A Characteristic Distill Arithmetic of Region Growing Method Based On Fuzzy Connectedness

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Abstract. To solve the problem that the traditional region growing algorithm cannot deal well with the fuzziness between the damage area and the background, and the segmentation result is sensitive to the initial seed pixel, a region growing method based on fuzzy connectedness is proposed. The method takes fuzzy connectedness as the similarity measure between the initial pixel and the growing pixel, which keeps the fuzziness among the pixels well. A growing criterion integrated gray-fluctuation control with USAN area is proposed to fit the gray fluctuation in the damage area and get edge position precisely. The experiment results show the validation of this method.

1. Introduction

The region growing method is an important image segmentation algorithm combining pixels with similar properties to form a region, which has the characteristics of strong human-computer interaction and high precision of segmentation. However, the damage types on actual military targets are diverse, with a wide range of area changes, complex shapes and blurred boundaries, which makes it difficult to extract damage by traditional region growing method. Therefore, this paper proposes a region growing method based on Fuzzy Connectedness to solve such problems as the traditional region growing method cannot deal with the fuzziness between damaged area and background and the sensitivity to growing results of the selection of seed points.

The basic principle of the region growing method is: At first find a seed pixel in the region of interest as the starting point of growth, and then merge the pixels in the neighborhood around the seed pixel with the same or similar properties into the region where the seed pixel is located. The above process is repeated continuously until the pixels that do not satisfy the condition. Current research in this field mainly focuses on the design of feature metrics, growth criteria, and improving the effectiveness and accuracy of algorithms. Different region growing methods are proposed in the literature [1, 2]. In [2], for the segmentation problem of the whole image, the concept of Symmetric Region Growing is proposed, and a set of theoretical criteria is defined. It is pointed out that under the guidance of the symmetric growing function, the regional growing results are insensitive to the initial seed point. In [1], for the extraction of single-structure targets, a model-based adaptive region growing method is proposed. The homogeneity criterion is defined as the similarity between gray value of the growth point and the Gaussian distribution belonging to a given mean and standard deviation. In order to ensure the invariance of the homogeneity criterion in the region growing process, the algorithm adopts the method of twice region growing, which learns the homogeneity parameter in the first growing process and extracts the region in the second one. Although the region growing results...
obtained by the algorithm in literature [1, 2] are insensitive to the location of the selected seed points, it is not able to segment the target and the background or the target and the target well when there is fuzzy gray level of pixel between them. To solve the problem of fuzzy segmentation between target and background, literature [3] proposes an improved fuzzy connectedness segmentation algorithm, which uses the continuous growth-merge strategy and the adaptive threshold technology combined with entropy guidance to determine the homogeneity parameters. The algorithm has a good performance on the segmentation of fuzzy objects, but it can only segment them between foreground and background. Besides, when the background of the target is complex, the algorithm is difficult to get accurate segmentation results. In order to accurately extract the damaged area in the single-phase remote sensing image, this paper proposes a region growing method based on fuzzy connectedness. The method takes fuzzy connectedness as the measure of similarity between growing point and seed point, effectively keeping the fuzziness of pixels. At the same time, the growth of the region is controlled by fuzzy connection of seed points from strong to weak, so that the growing result is insensitive to the selection of seed points. In addition, the combination of gray level fluctuation control and USAN area is adopted as the growing criterion to adapt to the change of gray level in the target area and obtain a better effect of edge positioning.

2. Region growing method based on fuzzy connectedness

2.1. Similarity criteria based on fuzzy connectedness

In the actual imaging process, the acquired digital image is blurred due to the influence of time, space and equipment; at the same time, there is no clear boundary between some adjacent similar objects due to the similarity of them. Therefore, when measuring the similarity between pixels in an image, it is necessary to preserve its ambiguity. Based on this idea [4-6], Udupa et al. proposed the fuzzy targets theory of n-dimensional digital space in 1996. According to this theory, similarity criteria based on fuzzy connectedness can be obtained:

