Morphological Enhancement for Remote Sensing Image Based on GAN Structuring Elements

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Abstract. A morphological image enhancement method based on the GAN (General Adaptive Neighborhood) structuring elements is proposed for some problems such as low overall contrast, noise and inter-target edge of some remote sensing images. Firstly, a pixel to be processed is selected as a seed point, and an adaptive neighborhood is defined according to the image pixel characteristic and the neighborhood constraint relation to obtain the self-adaptive structuring elements set. A corresponding self-adaptive morphological operation based on the self-adaptive structuring elements set is constructed with reference to the classical morphological operation definition, and the self-adaptive alternative filter is constructed by using the adaptive morphological operation combination so as to realize the enhancement of the remote sensing image. The experimental results show that the method can preserve the accurate positioning of the objects edge while enhancing the image, avoid the loss of information, has better noise removing performance. Compared with the classical morphological filter operator, the single-scale Retinex algorithm and bi-histogram equalization (BHE) algorithm, the contrast ratio and the signal-to-noise ratio of the enhanced image are improved.

1. Introduction
Remote sensing images have been widely applied to resource statistics, urban fine management and dynamic change monitoring etc. [1]. However, there are some problems such as noise, low signal-to-noise ratio and contrast due to the various factors such as illumination, data acquisition equipment and atmospheric scattering, which affect subsequent image analysis and recognition, such images are necessary to enhance. Various methods have been proposed for image enhancement [2-6], where morphological operation is one effective enhancement method. Srikrishna et al. [7] proposed a color image enhancement method based on parametric morphological transformation in poor-lighting; Bai[8] presented morphological enhancement of microscopy mineral image using opening and closing based toggle operator; Shrimali et al. [9] proposed the use of morphological non-linear Top-hat transform to enhance ultrasound images. Morphological filtering of 5 different liver images by using 10 different structuring elements, and then the filtered images were assessed quantitatively. At the same time, a multi-point rank order method has been used to identify small differences or trends in observation; Debayle et al. [10-12] proposed the use of adaptive neighborhood morphology to construct adaptive structuring elements, and to implement image enhancement through adaptive morphological dilation and erosion operators; An et al [13] proposed a multi-scale color image enhancement algorithm based on morphological Top-hat algorithm; Teng et al. [14] proposed a hyper-spectral image restoration method using adaptive morphological filtering and fusing structure information of an auxiliary color image. The adaptive structure of each pixel is constructed by information fusion, which can filter out the noise at the same time and keep the spatial structure of the...
target pixel; Liu et al. [15] proposed an adaptive enhancement algorithm based on morphological variable weights, where extension Omni-directional Multi-scale structure element is constructed to decompose image of different scale details in different direction by Top-hat translation.

The above methods can effectively enhance image, most of them are adaptive adjustment of the size of structuring elements. In fact, if the morphological filter with fixed shape structuring elements is used to enhance the remote sensing image, the location deviation and shape change of the target may be emerged, which is not conducive to subsequent analysis and recognition. Aim to highlight the main features of the image target (such as edges) and smooth the noise while maintaining the spatial shape of the target, the size and shape of the structuring elements should be both taken into account when the morphological filter is used to enhance the remote sensing image. For this consideration, a morphological enhancement method based on GAN structuring elements is proposed. In this method, the target pixel of the remote sensing image to be processed is selected as the origin of the structuring element, and the brightness value of the current pixel is used as a reference feature. According to the brightness variation range of the pixel where the structuring element is located, a corresponding GAN adaptive neighborhood is established, and all neighboring pixels falling within the tolerance range of the current pixel attribute characteristic value constitute the structuring element corresponding to the current pixel, that is, different pixels correspond to different structuring elements, thus forming a set of structuring elements; The basic operation of adaptive morphology is defined and the adaptive open and close filter operators are constructed. At last, the remote sensing image is enhanced, the noise is filtered, and the edge contour of the target is maintained.

2. The Construction of GAN Adaptive Structuring Element

For each pixel in image \( f \), assume that its adaptive neighborhood is represented as \( V^*_c(x) \), GAN is a subset of the spatial structure composed of connected pixels. If the difference between the pixel feature value and the pre-set standard is within a certain tolerance range, these GANs can be used as an adaptive sliding window for quantitative analysis of the image [12]. The establishment of GAN is based on the mapping \( h \) and tolerance \( m \) related to the specific features of the image. GAN is defined as follows [11, 12]:

\[
V^*_c(x) = C_x, \{ y \in E \mid |h(y) - h(x)| \leq m \}
\]

