Watershed segmentation based on hierarchical multi-scale modification of morphological gradient

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Abstract: Watershed segmentation is sensitive to noises and irregular details within the image, which frequently leads to a serious over-segmentation. Linear filtering before watershed segmentation can reduce over-segmentation to some extent, however, it often causes the position offset of object contours. For the purpose of reducing over-segmentation to preserve the location of object contours, the watershed segmentation based on the hierarchical multi-scale modification of morphological gradient is proposed. Firstly, multi-scale morphological filtering was employed to smooth the original image. Then, the gradient image was divided into multi-levels by the volume of three-dimension topographic relief, where the lower gradient layers were further modified by morphological closing with larger-sized structuring-elements, and the higher layers with the smaller one. In this way, most local minimums caused by irregular details and noises can be removed, while region contour positions corresponding to the target area were largely preserved. Finally, morphological watershed algorithm was employed to implement segmentation on the modified gradient image. The experimental results show that the proposed method can greatly reduce the over-segmentation of the watershed and avoid the position offset of the object contours.

Key words: watershed segmentation; gradient modification; hierarchical multi-scale morphological filtering; structuring element

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Watershed transform[1-2] is efficient in producing closed region contour and providing accurate localization of object boundary, and has been widely used for image segmentation. The idea is to regard the gray image as three-dimension landform, in which the gray value of each pixel stands for terrain height to determine the regional watershed by detecting the boundary of different regions corresponding to the local minimums. However, since the noise and irregular details within the image, classical watershed is liable to produce over-segmentation[3]. Many efforts[4-6,20-21] have been made to reduce the over-segmentation, where smoothing and filtering the image before watershed are widely used. However, it is not always sufficient. Traditional pre-filtering can reduce noise and irregular details, but it may also fuzzy or even lose important contours information and distort the location of object boundary. Morphological opening and closing filter could remove the details and noise commendably, but it dissatisfies scale causality and easily gives rise to new regional minimum and false contours. Meyer[7] investigated a class of filters called levelings to simplify an image without blurring or displacing contours. Leyza[8] explored the image simplification and contour regularization resulting from the application of the self-dual multi-scale morphological toggle (SMMT). Rafael[9] proposed anisotropic morphological filters with spatially-variant structuring elements which can locally adapt their shape and orientation across the dominant direction of the structures in the image.

In order to reduce over-segmentation while preserve accurate localization of object contours, watershed segmentation based on hierarchical multi-scale modification of morphological gradient is proposed. Multi-scale morphological filtering is firstly employed

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to remove noise and preserve target information. Then, the morphological gradient image is divided into multi-levels by the volume of three-dimension topographic relief. Each layer is regulated by multi-scale morphological closing with different sized structuring elements according to the gradient intensity respectively. In this way, the small regional minima which caused by irregular details and noises are largely eliminated, and object contours are less or not changed. Finally, morphological watershed transform is employed to implement segmentation on the basis of multi-scale modified image.

1 Multi-scale morphological filtering

It is obvious that without pre-processing, the watershed segmentation will produce serious over-segmentation, and the region contour is also poorly localized because of the noise and irregular details. Multi-scale opening and closing filtering are frequently adopted due to the fact that they are superior to multi-scale dilation and erosion in preserving the edge of image. Considering that the morphological opening and closing can smooth brighter and darker details, respectively, we use morphological weighted stacking opening-closing operations with different sized structuring elements to filter the image, that is

$$f' = \frac{1}{\sum_{i=1}^{N} a_i} \sum_{i=1}^{N} [a_i (f \circ b_i) \bullet b_i], \tag{1}$$

where f denotes the original image; f' is the filtered image; $\circ$ and $\bullet$ are morphological opening and closing, respectively; b is the disc structuring element with radius i, and its isotropy ensures less distortion of image feature; N is the maximal radius, and the weighted value $a_i = 5/i$ avoids the offset of object contour when using larger structuring elements.

After the multi-scale morphological filtering, the fine texture and noise in the original image are greatly removed and the object contours are preserved.

