Watershed segmentation based on gradient relief modification using variant structuring element*

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(Received 23 October 2013)

Watershed segmentation is suitable for producing closed region contour and providing an accurate localization of object boundary. However, it is usually prone to over-segmentation due to the noise and irregular details within the image. For the purpose of reducing over-segmentation while preserving the location of object contours, the watershed segmentation based on morphological gradient relief modification using variant structuring element (SE) is proposed. Firstly, morphological gradient relief is decomposed into multi-level according to the gradient values. Secondly, morphological closing action using variant SE is employed to each level image, where the low gradient level sets use the large SE, while the high gradient level sets use the small one. Finally, the modified gradient image is recomposed by the superposition of the closed level sets, and watershed transform to the modified gradient image is done to implement the final segmentation. Experimental results show that this method can effectively reduce the over-segmentation and preserve the location of the object contours.

Document code: A **Article ID:** 1673-1905(2014)02-0152-5
DOI 10.1007/s11801-014-3209-5

Watershed transform[1] is powerful in producing closed region contour and providing an accurate localization of object boundary. However, due to the noise and irregular details within the image, the watershed transform frequently results in over-segmentation[2]. Solutions[3-11] have been proposed to handle the problem. Among all the methods, pre-filtering and morphological operations have been widely used to smooth the image before watershed segmentation. However, linear smoothing filtering tends to distort the location of object boundary. For this reason, nonlinear smoothing techniques have emerged to avoid smoothing across object boundary. Meyer[12] investigated a class of filters called leveling to simplify an image without blurring or displacing contours. Whitaker[13] used an anisotropic diffusion filter to eliminate the noise while preserving the edges in the image. Dagher[14] combined both watershed segmentation and the active contour model known as balloon snake model to reduce the over-segmentation. In Ref.[15], several operators, such as contrast, self-dual, area and volume filtering, were presented for image simplification. It has been verified that without pre-processing, the watershed segmentation of contours is precise but persists the over-segmentation, while with pre-filtering, the segmentation is robust but less precise[16]. In this paper, our aim is to find a good trade-off between smoothing and good localization of object boundary.

Watershed segmentation is usually based on gradient image, where the over-segmentation is generally caused by irregular minima. One way for removing the noise caused by regional irregular minima is to modify the relief of gradient image. The simplest modification is morphological closing in the gradient image. The high gradient pixels correspond to object contours, while the low gradient pixels correspond to details and noise. However, morphological closing with the constant size structuring element (SE) can bring a problem. If the size of the SE is too large, more noise caused by irregular minima will appear, and object boundary location may be less precise. While if the size is too small, the irregular regional minima still exist. For getting the good watershed segmentation, both the contour precise localization and the over-segmentation should be simultaneously considered.

In this paper, morphological closing with variant SE is employed to modify the relief of gradient image. Firstly a gradient image is obtained by morphological dilation and erosion with small SE, and then morphological closing action using SE with different sizes is employed according to the gradient intensity respectively. During the closing action, high gradient corresponds to small SE and low to large SE. By such a way, the irregular regional minima caused by details and noise can be removed, and object contours are less or not modified. Finally, the gra-

* This work has been supported by the National Natural Science Foundation of China (No.61261029), the Jinchuan Company Research Foundation (No.JCYY2013009), the Gansu Province Science and Technology Support Program (No.1204GKCA051), and the Gansu Province Higher Education Fundamental Research Funds (No.212090).
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dient image is reconstructed by the stack of all the levels of modified image relief. On the basis of the regulated gradient image, a better watershed segmentation is obtained. This way not only creates the precise localized contours but also avoids the over-segmentation as much as possible.

