Material image segmentation based on feature similarity and non-spherical clustering

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Abstract. The microstructure of the material determines its physical and chemical properties. Although image segmentation and target extraction algorithms have advanced rapidly in recent years, few segmentation algorithms for material images have emerged. By analyzing the characteristics of material images, a new image segmentation method based on feature similarity and non-spherical clustering is proposed in this paper. First, the central pixels of the region are selected according to the feature similarity, and secondly, the attribution of the remaining pixels or the non-region central points are determined by the non-spherical clustering method. In this paper, ceramic images are used as experimental materials. The results show that the proposed method achieves satisfactory segmentation effect and provides some help for subsequent image-based material analysis.

1. Introduction
The internal structure of the material, also known as the microstructure, stores the genes of the material and all its physical, chemical and other important properties. Obtaining the properties of materials by studying the structural information in the microscopic images of the cross-section of materials has always been an important research direction in the field of materials science [1, 2]. Although the importance of material microstructures is well known, automatic segmentation of microstructures in material microscopic images is still very challenging. As the first and most important part of acquiring image information, the quality of segmentation directly determines the accuracy and precision of subsequent information acquisition. The difficulty of material image segmentation mainly comes from the characteristics of the material itself and its imaging method. Scanning electron microscopy (SEM) is often used in materials science, which can provide high resolution, up to 200,000 times. In this situation, the microstructure of material image can be observed, but the target area of material cross-section in high resolution image usually contains complex textures, or even different phases. Besides, the grinding process of imaging sample can increase noise, artificially. In comparison, natural images do not have such problems. This leads to two problems. The first one, the commonly used natural image segmentation methods can’t be effectively applied to material image segmentation. The second one, the intersection of different regions in material image contains a lot of noise, which is difficult to segment. Therefore, how to extract effective features according to the characteristics of the target area in the material image and design the corresponding segmentation algorithm is an urgent and valuable problem.
2. Related work

Image segmentation has always been a popular research direction in image processing field. According to the complexity of the features used, it can be divided into low-level semantic segmentation, middle-level semantic segmentation and high-level semantic segmentation[3-5]. At present, there is no segmentation algorithm designed for the characteristics of material images, and most of the existing researches are based on low-level semantic segmentation with single pixel features[6], such as watershed[7] and Markov[8] model based methods. In addition, interactive segmentation methods have also developed in recent years. For example, Zhang et al.[9] used threshold binarization method combined with mathematical morphology operation to segment the SEM image of compact rock, and calculated the pore size distribution (PSD) of samples. Sourov et al.[10] used interactive segmentation method combined with binarization to segment SEM images of the catalyst layer cross-section in a polymer electrolyte membrane fuel cell. Ruth et al.[11] proposed a spectral clustering segmentation algorithm which combines LBP features and gray-scale features, which is applied to ceramic image segmentation. N.Vyas et al.[13] combined fast random forest with interactive segmentation to segment the surface SEM images of complex biomaterials covered with biofilm. L.Drumetz[14] proposes a semi-automatic segmentation method based on SVM and binary partition trees (BPT), which can be used for segmentation of gel material SEM images.

In general, the shortcoming of the above method is that the area information of the image is not used, and only the single pixel feature is processed, so that the segmentation result is sensitive to noise, the segmentation is inaccurate, images that with complex textures cannot be effectively segmented.

3. Algorithm

In order to solve the above problems, a new material image segmentation method based on feature similarity and non-spherical clustering is proposed in this paper. By analyzing the characteristics of the material microscopic image, the pixels of the image are divided into two categories: the regional central pixels and the non-region central pixels. Among them, the regional central is relatively flat, and the feature similarity between pixels is relatively high, which can be selected by constructing similarity measure function and setting threshold. On the contrary, the feature difference of the non-region central pixels is large, to ensure the connectivity of the pixel class, the class to which it belongs is discriminated by non-spherical clustering. The algorithm is described in detail below.

3.1. Selection of Regional Central pixels

In the previous region segmentation methods, seed point selection is usually random, and then transits to flat region by iteration. This method has two shortcomings: First, iteration requires a large amount of computation and takes a long time. Second, the number of seed points has nothing to do with the number of regions, which easily leads to over-segmentation. Aiming at this problem, this paper proposes a region central pixel set extraction algorithm based on feature similarity.

3.1.1. Construction of feature vectors

As mentioned above, the texture of material images is complex and there are abundant changes even within the same region. As a result, the difference discrimination method based on single-pixel feature, which is often used in natural images, will be affected by a lot of noise and can not accurately distinguish the category of pixels. Therefore, in this paper, the statistical feature of gray histogram in the 5×5 region around a pixel are taken as the feature of the pixel. Assuming that there are $L$ gray levels in the region, and $f$ represents the frequency of the level, then the mean value of the gray in the region can be expressed by $m$, and the n-order statistical moments of the region can be expressed by $u$, that is:

$$m = \sum_{g=1}^{L} r_g f(r_g)$$
\[ u_n = \sum_{g=1}^{L} (r_g - m)^n f(r_g) \] (2)

In this paper, mean, second-order statistical moment, third-order statistical moment and fourth-order statistical moment are used as the characteristics of pixel. That is:

\[ V=(m,u_2,u_3,u_4) \] (3)

Due to considering the information of the surrounding area, the construction of the feature vector can effectively reduce the impact of complex texture in the material microscopic image.