2 Multi-scale morphological gradient

Watershed transform realizes region segmentation by extracting the boundary of different regions corresponding to the local minimums, while watershed reflects the steepest descent of gray level within the image. Gradient can enhance the edge where gray level changes dramatically and highlight the contour boundary between different regions. Therefore, watershed segmentation is usually based on gradient image. For the purpose of highlighting the object contour precisely, multi-scale morphological gradient algorithm[10] is employed and expressed as

$$g(f') = \frac{1}{K} \sum_{i=1}^{K} \{[f' \oplus s_i) - (f' \Theta s_i)] \Theta s_{i-1}\}, \tag{2}$$

where g is the multi-scale morphological gradient image; $\oplus$ and Θ are morphological dilation and erosion operation, respectively; K denotes the number of the adopted structuring elements; s_i is structuring element with radius equal to $(2i+1) \times (2i+1)$, s_0 only contains one pixel and s_1 is 3×3 a square, and so on. The remaining noise and quantization errors in the homogenous regions of the image may produce many insignificant minimums, while the multi-scale gradient can eliminate these irrelevant minimums and produce a gradient image suitable for watershed segmentation. This is feasible as illustrated in Figs. 1 and 2.

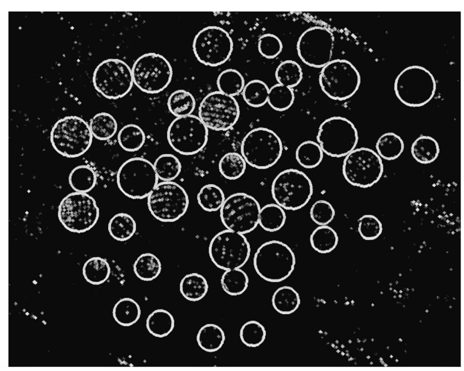


Fig. 1 Conventional morphological gradient

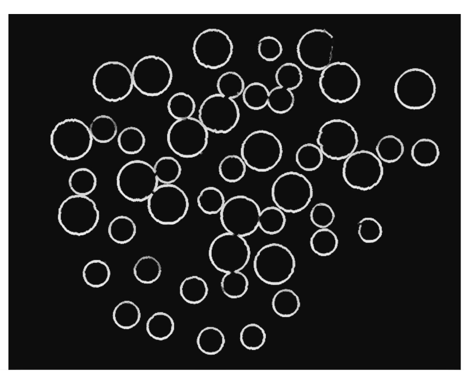


Fig. 2 Multi-scale morphological gradient

3 Layered multi-scale gradient modification

Although the gradient image highlights the objects contour boundary, but the remaining noise and irregular details are also highlighted stimulatingly. In this case, if the watershed transform is directly used, it still produces over-segmentation and region contours offset. This requires the gradient image must be modified, that is noise and irregular details must be removed as possible while the objects without boundary blurring or contour displacement must be preserved.

Morphological multi-scale modification is mainly based on the theory of viscous morphology[11], which regards the image as three-dimension relief. It is noted that the degree of fluid immersing catchment basins depend on its viscosity: when the fluid gets less viscous, it can enter more and more deeply in a narrow isthmus or fjord, and the space filled by the fluid gets larger; inversely, it can only reach the wide areas. Such phenomena inspired us that narrow isthmus caused by noise and irregular details can be flooded by viscous fluid, that is to say, less viscous fluid can fill the target area and keep the accurate localization of region contour while stickier fluid may get across the narrow isthmus caused by noise and irregular details to remove the false regional minima. In fact, the morphological closing operator can eliminate the dark details less than the size of structuring element. When the viscosity of fluid is associated with the size of structuring element, the viscous flooding simulation of the relief is similar to employing morphological closing operations with variant structuring elements to modify gradient image. High viscosity amounts to larger-sized structural elements, while low viscosity corresponds to smaller-sized ones.

3.1 Variant structuring element

For the gradient image modification, the crucial step is to determine the scales of different structuring elements. Considering that the neighbourhood pixels in the image tend to have similar characteristics and attributes[12-13], the gray distinction within the same region is small, while the difference among the marginal or noisy areas is usually large, which manifests the compactness of pixels within the same region and the separability of pixels between different areas. In gradient image, higher gradients usually represent the well defined object contours and the watershed line should follow the relief more faithfully in these areas, while the low gradient maybe denote the blurring which should be removed by a higher modification. In order to avoid the over-segmentation and preserve the precise localization of contours, the gradient image has to be modified hierarchically; each layer of the gradient image employs morphological closing with variant structuring element. The scale mainly depends on the gradient value of each layer. The layers with low gradient value correspond to the large modification with large scale, while high gradient value with small one. Other layers between low and high gradient maybe represent the weak object contours or the irregular blur details and noise[21], and the modification degree in these parts should be a trade-off. In this way, most local minimums caused by irregular details and noises are removed, while region contour positions corresponding to the target area are persevered.