The gradient is to enhance the contrast of the object edges of interest in the original image. The gradient generated by morphology can be defined as the difference of dilation and erosion, which can be expressed as

$$g(f) = \delta(f) - \varepsilon(f)\ , \tag{1}$$

where g denotes the morphological gradient of the original image f, $\delta(f)$ and $\varepsilon(f)$ are the dilation and erosion with small SE, respectively. In the gradient image, pixels with high gradient values usually correspond to the object contours, which need no or less modification, while pixels with low gradient values correspond to the irregular blur details and noise in the objects, which need important modification. Other pixels between low and high gradient values maybe represent the weak object contours or the irregular blur details and noise, where the modification degree should be a trade-off.

In fact, the gradient image relief modification is a process of image simplification with appropriate filter, which is concerned with noise and redundant information removal, resulting in a smoother image. The filtering of the gradient image should retain the meaningful information but at the same time suppress the pointless structures without causing boundary blurring or contour displacement. In this case, filters should modify the gradient image's relief adaptively, since noise and redundant information in gradient image maybe have high gradient values as object. In general, noise and redundant details possess the smaller area or volume (area multiply height) than the meaningful objects in the gradient image relief. Such a property indicates that the relief can be adaptively modified according to the gradient value (height), area or volume. Object contours possess higher values, therefore it is brighter than others, and the morphological closing operator is suitable to keep only larger area objects. In the process of modification, higher gradient applies smaller SE and lower with larger SE.

The modification of the gradient image relief by morphological closing with variant SE is shown in Fig.1. For the pixels with lower gradient values, the large modification is needed by closing with large size SE, while the weak modification is sufficient with the pixels with high gradient values by closing with smaller SE. In such a situation, the size of the SE is the fundamental parameter of the gradient values.

It is well known that the classical closing operator uses invariant size SE, but our gradient relief modification needs the variant SE changing with the gradient values. In order to apply the classical closing operator to gradient relief modification, the level set in Ref.[17] is used to decompose the gradient image into a family of gray level images. Each level image performs the classical closing with fixed SE according to its gradient value (equal to level). When all level image reliefs are regulated, compose them into a finally modified relief.

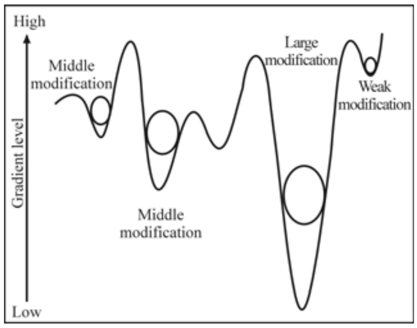


Fig.1 The modification of the gradient image relief by morphological closing with variant SE

Suppose that the gradient values of g are limited to $[L_{\min}, L_{\max}]$,

$$g_l = \{x \in g, g(x) \geq l,\ l \in [L_{\min}, L_{\max}]\}\ , \tag{2}$$

where l denotes gradient level, and g can be decomposed into $(L_{\max} - L_{\min})$ level images.

In each level, morphological closing operator is defined as

$$\phi_l(g) = \phi_{r(l)}(g_l)\ , \tag{3}$$

where φ denotes the classical closing, and $r(l)$ is the SE corresponding to level l. g_l decreases when l increases, $r(l)$ also decreases, and thus the operator $\varphi_{r(l)}(g_l)$ decreases. It means that g can be processed level by level with the gradient from $L_{\min}$ to $L_{\max}$, and a series of level modified images relief $\{\varphi_{l\min}(g), \varphi_{l\min+1}(g), \cdots, \varphi_{l\max-1}(g), \varphi_{l\max}(g)\}$ are produced. They are really the level sets of a function $\varphi(g)$. The modified image relief is the supremum superposition of the closed level sets. The sets repositioned at their initial altitude can be expressed as

$$g_{\mathrm{c}} = \bigvee_{L_{\min} \leq l \leq L_{\max}} l.\chi_{h}[\phi_l(g_l)]\ , \tag{4}$$

and

$$\chi_{\mathrm{h}}(g)(p) = \begin{cases} 1 & \forall p \in g \\ 0 & \text{Otherwise} \end{cases}, \tag{5}$$