### 3.1.2. Similarity measure function

As mentioned above, relative to the edge, the inner region is relatively flat, and the feature similarity between the pixels is large. Assuming the feature vector of the pixel \( P_{(i,j)} \) is \( V_{(i,j)} \), the feature similarity measure function \( \text{diff}_{(i,j)} \) of the pixel \( P_{(i,j)} \) is defined as follows:

\[ \text{diff}_{(i,j)} = \max_{(x,y)} \| V_{(i,j)} - V_{(x,y)} \|^2 \] (4)

Where \( V_{(m,a)} \) is the feature vectors of point \( P_{(m,a)} \), \( P_{(m,a)} \) satisfies the chessboard distance from point \( P_{(i,j)} \) less to \( T_{\text{dist}} \), which is set to 5 in this paper. That is to say, firstly, all the pixels whose chessboard distance to \( P_{(i,j)} \) is less than 5 constitute the neighborhood; secondly, in this neighborhood, the feature vectors of each pixel are calculated according to the method of 3.1.1; finally, the maximum Euclidean distance between the feature vectors of each pixel and all the pixels in its neighborhood is selected as the similarity. It can be seen that the smaller the value of the function, the higher the degree of similarity within the neighborhood, the more likely it is to be the central pixel of the region. On the contrary, the larger the value of the function, the lower the degree of similarity within the neighborhood, and the more inclined the edge is the non-regional central pixel.

Let the similarity threshold be \( T_{\text{diff}} \), which is set to 50 in this paper, then:

\[ \text{type}_{P_{(i,j)}} = \begin{cases} 1 & , \text{diff}_{(i,j)} \leq T_{\text{diff}} \\ 0 & , \text{others} \end{cases} \] (5)

If \( \text{type}_{P_{(i,j)}} \) equals 1, then the pixel \( P_{(i,j)} \) is the regional central pixel, otherwise it is the non-regional central pixel.

### 3.2. Non-spherical clustering of non-regional central pixels

For non-regional central pixels, the existing methods mostly use spherical clustering to determine their categories, that is, to calculate the similarity between the pixel and all the class central to determine their attribution. However, this method can not guarantee the connectivity of the pixel categories. Inspired by[15], this paper proposes a non-spherical clustering based discriminant method: each non-regional central pixel should be classified into one group with the most similar feature in its eight-connected neighborhoods. That is:

\[ \text{label } [P_{(i,j)}] = \text{label } [P_{(x',y')} ] \] (6)

s.t. \[ \|V_{(i,j)} - V_{(x',y')} \|^2 = \min_{(x,y)} \|V_{(i,j)} - V_{(x,y)} \|^2 \] (7)

The specific flow chart is shown in Figure 1.
Figure 1. Clustering process of non-regional central pixels

Firstly, a non-regional central pixel $P$-initial in the image is taken and stored in the list. In its eight-connected neighborhoods, the pixel $P$-next which is most similar to $P$-initial is obtained. If $P$-next is the central pixel of a class, $P$-initial is classified as that class; otherwise, $P$-next is also stored in the linked list, and the pixel with the smallest feature difference from $P$-next in its eight-connected neighborhoods is searched until it is connected to the regional central pixel. Then all the non-regional central pixels in the list are classified into this class. The non-spherical clustering process of non-regional central pixels is completed by traversing the image.

4. Experiment

In order to verify the effectiveness of the proposed segmentation algorithm, the ZrB2-SiC ceramic images are selected as experimental materials, as shown in Figure 2. It can be seen that, firstly, there are areas with obvious contrast and areas with low contrast in the image; secondly, there are complex textures in the same area; thirdly, there are obvious artificial polishing marks in the image, which are the typical characteristics of material images.

Figure 2. ZrB2-SiC ceramic image

Firstly, we use Canny operators with different thresholds to extract the edges of ceramic images. The results are shown in Figure 3. It can be find that with the increase of high threshold, Canny operator can extract more obvious edges. With the increase of low threshold, trivial edges can be significantly reduced. However, no matter how to adjust the parameters, the complex texture of the material image makes it difficult for Canny operator to extract the closed region, and there are still trivial edges. In addition, it can be found that many important edges Canny operators have not been extracted, such as the dark region in the upper left corner of the original image.
Figure 3. Edge Extraction Using Canny Operator. (a) LT=50, HT=150. (b) LT=50, HT=200. (c) LT=100, HT=150. (d) LT=100, HT=200.