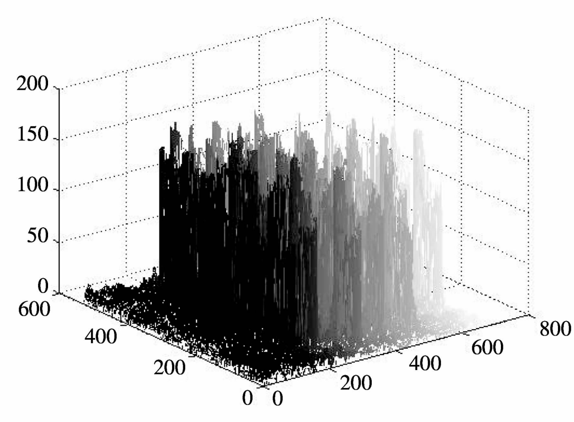


Fig. 3 Topographic relief of gradient image

From the view of the qualitative analysis, the size of structuring element $r(l)$ is really the monotonic decreasing function of the gradient value (l): when $l=0$, $r(0)$ is the maximum size, and if l is the maximum $l_{\max}$, $r(l_{\max})=0$. There are numerous functions satisfying this relationship, however, it is hard to choose a precise one to describe the relationship between $r(l)$ and l. Moreover, if all the gradient layers are modified one by one, it will cost more computing time. Take into account the three-dimensional histogram of the gradient image g as shown in Fig. 3, the altitudes of the topographic relief correspond to gradient values. Supposing that the length and width of every pixel are both 1 pixel, the pixel volume is equal to its altitude, and thus the total volume of the relief can be obtained by adding up the altitude values of all the pixels. In this case, the gradient image can be layered according to the volume of the relief, and morphological closing operations with decreasing structuring elements that follow the ascending gradient values are employed to modify each hierarchy of gradient image as shown in Figs. 4 and 5. Such hierarchical multi-scale modifications of the gradient image greatly alleviate the computing complexity compared to the modification of level by level, and also satisfy the monotonic decreasing function relationship.

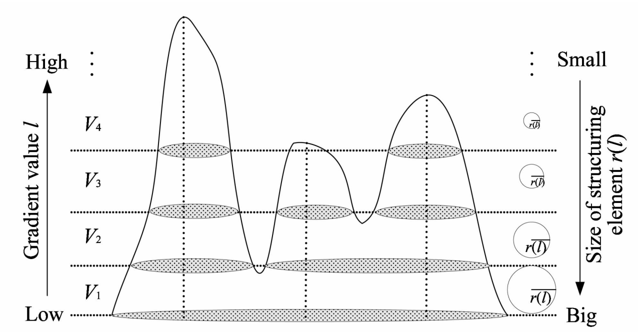


Fig. 4 Principle of gradient relief modification

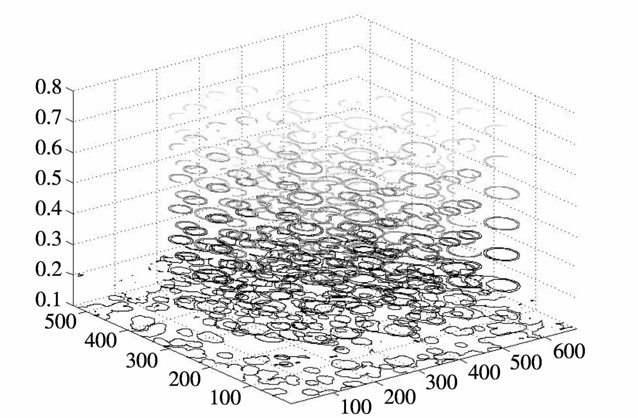


Fig. 5 Effect of gradient layered multi-scale modification

3.2 Gradient layered multi-scale modification

In fact, the hierarchical multi-scale modification is to decompose the gradient image into a family of gray level images from bottom to top according to its gradient value. Each level image performs the classical closing with different structuring elements determined by its gradient value. When all the level image relieves are regulated, they are composed into one relief. The main steps of the gradient layered multi-scale modification are explicated as follows.