where φ denotes the supremum. In the processing of relief modification, the selections of the size and the shape of SE are very important. To simplify the description, here we take the disk shaped SE as an example. In such a case, $r(l)$ in Eq.(3) is the disk radius, and is a decreasing function of l. Radius $r(l)$ should satisfy two limitations. One is when l=$L_{\min}$, $r(L_{\min})$=R_0 (R_0 is the maximal radius), and the other is when l approaches $L_{\min}$, $r(L_{\min})\rightarrow 0$, i.e., radius $r(l)$ satisfies the function expression of

$$r(l) = R_0(L_{\max} - l) / (L_{\max} - L_{\min})\ . \tag{6}$$

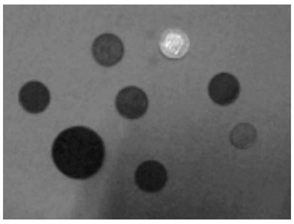
Note that the low gradient level sets are severely closed, whereas the higher level sets are nearly preserved. Furthermore, the level closing computed on gradient images, which presents a reduced number of gray levels, really reduces the computing cost. When the gradient relief modification is complemented, the watershed transform can be directly applied, and the segmenting result is obtained.

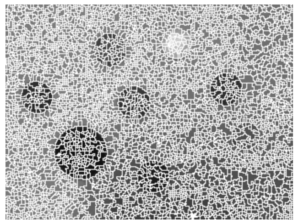
Several experiments are undertaken to testify the validity of the proposed method which is compared with other watershed-like methods on MATLAB 7.0 platform.

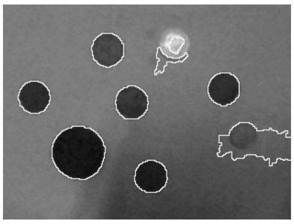
The first experiment selects a relatively simple coin image as shown in Fig.2(a), and its size is 246×300 pixels. Our purpose is to segment the seven coins precisely. Firstly, the classical watershed transform is directly used, and the segmentation result is shown as Fig.2(b). It can be seen that the result leads to serious over-segmentation. Fig.2(c) shows the marker-controlled watershed (MCW) segmentation result, where the over-segmentation is basically eliminated, but the two coins are improperly segmented. Fig.2(d) gives the result of another watershed-like segmentation method, in which morphological reconstruction closing operator is firstly applied to the gradient image, and then watershed transform is employed. It is obvious that there is no over-segmentation phenomenon, but three coins fail to be segmented. We also attempt to use morphological opening-closing filter to smooth the original image, and then apply watershed transform to obtain its gradient. The segmentation result in Fig.2(e) shows that the over-segmentation phenomenon is largely alleviated compared with that in Fig.2(b), and six coins are segmented, but at least two coins present the position bias, and the bright coin fails to be segmented. Fig.2(f) shows the result of the proposed method, where the maximum radius is R_0=20. As can be seen, the over-segmentation phenomenon is eliminated, and all the coins are completely segmented except the bright one.

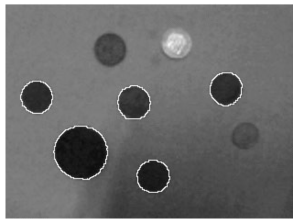
In the second experiment, we select the ore gray image as shown in Fig.3(a). Fig.3(b) is the gradient image of Fig.3(a), and it can be seen that object contours are located at high gradient levels, while details and smooth regions at low levels. When watershed transform is directly applied to gradient image, there is serious over-segmentation as shown in Fig.3(c). Fig.3(d) exhibits our gradient modification image by variant SE (R_0=25). It is obvious that over-segmentation is greatly reduced compared with Fig.3(b), and the locations of various object contours are precisely preserved. We also notice from Fig.3(f) and (g) that the choice of the initial radius R_0 is very important for the final segmentation, and it directly determines the number of the segmentation regions. When R_0 is large, more small objects maybe merge with each other, and on the contrary, small objects can be detected.