Assume that $R$ is the region of interest on the image to be grown, $a$ is a seed point inside it, and $b$ is any point on the image, as shown in Figure 1. If the region $R$ contains the point $b$, then there must be a path $P_{ab}$ from point $a$ to $b$. According to the concept of fuzzy connectedness, the value of $\mu_K(a, b)$ is unique and is the strongest path connectedness of all. In addition to the symmetry of fuzzy relationship $K$, if setting $b$ as the seed point of area, there must be the same path $P_{ba}$ from the seed point $b$ to the image point $a$, and the fuzzy degree of path connection is $\mu_K(b, a) = \mu_K(a, b)$. It can be inferred fuzzy degree of connection as similarity measurement of growing points and seed points, while its size to control the growing process which has the symmetry that growing point $b$ can also grow out point $a$. Similarly, the growing process is also reflexive and transitive. Since the selection of points $a$ and $b$ is arbitrary, the fuzzy connection degree is used as the similarity measurement between growing point and seed point, and the growing point is controlled to grow in a strong to weak order according to the fuzzy connectedness with the seed point. It shows that region growing results are insensitive to the selection of seed points.

![Figure 1. Growing schematic diagram based on fuzzy connectedness.](image-url)
2.2. Growing criterion based on gray-scale fluctuation control combined with USAN area

The region growing algorithm is a segmentation method that continuously expands from inside to outside near the seed point. After the similarity measurement is selected, the most significant thing is to determine the growing criterion of the region, that is, the new growing point grows under what conditions, and what to be stopped. The actual damage area has the characteristics of large fluctuation range of gray scale and blurred boundary. In order to accurately extract the damage in area, the region growing criterion should satisfy the following conditions [7-8]:

1. Adaptability to the gray distribution of the target;
2. Stop growing at edge point of the target with positioning capability.

To this end, this paper proposes a method based on the combination of gray-scale fluctuation control and USAN (Univalue Segment Assimilating Nucleus) area as a growing criterion.

2.2.1. Criterion based on gray-scale fluctuation control. In this paper, we use a growing criterion based on gray-scale fluctuation to control the growth of gray scale. The basic principle is: The gray threshold of current point to be grown is controlled according to the gray-scale fluctuation condition of the growing region. When there is large gray-scale fluctuation in grown region, the tendency of current growth will be suppressed by a certain control; In contrast, when the fluctuation is small, the current growth is encouraged to grow in a large range. The gray-scale fluctuation control ensures that the region fluctuation reaching a dynamic balance, avoiding that the segmentation result is over-segmented or under-segmented due to the fixed-threshold control strategy.

Assume the mean value and standard deviation of the grown region \( R_o \) containing the seed point \( o \) are respectively \( u \) and \( \sigma \), and the number of image cells is \( n \), then the gray-scale mean value and standard deviation of the grown region are:

\[
\begin{align*}
    u &= \frac{1}{n} \sum_{i \in R_o} f(c) \\
    \sigma &= \frac{1}{n} \sum_{i \in R_o} (f(c) - u)^2
\end{align*}
\]  

(1)

(2)

Calculate the gray-scale constraint threshold based on the mean value and standard deviation of the grown region:

\[
T_g = T_a \left( 1 - \frac{\sigma}{u} \right)
\]  

(3)

Where \( \frac{\sigma}{u} \) reflects the oscillation of variance with respect to gray mean, and \( 1 - \frac{\sigma}{u} \) adjusts the gray-scale oscillation in an opposite direction. \( T_a \) is the allowable adjustment term that reflects the severity of growing conditions and is used to control the growth of area. When the value of \( T_a \) is small, a higher homogeneity region is supported; when the value of \( T_a \) is large, the growing region is allowed to have large gray-scale oscillations. \( T_g \) is the calculated threshold.

The meaning of the formula (3) is: when the gray-scale oscillation of the grown region is large, the points to be grown with small oscillation have priority to grow firstly, and the points with large oscillation will be suppressed; In contrast, when the gray-scale oscillation of the grown region is small,
the situation will be reversed. This mechanism controls the gray-scale oscillation during the region growing process to reach an equilibrium state.

In the region growing process, assuming $e$ as the current point, if its gray value satisfies the following formula, the growth is performed, otherwise stopped.

$$|f(e) - u| < T_g$$ (4)

Where $f(e)$ is the gray level of the current point $e$, $u$ is the mean value of the grown region calculated by equation (4), and $T_g$ is the threshold calculated by equation (3).