Where \( C_x \) is the connected component, \( E \) is the pixel feature set, \( h^{-1}(Y) = \{ x \in D \mid h(x) \in Y \}, Y \subseteq E \), \( D \in \mathbb{R}^2 \) is the Euclidean topological space. The expression shows that when the feature deviation of the neighborhood pixel is within the tolerance, the pixel and the current pixel belong to the same GAN set. There are many features of GAN pixels, such as gray, color, gradient, contrast, curvature, convexity, thickness and direction, etc. In this paper, the gray value of image pixel is selected as the feature standard. The simplest way to select seed points is to take the first pixel in the upper left corner of the image as the first seed point, and then select the seed points from left to right and from top to bottom, the pixels that have been subsumed into a GAN neighborhood are no longer used as seed points. Different object regions in the image can also be designated as seed points. The selection of tolerance \( m \) should not be too large, otherwise, the structuring elements may be too large, which may easily lead to the loss of image details after enhancement. According to the above criteria, new 8-neighborhood pixels are included continuously until no new pixels appear in the adaptive neighborhood pixel set, and the region expansion ends. These pixels included in different GAN regions form the corresponding GAN adaptive structuring element set. It can be seen that different pixel regions correspond to different structuring elements, and their shape and size are adaptively changed according to the features (gray scale) of the pixel neighborhood. Using this structuring element to perform morphological operations on the image can better follow the shape and size of the image target to refine the corresponding region. Figure 1 selects X and Y as the seed points to be processed in the original image.

In Figure 2 (b), the gray is served as the standard. When \( m = 28 \), the adaptive neighborhood GAN corresponding to the seed points X and Y is the white region. Since GAN has good spatial adaptability, it satisfies the local detail information of image, and has symmetry, which can simplify morphological...
operations. In order to obtain the structuring elements required for the basic operation of adaptive morphology based on GAN, the traditional morphological structuring elements can be replaced by adaptive neighborhoods, which are defined as follows:

$$\lambda(x) = \bigcup_{z \in \mathcal{E}_z} \{x \in \mathcal{V}_x \}$$

(2)

Figure 1. GAN schematics. (a) Seed points X and Y to be processed; (b) GAN region of X and Y (white)

Figure 2. (a) non-adaptive structuring element; (b) GAN-based self-adaptive structuring element

It can be seen from Figure 2 that the adaptive structuring element of GAN can accurately describe the shape and size of the target and the structuring element can vary from line to any shape and size adaptively.

3. Morphological Operations Based on GAN Adaptive Structuring Element

The definition of morphological operations based on GAN adaptive structural elements is the same as that of classic morphology, but the difference is that the morphological operations based on GAN adaptive structuring elements are calculated using structuring elements of corresponding shapes and sizes for different pixels. Corresponding to the dilation and erosion of classical morphological basic operations, the corresponding adaptive dilation $D^x(f)$ and erosion $E^x(f)$ are respectively defined as:

$$D^x(f)(x) = \sup_{w \in \mathcal{D}_x} f(w)$$

(3)

$$E^x(f)(x) = \inf_{w \in \mathcal{I}_x} f(w)$$

(4)

Similarly, GAN-based adaptive morphological opening $O^x(f)$ and closing $C^x(f)$ can be defined as:

$$C^x(f) = E^x(D^x(f))$$

(5)

$$O^x(f) = D^x(E^x(f))$$

(6)

If the gray serves as the feature standard, for all seed points $(x,y)$ in the neighborhood, if $h(x) = h(y)$, then $\lambda(x) = \lambda(y)$, $D^x(f)(x) = D^y(f)(y)$, $E^x(f)(x) = E^y(f)(y)$. In this way, the complexity of adaptive morphological operation can be reduced.

4. Morphological Image Enhancement

The GAN adaptive morphological opening operation can remove the bright details smaller than the current structuring element and keep the other components unchanged, while the GAN adaptive morphological closing operation can remove the dark details smaller than the current structuring element in the image, and keep the bright parts unaffected. Therefore, the image can be enhanced by the combination of adaptive morphological closing-opening operation. It can effectively retain useful contour edges and reduce complex background details and noise, make important feature information such as image edges more clear, and at the same time, preserve the integrity of target shapes and spatial locations in the image as much as possible.
The adaptive morphological closing-opening filter can be obtained by combining the adaptive morphological opening and closing operations as follows:

\[ OC_{Ad}^m(f) = OC_{Ad}^m(C_m^a(f)) \]  

(7)

The concrete image enhancement steps are as follows:

**STEP 1:** Convert the remote sensing image to grayscale image, and find the first pixel that has not yet been assigned, let that pixel be \( P(x_0, y_0) \);

**STEP 2:** Let \( P(x_0, y_0) \) as the center, consider its 8-neighborhood pixel \( Q(x, y) \), take the gray as the feature standard, and select the corresponding tolerance \( m \) as the threshold according to the size of the neighborhood pixel value of the seed point. If \( Q(x, y) \) meets the growth criterion, then \( Q(x, y) \) is included in the neighborhood of \( Q(x, y) \), and \( Q(x, y) \) is pushed into the stack;