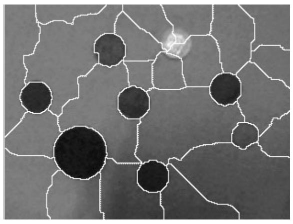
For the comparison with pre-filtering and gradient modification by variant SE, we first employ morphological opening-closing by reconstruction filter to filter the original image, and perform the watershed transform to its gradient as shown in Fig.3(h). As a result, the over-segmentation disappears, but the locations of object contours show a serious bias. Fig.3(i) presents the watershed segmentation result of the gradient modification by classical closing with constant SE (disk radius R_0=25). It shows that the over-segmentation is also reduced to some degree, but the contour locations are less precise.


(a) Original coins image


(b) Classical watershed segmentation


(c) MCW segmentation


(d) Watershed segmentation after reconstruction closing


(e) Watershed segmentation after opening-closing filtering

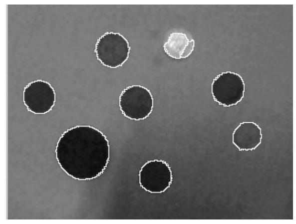
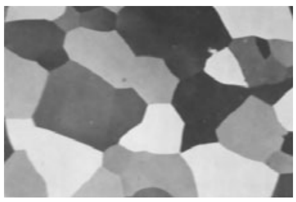
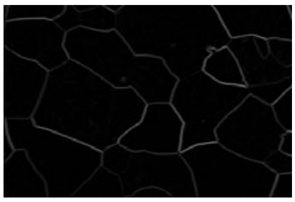
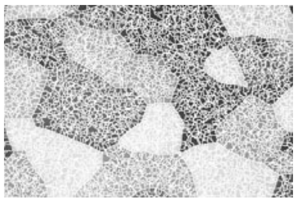
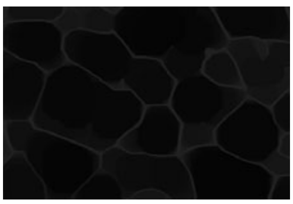

(f) Proposed method (R_0=20)

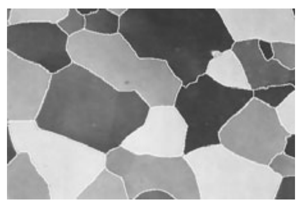
Fig.2 Coins image segmentation results using different watershed-like methods

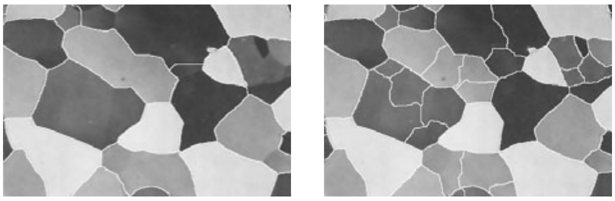

(a) Original image


(b) Gradient image

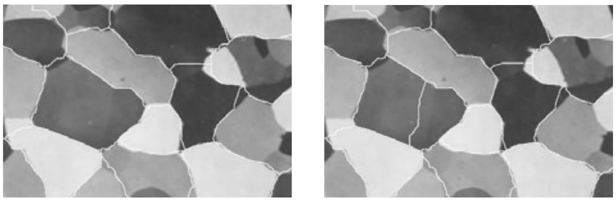

(c) Watershed segmentation of (b)


(d) Proposed gradient modification image (R_0=25)


(e) Watershed segmentation of (d)



(f) Proposed segmentation with R_0=35 (g) Proposed segmentation with R_0=15



(h) Watershed segmentation of the original image after opening-closing by reconstruction filtering (i) Watershed segmentation of gradient modification by closing with constant SE (R_0=25)