2.2.2. Criterion based on USAN area. SUSAN (Small Unvalue Segment Assimilating Nucleus) operator was proposed by Oxford University scholar Smith [9-11] and Brady in 1997. It is a feature point acquisition method based on gray-scale suitable for detection of edge and corner in images. It has the characteristics of simplicity, effectiveness, strong anti-noise ability and fast calculation speed. The principle is that an approximate circular template is used to move on the image, and the gray value of each image pixel in the template is compared with that of the center pixel, if the difference between any point pixel and the center pixel (core) of the template is less than a certain value, the point is considered to have the same (or similar) gradation as the nucleus, and the area composed of the pixels satisfying this condition is called the equivalent nucleus absorption USAN area.

Algorithm implementation steps:

Set $\lambda_o$ as the selected seed point, $Q$ as an array, and $\lambda_o$ is the member scene image connected to the seed point. Record the fuzzy connectedness between growing point and seed point, and the target extraction result is $I_{output}$, then the region growing algorithm based on the fuzzy connectedness can be Proceeded as follows:

Step1 sets the point $o$ in $\lambda_o$ to 1, and the remaining elements to 0;

Step2 pushes all the points $c \in C_o$ that satisfy the condition $\mu_k(o, c) > 0$ into the stack;

Step3 determines whether the stack $Q$ is empty, when it is empty, go to Step9; when it is not, order $Q$ according to the $\lambda_o$ value of points (grow the points most similar to the seed point at first), then enter Step4;

Step4 removes a spatial element $c$ from the stack $Q$, and calculates the fuzzy connectedness $\mu_k(c, e)$ between the point $e$ ($\|e - c\| \leq 1$) of the neighborhood and itself;

Step5 If $\min(u_k(c, e), l_o(e)) > l_o(e)$, press point $c$ into $Q$, and update the fuzzy connectedness as $l_o(c) = \min(u_k(c, e), l_o(e))$;

Step6 If $\min(u_k(c, e), l_o(e)) > l_o(e)$, update the fuzzy connectedness of point $e$, which is $l_o(e) = \min(u_k(c, e), l_o(e))$, and calculate adaptive threshold as well as the USAN area by equations (3) and (4);

Step7 If $U_{area}(e) > T_{usan}$ are satisfied, push the point into stack $Q$; otherwise, judge whether $U_{area}(e)$ is a local minimum value;

Step8 If $U_{area}(e)$ is not a local minimum value, push the point into the stack $e$, and otherwise go to Step3;

Step9 Output region growing result $I_{output}$.
During the specific growing process, different growing objectives can be achieved by adjusting the thresholds $T_\alpha$ and $T_{usan}$. For example, when it is desired to increase the gray-scale consistency of the growth region while improving the positioning ability of the edge, it can be achieved by reducing $T_\alpha$ and increasing $T_{usan}$.

3. Experimental results and analysis

In addition to the true value data lacks of actual damage image, this paper selects the brain images having the similarity of shape and gray distribution with the damage on the remote sensing image for analysis and comparison. The white matter region of the MR brain slice image has a complex shape, and its boundary blur among the gray matter and cerebrospinal fluid is similar to the case of damage extraction in this paper. Figure 2 is an experimental MR image of human brain, where (a) is the original image, and (b) is the true value image corresponding to the white matter in the original image, the image size of them are both 128×128. In order to verify the effectiveness of the proposed algorithm, the algorithm in this paper and the literature [1] were used to extract the white matter region in the slice image of brain. Besides, in order to compare the sensitivity of the two algorithms to the position of seed points, four points were randomly taken in the upper left, upper right, lower left and lower right areas of the white matter region, as shown in Fig. 3(a)~(d). These points were used as the initial seed points of the region growing method. The growing results of the two algorithms are shown in Fig. 3(e)~(h) and Fig. 3(i)~(l) respectively. Among them, Figures 3(e)~(h) are the results of the algorithm, in which $T_g = 25$ and $T_{usan} = 0.7$, and Figures 3(i)~(l) are the results of literature [1].