**STEP 3:** Take another new pixel from the stack as the center pixel and return to **STEP 2**;

**STEP 4:** When the stack is empty, return to **STEP 1**;

**STEP 5:** When the image pixel traversal ends, the neighborhood expansion is finished. At this time, all the neighboring pixels falling within the tolerance range of the current pixel eigenvalue consist of a pixel set, which is a GAN adaptive structuring element;

**STEP 6:** The remote sensing image is enhanced by Eq. (7).

5. Experimental Results and Analysis

To verify the enhanced performance of the proposed method on remote sensing images, the simulations are implemented on a 2.5GHz/4GB computer using MATLAB, and the proposed method is compared with single-scale Retinex, BHE and classical morphological filtering enhancement under the condition of noiseless and noise.

Figure 3 shows the enhancement results of the urban area remote sensing image by single-scale Retinex, BHE and classical morphological closing-opening filter and the proposed method, respectively. The image size is 256×256. It can be seen from the comparison of enhancement effects and histograms, the Retinex enhancement image (Figure 3 (b)) appears halo phenomenon, the overall brightness of the image is too high, and the buildings and vegetation are blurred in some extent; the overall brightness is improved by BHE enhancement algorithm (Figure 3 (c)), and the dynamic range of gray distribution is expanded; Figure 3 (d) is the result of morphological closing-opening filtering with fixed structuring elements, where buildings and roads, etc appear fuzzy; In contrast, the proposed method (Figure 3 (e)) enhances the image, smooth the small interference in the internal region of the target while preserve the accurate position of the target contour. Compared with the histograms of other enhancement methods, the dynamic range of the gray distribution of the proposed method is enlarged, the brightness of the dark region is increased, the gray value of the highlighted region is maintained or suppressed, and the overall visual effect of the remote sensing image is enhanced.
Figure 3. Urban image enhancement and histogram
To further verify the anti-noise performance of the proposed method, pepper and salt noise with a variance of 0.01 are added into the remote sensing image as shown in Figure 4 (a). It can be seen from Figure 4 (b) that after median filtering using the non-local noise intensity balance parameter factor combined with classic morphological closing and opening operations, the noise is basically eliminated, but the edges of buildings and houses in the image are relatively blurred. The overall brightness of the image is not high and the contrast is low. In Figure 4 (c), the brightness of building area, road and vegetation is too high. Figure 4 (d) is the result of the BHE algorithm after removing the noise. It can be found that the overall brightness of the image is too high and the building area is not clear. After removing noise using the classic morphological method (Figure 4 (e)), the objects such as buildings and roads in the image are relatively blurred, and part of the edge are damaged, making it difficult to clearly reflect the buildings. The proposed method as shown in Figure 4 (f) can filter out the noise while maintaining the internal information and edge contours of street houses, etc., and the overall contrast is high.

The peak signal-to-noise ratio, information entropy and contrast are used to quantitatively test the enhanced performance of the proposed method. The peak signal-to-noise ratio (PSNR) is defined as follows:

$$PSNR = 10 \log \frac{(2^n - 1)^2}{MSE}$$ \hspace{1cm} (8)

Where $n$ is the number of bits per pixel, and $MSE$ is mean square error, defined as:

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} [I(i, j) - G(i, j)]^2$$ \hspace{1cm} (9)

Where $M \times N$ is the image size, $I(i, j)$ is the original image, and $G(i, j)$ is the enhanced image. When $PSNR$ is smaller, it means that the less detail loss of the enhanced image, the better the smoothing effect of noise.

The information entropy $H$ is defined as follows:

$$H = -\sum_{i=1}^{L} p_i \log p_i$$ \hspace{1cm} (10)

Where $L$ is the maximum gray level of the image and $p_i$ is the gray level probability. When $H$ is larger, the image contains more detailed information.
Figure 4. Comparison of noise image enhancement with different methods. (a) Noise image; (b) Morphological closing-opening; (c) Single-scale Retinex algorithm; (d) BHE algorithm; (e) Classical morphological algorithm; (f) The presented method.

