Bone Region Segmentation in Medical Images Based on Improved Watershed Algorithm

Jun Zhou and Mei Yang

1 School of Artificial Intelligence, Chongqing Business Vocational College, Chongqing 401331, China
2 Chongqing Research Institute of Business Economics, Chongqing, China
3 Baliuag University, Baliuag, Bulacan, Philippines
4 School of General Education, Chongqing Business Vocational College, Chongqing 401331, China

Correspondence should be addressed to Mei Yang: 1198768040@qq.com

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Abstract

Watershed algorithm is widely used in image segmentation, but it has oversegmentation in image segmentation. Therefore, an image segmentation algorithm based on K-means and improved watershed algorithm is proposed. Firstly, Gaussian filter is used to denoise human skeleton image. K-means clustering algorithm is used to segment the denoised image and the connected component with the largest area is extracted as the initial human skeleton region. The initial bone region was morphologically opened and then morphologically closed to eliminate the noise. Morphologically open operation is used to disconnect other human tissues that adhere to the human bone region and eliminate the background noise with small area, while closed operation smoothes the edge of the human bone region and fills the fracture in the contour line. Secondly, the watershed segmentation algorithm is implemented on the image after morphological operation. The similarity degree of two blocks is defined according to the mean difference of gray level of adjacent blocks and the mean value of standard deviation of gray level of pixels in the edge of the block 4-neighborhood. Adaptive threshold $T$ is generated by Otsu method for histogram of gradient amplitude image. If the similarity degree is greater than $T$, the image blocks will be merged; otherwise, the image blocks will not be merged. The proposed image segmentation algorithm is used to extract and segment the human bone region from 100 medical images containing human bone. The number of blocks segmented by watershed algorithm is 2775 to 3357, but the number of blocks segmented by the proposed algorithm is 221 to 559. The experimental results show that the proposed algorithm effectively solves the oversegmentation problem of watershed algorithm and effectively segments the image target.

1. Introduction

A series of classic image segmentation algorithms—such as watershed segmentation algorithm, active contour growth methods, threshold-based segmentation methods, regional growth methods, clustering algorithms, and artificial neural network segmentation methods—have been applied to image segmentation over recent years [1]. The watershed transformation algorithm combining morphology algorithm and regional growth method features good extraction of enclosure edges and high precision of target segmentation. Image segmentation refers to a process whereby an image is segmented in accordance with certain rules into a number of parts or subsets; it works as a key step from image processing to image analyzing [2]. To well perform image segmentation and processing, watershed transformation has been extensively used. Reference [3] segmented by using watershed transformation the gray and white target objects from medical nuclear magnetic resonance (MR) images. This algorithm introduces geographical definitions of such as mountain ridge lines and catchment basin into the recognition of image targets, where the gray pixel is considered as the altitude. This algorithm starts with a lower threshold which, however, enables effective target segmentation and achieves the most optimal segmentation progressively as the threshold increases, while
keeping adjacent targets from merging. In this way, it cracks the problem where adjacent targets cannot be segmented correctly by global thresholding because of their closeness. Watershed transformation is sensitive to noises and potential for excessive image segmentation, though featuring rapidness, simplicity, and directness and a good performance in segmenting images with lower contrast and in simplifying subsequent processing [4].

Fuzzy clustering segmentation algorithm is highly concerned in the research of image segmentation. It adopts the degree of membership to represent the category to which a pixel belongs and the fuzzy C-means algorithm to segment MR images. This algorithm, however, increases the complexity of computation and notably, requires further improvement on its antinoise performance [5–7]. Compared with the fuzzy C-means algorithm, the K-means algorithm features a lower complexity of computation and a lower degree of overlapping of its segmentation targets [8, 9].