![Figure 2. MR slices image and true value image of Human brain.](image)

![Figure 3. Comparison of the algorithm extracted results in this paper and the literature [1].](image)
It can be seen in Figure 3 that the results extracted by the algorithm in this paper are significantly better than those in literature [1]. The algorithm in literature [1] produces under-segmentation when extracting the white matter regions for the reason that the method assumes the gray scale satisfies the Gaussian distribution, but the actual image is often not well satisfied. In this paper, the growing criterion of gray oscillation control combined with USAN area is adopted. The gray-scale oscillation in the interesting region and the ability to locate the edge are considered. The edge orientation effect is obtained while adapting to the gray-scale variation of the target region.

To estimate the performance of the two algorithms, the FOM (Figure of Merit) map is used. The definition of FOM is as follows:

$$FOM = \left[ 1 - \frac{|C_r \otimes C_G|}{|C|} \right] \times 100$$

(5)

Where the true value is expressed as $C_G$, the extracted result is $C_r$, $|C|$ indicating the potential of the congregation $C$, and $\otimes$ represents the OR operation of the binary image. Besides, FOM indicates how well the original target area matches the target area.

Figure 4 shows the FOM diagrams of the two methods, where the abscissa corresponds to the location of the different initial seed points in Figure 3. The ordinate corresponds to the matching degree between the original target region $C_G$ and the growing region $C_r$. The higher the value, the closer the result of the algorithm extraction is, with a maximum value of 1. The blue solid line and the red dotted line are the matching curves between extraction result and the true value image of the method in this paper and the literature [1] respectively.

![Figure 4. FOM diagram of the method in this paper and literature [20].](image)

It can be seen from the Fig. 4 that the curve of the algorithm in this paper is far above that of the literature [1], and the distribution is flat, indicating that the extraction result obtained by the algorithm is higher in precision and is insensitive to selected position of the point; while the curve of the literature [1] algorithm fluctuates greatly, which indicates that the accuracy is poor, and it is sensitive to the selection of the seed point position. Table 1 shows the time taken by the two algorithms to perform region growing at different seed point locations.
Table 1. Running time comparison of the algorithm in this paper and literature [1].

| Position number | Coordinates | Algorithm in this paper (seconds) | algorithm in literature [20] (seconds) |
|-----------------|-------------|----------------------------------|----------------------------------------|
| 1               | (52, 42)    | 2.1203                           | 3.9010                                 |
| 2               | (77, 39)    | 2.1201                           | 3.8907                                 |
| 3               | (50, 86)    | 2.1200                           | 4.0110                                 |
| 4               | (81, 87)    | 2.1101                           | 4.0061                                 |

It can be seen from Table 1 that the algorithm in this paper is better than that of literature [1] in terms of time efficiency, which is about 1/2 of the latter. The reason is that the algorithm of the literature [1] needs to perform twice Sub-regional growth, the first time to estimate the parameters of the model, and the second time for region growing, while our algorithm only needs once, reducing the amount of calculation obviously.

Figure 5 shows the extraction results of the typical military target damage in Figure 5(a) using the algorithm in this paper. Where Figure 5(a) is the original extracted damage image, the position marked by red "×" in the figure is the seed point set by the damage extraction experiment, Figure 5(b) is the damage extraction result, and Figure 5(c) is the superimposed effect of extracted damage area outline on the original damage image.

(a) Selected location of seed point            (b) Region growing result

(c) The superposition of the growing result on the original image

**Figure 5.** Simple extraction result of structure damage graph by algorithm in this paper.

It can be seen that the proposed algorithm can better accomplish the damage extraction task in single-phase image, and the edge localization is better.
4. Conclusion
In this paper, the damage in image extracted by the region growing algorithm is studied. Firstly, aiming at the damage of military target with complex shape, blurred boundary and large range of internal gray scale oscillation, a region growing method based on fuzzy connectedness is proposed. The algorithm uses the fuzzy connectedness as a measure of the similarity between growing point and seed point, and controls the growing point to grow in a strong to weak order according to the fuzzy connectedness with the seed point, which reduces the sensitivity to the growing results while maintaining the blur between the pixels; Furthermore, the combination of gray-scale oscillation control and USAN area is used as the growing judgment condition, and edge orientation effect is good while adapting to the gray scale change of the target area. The experimental results show that the proposed method based on fuzzy connectedness is insensitive to the selection of seed points, which has good edge localization ability and human-computer interaction in the extraction of damage.

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