Step 1: Calculate the total volume of the gradient relief as

$$V = \sum g(x,y), \tag{3}$$

where $g(x,y)$ denotes the gradient value of (x,y).

Step 2: Assume that the gradient image is divided into M layers ($2 \leqslant M \leqslant 235$, M is even), then the unit layer volume is

$$V_M = V/M. \tag{4}$$

In order to expand the intervals of the gradient level between different layers, the actual delaminating is in an odd increasing order, and every layer is marked with V_m according to its gradient value from small to large, where $m=(1,2,\cdots,M/2)$, $V_1 = 1 \times V_M, \cdots$, $V_m = (M-1)V_M$.

Step 3: For each level set of the topographic surface, morphological closing with the corresponding structuring element is performed as

$$C_m = V_m r(M/2 - m + 1), \tag{5}$$

where C_m is the modified result of each layer; • is the morphological closing operation; and $r(M/2-m+1)$ denotes the disk structuring element whose radius is $M/2-m+1$. As the layer m follows the increasing order from low to high gradient, the radius of structuring element meets reverse order from large to small, which satisfies the decreasing function relationship between $r(l)$ and l.

Step 4: After all the level regulated, compose them into one relief one by one level, and produce the final modified gradient image g' as

$$g' = \bigcup_{1 \leqslant m \leqslant M} C_m. \tag{6}$$

3.3 Watershed segmentation

Compared to the modification using fixed-size structuring elements, the proposed method performs hierarchical multi-scale amending. In this case, most local minimums caused by irregular details and noises are removed while region contours corresponding to the target area are preserved. The final segmentation is just to apply watershed transform to the modified gradient image as

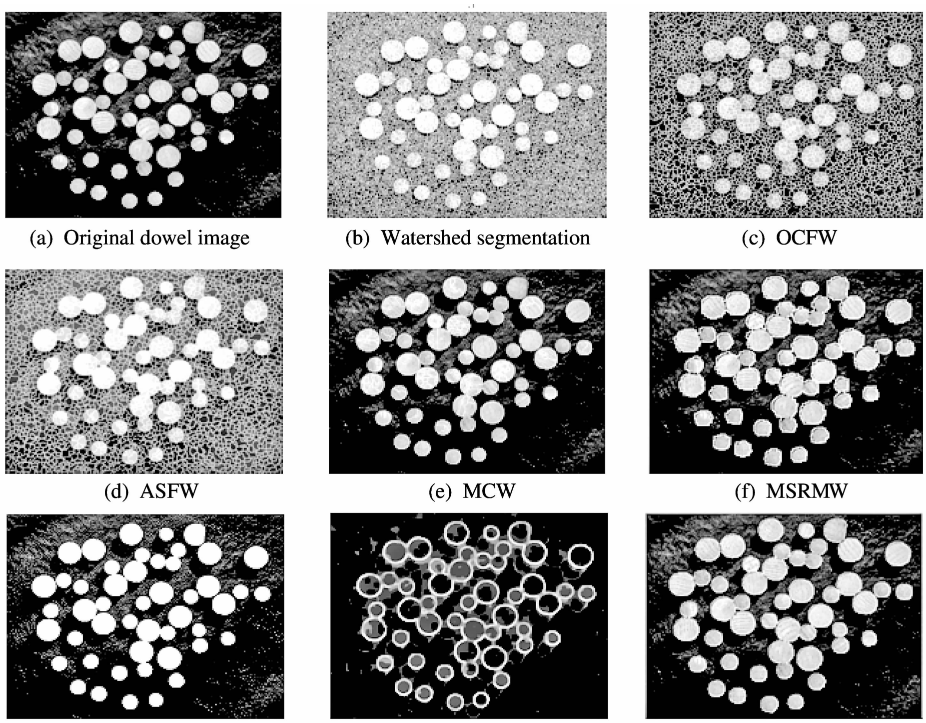
$$W = Wsh(g'), \tag{7}$$

where Wsh denotes the watershed transformation. Since the innate characteristics of watershed transform, there may exist some redundant lines, which can be removed by the maximal similarity based region merging[14].

4 Experiments and analysis

Several experiments are carried out on different images to test the proposed method on Matlab 7.0 platform, and the proposed segmentation is also compared with other watershed-like methods.