We come up with a new image segmentation algorithm that integrates K-means clustering algorithm and improved watershed algorithm. First of all, we used K-means clustering algorithm to carry out initial clustering and, thus, to extract the interested targets. Then, a 4-neighboring zone similarity-based improved watershed algorithm was proposed to segment target zones on the images initially clustered by the K-means. Finally, the human bone zones were extracted from 100 medical bone images. The experimental results demonstrate that our proposed algorithm effectively cracks the excessive segmentation problem of watershed algorithm and also enables the segmentation of image targets. Compared with the watershed segmentation algorithm, the proposed algorithm can solve the problem of image oversegmentation and is easy to be disturbed by noise.

2. Methods and Materials

2.1. Gaussian Filter Denoising. It is necessary to denoise the images before the target segmentation on them; the purpose of Gaussian filter denoising was making the target boundary clearer in the image and removing noise from the image. Gaussian filter is a linear filter, which can effectively suppress noise and smooth images. The working principle is similar to the mean filter, which takes the mean value of pixels in the filter window as the output. However, the coefficients of the window template are different from those of the mean filter. The template coefficients of the mean filter are all the same as 1, while the template coefficients of the Gaussian filter decrease with the increase of distance from the center of the template. Therefore, compared with the mean filter, Gaussian filter has less blur on the image. Gaussian filter was used to carry out the denoising. Its template coefficient decreased as its distance to the center of the template expands, and the images it processed featured a lower degree of fuzziness [10, 11]. Therefore, the Gaussian filter is capable of controlling noise effectively and flattening images when in comparison with other mean filters. The 2-dimensional Gaussian filter used for image denoising is shown as

$$h(x, y) = e^{-\frac{x^2 + y^2}{2\sigma^2}},$$  \tag{1}$$

where \( (x, y) \) represents the coordinates of pixels in an image and \( \sigma \) the standard deviation. The larger the standard deviation \( \sigma \) is, the more blurred image will be after noise elimination by Gaussian filtering. Therefore, in order to make the subsequent target contour clearer, the value of \( \sigma \) is set to a smaller range from 0 to 1.

2.2. K-Means Clustering Algorithm. Clustering is to divide a data set into different classes or clusters according to a specific standard (e.g., distance) so that the similarity of data objects in the same cluster is as large as possible, and the difference of data objects not in the same cluster is as large as possible. After clustering, the data of the same class should be gathered together as much as possible, and the data of different classes should be separated as much as possible. K-means is the most commonly used clustering algorithm based on Euclidean distance, which holds that the closer the distance between two objects, the greater the similarity. K-means has the following advantages: easy to understand, the clustering effect is good, although it is local optimal, but often local optimal is enough [12]. When dealing with large data sets, the algorithm can ensure good scalability. The effect is good when the cluster approximates Gaussian distribution. The algorithm has low complexity. The K-means clustering algorithm is an unsupervised clustering algorithm and capable of initializing the segmentation. There are usually a host of zones with similar greyscale, which could lead to a great many local minimums. Given this account, the K-means clustering algorithm was first used to perform initial clustering in order to decrease the excessive segmentation of the original watershed algorithm. Also, this algorithm features rapidness, simplicity, and effectiveness in categorizing [13]. Let us set \((x, y)\) as the pixel coordinates of digital images and \(f(x, y)\) as the greyscale function. Meanwhile, \(Q^m_{(i)}\) represents the \(j\)th zone after the \(i\)th clustering and \(Q^m_{(i+1)}\) the mean of the \(j\)th category (the clustering center) after the \(i+1\)th clustering.

After the K-means segmented the image clustering into \(K\) categories, the connected components with the largest area \(S_i (i = 1, 2, \ldots, k)\) were extracted to be the human bone zones given the fact that the bone zones are often a piece of connected zone, which is relatively completed and largest in area in a medical image [14]. Let \(S_i\) be a pixel subset of an image. If there are connection paths between all the pixels of the \(S_i\), then the pixels are considered to be connected with each other. To extract the objects of interest to the maximum extent, the 8-neighboring pattern was applied. For any pixel \(p\) in \(S_i\), the set of pixels that connects to this pixel in \(S_i\), called the connected component of \(S_i\). The area of the connected component \(S_i\) is the count of the number of pixels in \(S_i\), \(\text{argmax}\), represents that if the maximum area zone value in the brackets is corresponding to \(S_i\), then the corresponding zone \(S_i\) is the human bone zone.

