. Fritts, and S. A. Goldman, “Image segmentation evaluation: A survey of unsupervised methods,” Comput. Vis. Image Understand., vol. 110, no. 2, pp. 260–280, 2008.

[55] C. M. Holt, A. Stewart, M. Clint, and R. H. Perrott, “An improved parallel thinning algorithm,” Commun. ACM, vol. 30, no. 2, pp. 156–160, 1987.

ZHEN ZHENG was born in Hubei, China. He is currently pursuing the Ph.D. degree in mechanical engineering with the Nanjing University of Science and Technology (NJUST), Nanjing, China. His current research interests include laser detection, laser target recognition, and image processing.

YOUSHI XUCHEN was born in Zhejiang, China. He is currently pursuing the Ph.D. degree in armament science and technology with the Nanjing University of Science and Technology (NJUST), Nanjing, China. His current research interests include laser detection and laser anti-dust interference.

BINGTING ZHA was born in Jiangxi, China. She received the Ph.D. degree in armament science and technology from the Nanjing University of Science and Technology (NJUST), Nanjing, China, in 2015, where she is currently a Lecturer with the School of Mechanical Engineering.

Her current research interests include underwater laser detecting and laser applications.

HAILU YUAN was born in Shanxi, China. She is currently pursuing the Ph.D. degree in armament science and technology with the Nanjing University of Science and Technology (NJUST), Nanjing, China. Her current research interests include underwater laser scanning imaging technology and laser target detection.

YANLIANG GAO was born in Hebei, China. He is currently pursuing the M.S. degree in armament science and technology with the Nanjing University of Science and Technology (NJUST), Nanjing, China. His current research interests include laser detecting and laser applications.

HE ZHANG was born in Henan, China. He received the Ph.D. degree in measurement technology and instruments from the Nanjing University of Aeronautics and Astronautics, Nanjing, China.

He is currently a Professor with the School of Mechanical Engineering, Nanjing University of Science and Technology, China. He is also the Director of the Institute of Mechanical and Electrical Engineering, NJUST, and the Associate National Defense Key Laboratory. His current research interests include mechatronics and weapon system applications. He serves on the Editorial Board for the Journal of Detection & Control.