The contrast $C$ is defined as follows:

$$C = \sum \delta^2(i, j) p_x(i, j)$$  \hspace{1cm} (11)

Where $\delta(i, j)$ is the gray level difference between adjacent pixels, and $p_x(i, j)$ is the probability of $\delta(i, j)$. Contrast reflects the quality of the image after enhancement. The higher contrast means the better enhancement effect. Table 1 shows the comparison of the information entropy, contrast, and running-time $T$ in Figure 3 when different image enhancement methods are used. It can be seen that compared with Retinex, BHE algorithm and classical morphological closing-opening method, the proposed method has higher information entropy and contrast, the running-time is relatively long but not much increased.

| Method                          | $H$ (bit) | $C$     | PSNR (dB) |
|--------------------------------|-----------|---------|-----------|
| Median filtering + Morphological closing-opening | 4.58      | 4.13    | 12.43     |
| Retinex                        | 6.59      | 5.28    | 7.66      |
| BHE                            | 2.46      | 5.13    | 6.11      |
| Classical morphology           | 4.01      | 6.01    | 10.25     |
| Proposed method                | 7.64      | 6.27    | 15.64     |

Table 1. Performance comparison under different enhancement methods for Figure3

Table 2. Performance comparison of different enhancement methods under noise
Table 2 shows the comparison of the information entropy, contrast, and PSNR of Figure 4 after median filtering combined with morphological closing-open operation, Retinex, BHE, and the proposed method. It can be seen that the three performance of the proposed method are improved compared with other methods, which shows that this method can enhance the image, at the same time, it has strong anti-noise performance and the ability to maintain details.

6. Conclusion
An adaptive morphological remote sensing image enhancement method based on GAN structuring element is proposed. The neighborhood is expanded according to the neighborhood establishment criteria through the inner pixel seed points of the image. The region formed after the expansion is the adaptive structuring element. The morphological dilation and erosion operator is redefined by adaptive structuring elements, and the adaptive morphological closing-opening operation is derived to achieve the enhancement of remote sensing images. Compared with single-scale Retinex, BHE and classical morphological closing-opening filtering, the proposed method can enhance the main feature information of the image target while maintain the original location of the target edge contour, avoid the loss of important feature information, and has strong anti-noise performance.

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8. References
[1] JIA K, LI Q Z, TIAN Y C, WU B F. A Review of Classification Methods of Remote Sensing Imagery. Spectroscopy and Spectral Analysis, 2019, 31, pp.2618-2623.
[2] Huang Z, Fang H, Li Q, et al. Optical remote sensing image enhancement with weak structure preservation via spatially adaptive gamma correction. Infrared Physics & Technology. 2018, 94, pp.38-47.
[3] Lu Liu, Zhenhong Jia, Jie Yang, Kasabov N. A remote sensing image enhancement method using mean filter and unsharp masking in non-subsampled contourlet transform domain. Transactions of the Institute of Measurement & Control. 2017, 39, pp.183-193.
[4] X. Fu, J. Wang, D. Zeng, Y. Huang and X. Ding, Remote Sensing Image Enhancement Using Regularized-Histogram Equalization and DCT, IEEE Geoscience and Remote Sensing Letters, 2015, 12, pp.2301-2305.
[5] SHAO S, GUO Y, LIU H, et al. Low-illumination Remote Sensing Image Enhancement in HSI Color Space. Optics and Precision Engineering, 2018, 26, pp.2092-2099.
[6] CHEN Y, ZHU M, LI Z Z. Remote Sensing Digital Image Enhancement Based on Gaussian Mixture Modeling. Chinese Journal of Lasers, 2014, 41, pp.229-235.
[7] Srikrishna A, Pompapathi M, Rao G S. Parametric based morphological transformation for contrast enhancement of color images in poor-lighting. Sadhana, 2015, 40 (2), pp.1-16.
[8] Bai X. Morphological enhancement of microscopy mineral image using opening and closing-based toggle operator. Journal of Microscopy. 2014, 253 (1), pp.12-23.
[9] Shrimali V, Anand RS, Kumar V, Srivastav RK. Medical feature based evaluation of structuring elements for morphological enhancement of ultrasonic images. Journal of Medical Engineering & Technology. 2009, 33(2), pp.158-169.
[10] V Gonzalez-Castro, J Debayle, Jean-Charles Pinol, Color Adaptive Neighborhood Mathematical Morphology and its application to pixel-level classification, Pattern Recognition Letters, 2014, 47 (4), pp.50-62.
[11] J. Debayle, J. Pinoli, Spatially adaptive morphological image filtering using intrinsic structuring elements, Image Anal. Stereol. 2005, 3(3), pp.145-158.
[12] J. Debayle, J.Pinoli, General adaptive neighborhood image processing-part I: introduction and theoretical aspects, Journal of Mathematical Imaging & Vision, 2006, 25 (2), pp.247-266.
[13] AN J, ZHANG G C, LIU Y N. Adaptive Color Image Enhancement Based on Multi-scale Top-hat Transform. Computer Engineering & Science, 2017, 39 (07), pp.1317-1321.
[14] Yidan Teng, Ye Zhang, Yushi Chen, et al. Adaptive Morphological Filtering Method for Structural Fusion Restoration of Hyperspectral Images, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2016, 9 (2), pp.655-667.

[15] LIU W J, ZHAO Q G, QU H C. Image Defog Algorithm Based on Variogram and Morphological Filter. *Journal of Image and Graphics*, 2016, 21, pp.1610-1622.