Fig. 6 shows the dowel image segmentation using different watershed-like methods, where Fig. 6(a) is the original image, and Fig. 6(b) is the result of traditional watershed segmentation without any modification. It can be seen that there exists serious over-segmentation.



(a) Original dowel image (b) Watershed segmentation (c) OCFW

(d) ASFW (e) MCW (f) MSRMW

(g) Parameterized morphological watershed (h) Gradient layered modification (i) Proposed method

Fig. 6 Dowel image segmentation under different watershed-like methods

Figs. 6(c) and (d) give the results of opening-closing filtering watershed (OCFW) and alternating sequential filtering watershed (ASFW), respectively, where the over-segmentation is eliminated to some extent since the image is filtered before the watershed transformation, but numerous meaningless regions still remain. Fig. 6(e) shows the marker-controlled watershed (MCW) segmentation, where the over-segmentation is almost eliminated, while some other targets are divided into several regions. Fig. 6(f) illustrates the segmentation of the maximal similarity based region merging watershed (MSRMW), where watershed is firstly used to the gradient image, and then the maximal similarity based region merging is employed. The over-segmentation is almost avoided, but region contours are not smooth enough and the object locations of contours occur serious bias. Fig. 6(g) shows the result of the parameterized morphological watershed segmentation, where almost all the dowels are segmented without over-segmentation, whereas the contour location of some dowels are slightly changed. The proposed segmentation as shown in Fig. 6(i) is on the basis of the layered multi-scale modification (Fig. 6(h)). It is obvious that the over-segmentation is reduced and the desired object regions are completely segmented without obvious position bias.

To validate the object region contours localization performance of the proposed method with other relative methods, such as MCW, MSRMW, fuzzy local information C-means (FLICM) and the method proposed in Ref. [16], a relatively complex brain magnetic resonance imaging (MRI) image is selected in the experiment, and the segmentation results are shown in Fig. 7. The evaluation of segmentation performance is quantitatively carried out by employing four volume metrics, including the similarity index (S), false positive volume function ($FPVF$), false negative volume function ($FNVF$)[17] and Jaccard index (J)[18], which are defined as

$$S = \frac{2 \mid A_i \cap B_i \mid}{\mid A_i \mid + \mid B_i \mid}, \tag{8}$$

$$FPVF = \frac{\mid B_i \mid - \mid A_i \cap B_i \mid}{\mid A_i \mid}, \tag{9}$$

$$FNVF = \frac{\mid A_i \mid - \mid A_i \cap B_i \mid}{\mid A_i \mid}, \tag{10}$$

$$J = \frac{\mid A_i \cap B_i \mid}{\mid A_i \cup B_i \mid}, \tag{11}$$

where A_i and B_i represent the pixels set belong to the object region of manual segmentation and algorithm segmentation result, respectively. The operation symbol $\mid * \mid$ denotes the number of pixels in region $*$. Generally speaking, high S and J, low FPVF and FNVF indicate that the method has good segmentation performance.