$$S_i = \text{argmax}_i (S_1, \ldots, S_j, \ldots, S_k).$$  \tag{2}$$
2.3. Denoising by Morphological Operations. Mathematical morphology developed from set theory, which was originally used to analyze the geometric structure of metal materials and geological samples. It uses structural elements with certain morphology to measure and extract the corresponding shape features in the image so as to achieve the purpose of image analysis and recognition [15]. At present, mathematical morphology has become a new method in the field of digital image processing and pattern recognition, and image processing using mathematical morphology has some unique characteristics.

(1) It reflects the logical relationship between pixels in an image, not the simple numerical relationship
(2) It is a nonlinear image processing method and has irreversibility
(3) It can be implemented in parallel
(4) It can be used to describe and define various set parameters and features of images

Mathematical morphology firstly takes binary images as the research object, which is called binary morphology. Later, it extends binary morphology to gray image processing, which is called gray morphology. Basic operations include Dilation, Erosion, Opening, and Closing, from which various morphological processing algorithms can be derived and combined.

The bone zone connection components extracted may be mingled with background images, so the bone zone connected component images Si extracted were converted into binary images BW. These images were denoised by first morphological open operations and then morphological close operations, where Θ denotes the morphological dilation and Θ the morphological erosion.

Morphological close operation:

\[ A \bullet B = (A \oplus B) \ominus B. \]  

(3)

Morphological open operation:

\[ A \circ B = (A \Theta B) \oplus B. \]  

(4)

Binary dilation could fill the small holes (compared with the structural elements) in the image and the small concave parts at the edge of the image so as to filter the outside of the image; binary erosion, in contrast, could remove the smaller structural constituents of the image so as to filter the inner of the image and shrink the image [16]. The process of erosion first and dilation then is an open operation, which enables smoothening the contour of the image and cutting off the disconnections and eliminate the tiny convex objects [17]. The process of dilation first and erosion then is a close operation, which also smoothenes the contour but, oppositely, removes the narrow disconnections and the long, thin gaps to clear up the small holes and patch the fractures in the contour line [18].

2.4. Watershed Segmentation Algorithm. Watershed segmentation based on mathematical morphology is widely used in the field of image segmentation. Judging from the description and definition process of watershed segmentation, each local minimum in the image to be segmented corresponds to a separate region in the segmentation result, and the region contour of the object to be segmented will be obtained at the end of segmentation [19]. The number of regions is determined by the number of local minima. Due to noise and local irregularity in the image to be segmented, the number of local minima will be larger than the target object with practical significance in the image, resulting in a large number of false contours, which interferes with the recognition of the target contour of interest in the image. This phenomenon is called “oversegmentation.” When watershed transform is directly applied to gradient images, the influence of noise and some local irregularities of gradient images often leads to oversegmentation. A common method to solve this problem is to preprocess the image to be segmented, bring prior information into the segmentation process, and limit the number of regions allowed to be segmented. The main idea of the watershed segmentation based on markers is to use the forced minimum calibration algorithm to determine the minimum region in the gradient image first and to compulsorily take the extracted markers as the minimum value of the gradient image to modify the original gradient image. Based on the modified gradient image, watershed segmentation is applied to complete image segmentation. The watershed segmentation algorithm based on markers adopts internal markers and external markers [20]. A marker is a connecting component. The internal marker is related to a target of interest and the external marker is related to the background. The selection of tags includes preprocessing and defining a set of criteria for selecting tags. Marker selection criteria can make gray value, connectivity, size, shape, texture, and other features. After having the internal marks, only these internal marks are used as the minimum value regions for segmentation, and the watershed of the segmentation result is used as the external mark. Then, other segmentation techniques, such as thresholding, are used for each segmented region to separate the background from the target. In this paper, a watershed segmentation algorithm based on markers is implemented by combining morphological preprocessing.