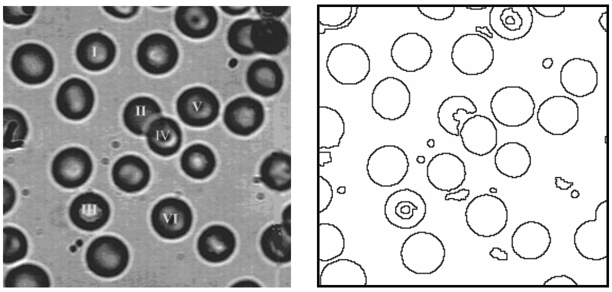
Fig.3 Ore gray image segmentation results using different watershed-like methods

In order to quantitatively validate the region contour localization performance of the proposed segmentation compared with other types of watershed-like methods, such as MCW segmentation, watershed segmentation with opening-closing pre-filtering (OCW) and watershed segmentation after the gradient image is performed with reconstruction closing (WRC), six number labels are respectively placed in the balls of the original image as shown in Fig.4(a), and each number represents a single region. The experimental result of localization accuracy comparison is shown in Fig.4. The corresponding region contour accuracy is defined as

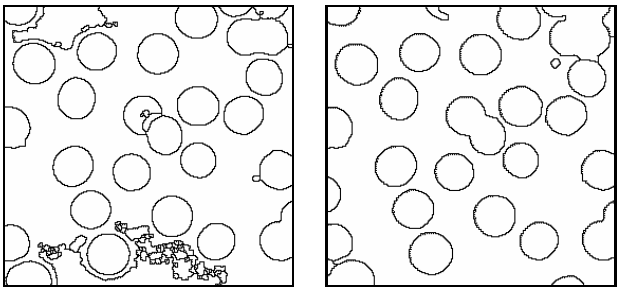
$$\rho_k = \frac{p(k)}{p_o(k)}, \tag{7}$$

where ρ_k is the kth region contour accuracy, $p(k)$ denotes the kth region overlapping pixel number between the current and manual segmentation results, and $p_o(k)$ is the kth region pixel number of the manual segmentation.

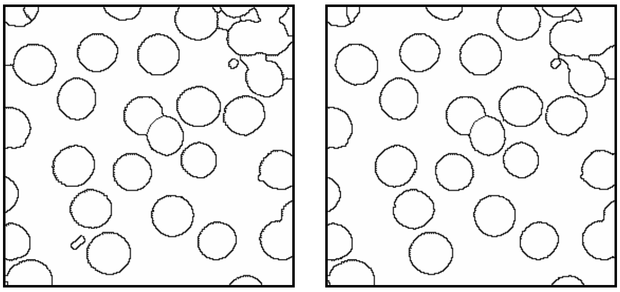
Tab.1 gives the localization accuracies of several labeled regions using different methods. It can be seen that the accuracy of the proposed method reaches more than 91%, and the region contours are more smooth and delicate. Especially, the proposed method successfully segments the overlapping regions II and IV with higher accuracy.



(a) Original image with labels I–VI (b) MCW segmentation



(c) OCW segmentation (d) WRC segmentation



(e) Proposed method with R_0=60 (f) Proposed method with R_0=70

Fig.4 Region contour localization performance comparison of different methods

Tab.1 Localization accuracy comparison of different methods (%)

Method	I	II	III	IV	V	VI
OCW	97.2	85.6	58.3	93.8	97.7	97.0
MCW	97.9	76.7	97.1	95.6	97.9	97.3
WRC	97.1	53.7	98.1	57.6	98.1	97.5
Proposed method R_0=60	98.2	91.2	98.5	96.7	98.0	98.7
Proposed method R_0=70	98.3	90.9	97.9	96.8	98.2	98.8

The watershed segmentation based on morphological gradient relief modification using variant SE is proposed. Gradient image relief is decomposed into multi-level according to the gradient intensity, and morphological closing by different size SE is used to modify gradient image's relief level by level. The high gradient level sets employ small SE, while low gradient level sets use large one. The final modified gradient image is recomposed by the stack of all the levels of modified image relief supremum. By this way, irregular regional minima caused by details and noise are removed, and the over-segmentation is avoided, while object contours are less or not modified.

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