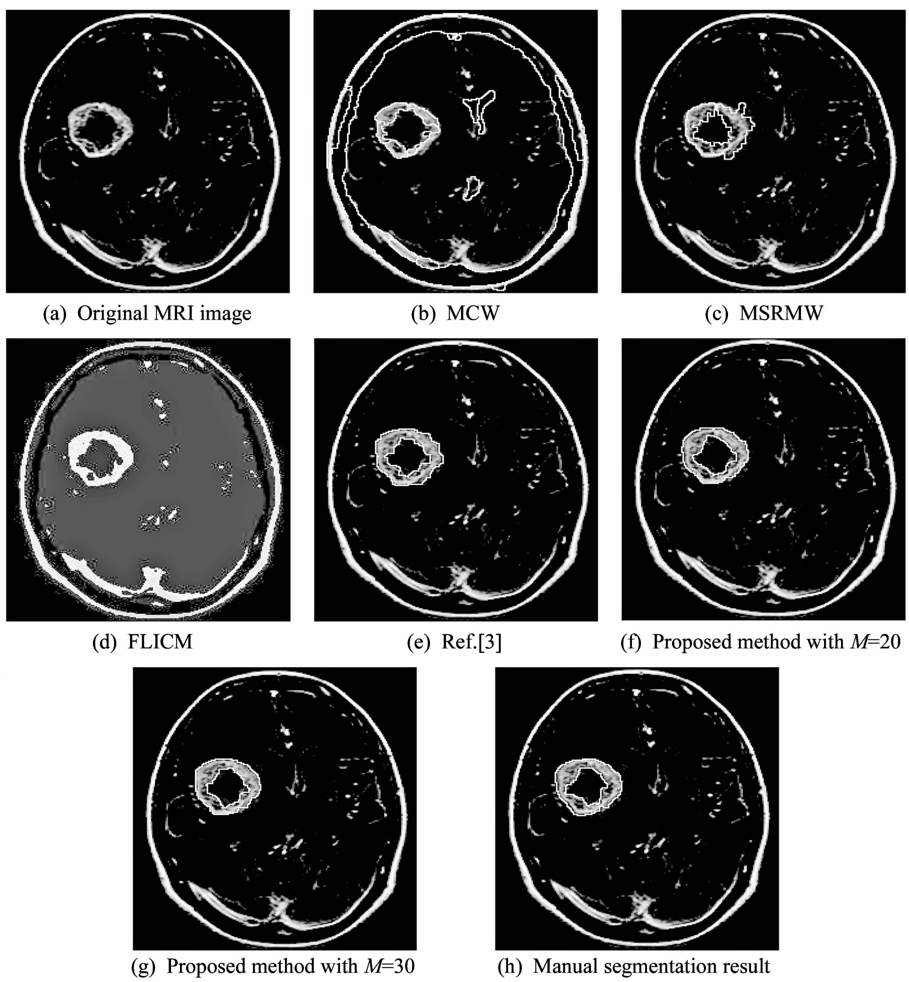


Fig. 7 Comparison of region contour localization performance using different methods

Table 1 shows the localization accuracy metrics of the object regions of different methods. It can be seen that S and J of the proposed method are 89.56% and 88.18%, respectively, which indicates that the overlap between the proposed and the manual segmentation is higher. $FPVF$ and $FNVF$ are

2.92% and 5.64%, respectively, which shows that misclassification and loss of desired pixels of the proposed method is lower. Compared with other methods, the proposed method has a better segmentation performance, especially the region contours are smooth and delicate.

Table 1 Localization accuracy metrics comparison of different methods (%)

	MCW	MSRMW	FLICM	Ref.[3]	Proposed method M=20	Proposed method M=30
S	78.62	79.02	85.13	89.60	88.07	91.05
$FPVF$	1.58	24.08	1.36	11.12	3.23	2.61
$FNVF$	34.92	18.36	25.03	9.82	6.36	4.92
J	64.77	75.32	75.96	81.15	87.59	88.76

5 Conclusion

The novel watershed segmentation based on hierarchical multi-scale modification of morphological gradient is proposed. Taking into consideration of removing noise and preserving object information, the original image is simplified by the multi-scale morphological filtering. The gradient image relief is decomposed into multi-level according to its three-dimension volume, and each layer is modified by morphological closing with different structuring element correspond to its gradient intensity. The experimental results show that the proposed method can not only eliminate over-segmentation, obtain desired object contours, but also preserve the location of the objects. The uncertain selection of function between the gradient and the size of structuring element are avoided, at the same time, the gradient image modification with level by level is also simplified.

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基于分层多尺度形态学梯度修正的分水岭分割

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摘　要： 形态学分水岭分割对图像中的噪声和非规则细节较为敏感，常常导致较严重的过分割。如果在分水岭分割之前采用线性滤波器进行平滑,可以在某种程度上消除噪声和非规则细节干扰造成的分水岭过分割，但是可能使分割出的目标轮廓产生位置偏移。为了能够在消除过分割的同时保持目标轮廓的位置不变，提出了一种基于分层多尺度形态学梯度修正的分水岭分割方法。首先对原始图像进行多尺度形态学滤波平滑；然后根据形态学梯度图像的三维地貌体积对其进行分层多尺度修正，自适应地确定修正所需的结构元素尺寸，对于低梯度层级采用较大尺寸结构元素进行形态学闭运算，消除因非规则细节产生过分割的非规则局部极小值，而对较高梯度层则采用较小尺寸的结构元素，保持区域轮廓的位置不变；最后在修正梯度图像基础上，运用标准分水岭变换实现图像分割。实验结果表明，该方法能够在消除过分割的同时，较准确的保持目标轮廓的位置。

关键词： 分水岭分割；梯度修正；分层多尺度形态学滤波；结构元素

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