Figure 4 shows the segmentation results of the algorithm proposed in this paper. Where Figure 4(a) is the result obtained by 3.1, the white pixels belong to the regional central and the black pixels belong to the non-regional central. We can see that although there are complex textures in the material image, because the local region similarity is taken into account in the design process of the algorithm, the regional central points maintain good connectivity. Even hand-polished traces rarely cause fracture in the same area. Figure 4(b) is the result of non-spherical clustering. It can be found that the segmentation accuracy has been significantly improved. It can effectively segment the connected regions with different degrees of difference. Although it has not been pre-processed by image smoothing, the algorithm in this paper has strong resistance to complex texture and strong noise. There are also some shortcomings in this algorithm. For example, a small number of unclassified black pixels appear at the boundary of the region, after analysis, self-locking phenomenon appears during non-spherical clustering, that is to say, the most similar pixel of pixel A, in its neighborhood, is pixel B; while the most similar pixel of pixel B in its neighborhood is pixel A, too, resulting in two pixels can not be classified. Besides, a few of details are not accurately segmented, possibly because the neighborhood scale is too large when acquiring features. The above problems can be solved by some mathematical morphological methods, but in the most of other areas, the algorithm proposed in this paper has achieved satisfactory segment results.

Figure 4. Experimental Results of the Proposed Algorithm. (a) is the regional center point. (b) is the result of non-spherical clustering.

5. Conclusion

Aiming at the characteristics of material image, a new image segmentation method is proposed in this paper. First, we construct a feature vector and similarity measure function to select the regional central
pixels. Secondly, we use non-spherical clustering to classify the non-region central pixels. The experimental results show that the proposed method can effectively reduce the influence of complex texture of material images, and can effectively segment various contrast regions. Due to self-locking, a small number of boundary pixels cannot be classified, which is a challenge. So how to build more effective local features and eliminate self-locking will be the focus of our future work.

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References
[1] Hu Q, Cai Q, He L, Zhao X, Shi R and Ye T 2017 Novel method to determine the image segmentation threshold during the quantitative test on meso-structure of geo-material Journal of Wuhan University of Technology-Mater. Sci. Ed. 32 1408-1412
[2] Carrera D, Manganini F, Boracchi G and Lanzarone E 2017 Defect detection in SEM images of nanofibrous materials IEEE Transactions on Industrial Informatics 13 551-561
[3] Watson M and Marshall M 2017 A Novel Image Segmentation Approach for Microstructure Modelling Coatings 7 166
[4] Li Y, Qi H, Dai J, Ji X and Wei Y 2017 Fully convolutional instance-aware semantic segmentation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp 2359-2367
[5] Dai J, He K, Li Y, Ren S and Sun J 2016 Instance-sensitive fully convolutional networks. In: European Conference on Computer Vision: Springer) pp 534-549
[6] Sanyal P, Bhattacharya U and Bandyopadhyay S K 2008 Analysis of SEM images of stomata of different tomato cultivars based on morphological features. In: 2008 Second Asia International Conference on Modelling & Simulation (AMS): IEEE) pp 890-894
[7] Jiang L-j and Zhu Y 2007 Region segmentation for SEM image based on watershed transform and concave spot JOURNAL-EAST CHINA UNIVERSITY OF SCIENCE AND TECHNOLOGY 33 861
[8] Zhu Y, Zuo T and Wang Y 2009 SEM Microscopic Image Segmentation Based on Markov Field Models. In: 2009 Fifth International Conference on Image and Graphics: IEEE) pp 177-782
[9] Zhang Y, Jin S, Wang Y and Wang Y 2015 Characterization of the pore size distribution with SEM images processing for the tight rock. In: 2015 IEEE International Conference on Information and Automation: IEEE) pp 653-656
[10] Ghosh S, Ohashi H, Tabata H, Hashimasa Y and Yamaguchi T 2015 Microstructural pore analysis of the catalyst layer in a polymer electrolyte membrane fuel cell: a combination of resin pore-filling and FIB/SEM International Journal of Hydrogen Energy 40 15663-15671
[11] Hinrichs R, Frank P R O and Vasconcellos M 2017 Short range shooting distance estimation using variable pressure SEM images of the surroundings of bullet holes in textiles Forensic science international 272 28-36
[12] Zhao Z, Ding G T, Fan M L, Zhang H R, Wang L and Chen L 2016 Material Image Segmentation Combined LBP Texture and Local Gray Level Feature Computer Technology & Development
[13] Vyas N, Sammons R, Addison O, Dehghani H and Walmsley A 2016 A quantitative method to measure biofilm removal efficiency from complex biomaterial surfaces using SEM and image analysis Scientific reports 6 32694
[14] Drumetz L, Mura M D, Meulenyzer S, Lombard S and Chanussot J 2015 Semiautomatic classification of cementitious materials using scanning electron microscope images Journal of Electronic Imaging 24 061109
[15] Rodriguez A and Laio A 2014 Clustering by fast search and find of density peaks Science 344 1492-1496