3. Improved Watershed Segmentation Algorithm

Watershed transformation is a typical segmentation method that is based on zones. Its conception originated from geography, and a watershed is geographically defined as the line that separates the zones in which rainwater accumulates (i.e., the catchment basins). Another conception is that the catchment basin is being immersed in the water and there is a hole at its local minimum point (the lowest part of the catchment basin). From this lowest point, the water slowly flows into the catchment basin. When the water originally in different catchment basins is about to converge together, dams are established to stop their convergency. When the immersing completes, each basin is inundated by the water and completely enclosed by the dams. These dams are termed as the watershed line, or the watershed for short [21].
The specific procedure of the watershed segmentation algorithm is as follows:

Let \( M_1, M_2, \ldots, M_k \) be the local minimum points of image \( f(x, y) \), respectively, and \( B_1, B_2, \ldots, B_k \) be the sets of all points in the catchment basin corresponding to each local minimum point. \( B^k_n \) represents the set of all points in the catchment basin \( B_k \) at the \( n \)th phase, and \( B^\text{max} \) represents the set of all \( B^k_n \). \( f_{\text{min}} \) and \( f_{\text{max}} \) represent the minimum and the maximum of the image greyscale, respectively. In the light of the description above, we obtain

\[
B^\text{max} = \bigcup_{k=1}^{k} (B^k_n). \tag{5}
\]

And the set of all catchment basins is

\[
B^{\text{max}+1} = \bigcup_{k=1}^{k} (B_k). \tag{6}
\]

\( T(n) \) represents the set of the points immersed in the water in the image; that is, \( T(n) = \{(i, j) | f(i, j) < n \} \), and then, there is

\[
B^k_n = B_k \cap T(n). \tag{7}
\]

In this way, a binary image corresponding to the original image could be structured. If the point of the original image has \( f(i, j) \in T(n) \), then this point is set as 0, and otherwise, as 1. By this way of counting the "0," the number of points below the water level at the \( n \)th phase could be acquired [22]. The specific steps are as follows.

First, the set of initial catchment basins was set as \( B^{\text{max}+1} = T(f_{\text{max}+1}) \), and then, the algorithm begins the recursive step. The water level rose from \( n = f_{\text{min}} + 1 \) to \( n = f_{\text{max}} + 1 \) by integer value, and the sets of points immersed in each phase were recorded as \( T(n) \). Let there be \( Q \) connected components \( B^k_n \) at the \( n \)th phase \( T(n) \), where \( q \leq Q \). Let there be an established \( B^\text{max} \) at the \( n - 1 \)th phase. For each \( q \), the connected components \( B^q_n \) and \( B^\text{max} \) were compared. If the two components meet different relationships, then different operations are carried out.

1. \( B^q_n \cap B^{\text{max}+1} = \Phi \), then a new connected component appears; that is, a new catchment basin comes into being. \( B^q_n \) and \( B^{\text{max}+1} \) are merged.

2. \( B^q_n \cap B^{\text{max}+1} \) contains a connected component of \( B^q_n \cap B^{\text{max}+1} \). This indicates the presence of this catchment basin in \( B^{\text{max}+1} \). \( B^q_n \) and its corresponding part in \( B^{\text{max}+1} \) are merged.

3. \( B^q_n \cap B^{\text{max}+1} \) contains two or more connected components of \( B^{\text{max}+1} \).

A watershed is required to establish in \( B^q_n \), and its structure may adopt the morphological dilation operation in order to stop the combination of catchment basins [23]. If the images are segmented by the original watershed algorithm, excessive segmentation will be engendered, usually. Here, we come up with an improved watershed algorithm, which mainly aims to subsequently process the segmentation results and to merge the excessively segmented pieces in accordance with certain rules. The specific steps are as follows:

1. Let the image be segmented by watershed segmentation into \( N \) pieces, and each piece be \( S_i \) and as large as \( n_i \) (where \( 0 < i < N \)), and the greyscale at \( (x_i, y_i) \) be \( I(x_i, y_i) \). The mean greyscale of each piece \( M_i \) is counted by

\[
M_i = \frac{1}{n_i} \sum_{x_i, y_i} I(x_i, y_i). \tag{8}
\]

2. Let \( S_i \) and \( S_j \) be neighboring pieces; then, the greyscale mean difference of the two pieces \( M_{ij} \) is

\[
M_{ij} = \sqrt{\left(M_i - M_j\right)^2}. \tag{9}
\]

3. Let \( S_i \) and \( S_j \) be neighboring pieces, \( (x_i, y_i) \in S_i \) \( (x_j, y_j) \in S_j \); and let \( (x_i, y_i) \) and \( (x_j, y_j) \) be two neighboring points on the edge of the segmented piece, and both meet the 4-neighboring zone relationship. \( N_{ij} \) represents the number of pixel points on the edge of the segmented piece, which meets the 4-neighboring zone relationship. The mean greyscale standard deviation of these pixel points is defined as

\[
P_{ij} = \frac{1}{N_{ij}} \sum_{(x_i, y_i) \in S_i } \sqrt{\left(I(x_i, y_i) - I(x_j, y_j)\right)^2}. \tag{10}
\]

4. The similarity of two neighboring segmented pieces is defined as

\[
C_{ij}=\frac{\sqrt{(M_{ij}+P_{ij})^2}}{2}. \tag{11}
\]

5. Neighboring pieces are merged.

The histogram based on gradient amplitude images generates a self-adaptive threshold \( T \). The gradient amplitude of the image is first computed. The gradient of the image function \( f(x, y) \) is a vector with size and direction at point \( (x, y) \). Let \( G_x \) and \( G_y \) represent the gradients in the \( x \)-direction and \( y \)-direction, respectively. The vector of this gradient can be expressed as the following formula:

\[
\nabla f(x, y) = \begin{bmatrix} G_x \nabla y \end{bmatrix}^T \tag{12}
\]

Vector amplitude is

\[
\text{mag}(\nabla f) = g(x, y) = \sqrt{\frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}} \tag{13}
\]

Direction angle is

\[
\phi(x, y) = \arctan\left(\frac{\partial f/\partial y}{\partial f/\partial x}\right). \tag{14}
\]
For digital images, difference is often used to approximate derivatives:

\[ G_x = f(x, y) - f(x - 1, y), \]
\[ G_y = f(x, y) - f(x, y - 1). \]

After the gradient amplitude of the image is computed, the Otsu method [24] is employed for global thresholding, and the globally optimal threshold \( T \) is self-adaptively generated. Let us assume that the histogram distribution of an image is expressed as

\[ p_q(r_q) = \frac{n_q}{n}, \quad q = 0, 1, 2, \ldots, L - 1, \]

(16)

where \( n \) represents the sum of pixels in the image, \( n_q \) the number of pixels of greyscale \( q \), and \( L \) all the possible greyscales in the image. Let the initially selected threshold be \( T \), \( C_1 \) be the pixel at the greyscale \( \{0, 1, \ldots, k\} \), and \( C_2 \) be a group of pixels at the greyscale \( \{k + 1, \ldots, L - 1\} \). The Otsu methods selects the threshold \( T \) such that interclass variance between \( C_1 \) and \( C_2 \) maximizes. The ratio of interclass variance to overall image greyscale variance is a measurement that can divide the image greyscale into two categories [25], and its value range is \([0, 1]\). At last, the threshold \( T \) generated was used to threshold the neighboring segments.

\[
\begin{cases} 
\text{if } C_{ij} > T, \quad S_i \text{ and } S_j \text{ do not merge}, \\
\text{if } C_{ij} < T, \quad S_i \text{ and } S_j \text{ merge}.
\end{cases}
\]

(17)

4. Experimental Results and Analysis

The algorithm proposed was compared with the original watershed algorithm in terms of the segmentation performance, where 100 2D medical images of human bones were selected as the experimental subjects. The bone images interfered with salt-and-pepper noise served as the experimental subjected (shown as Figure 1) and denoised by
Gaussian filter (shown as Figure 2), the standard deviation $\sigma$ of Gaussian filter is 0.8. The K-means was applied to carry out initial clustering, with the parameter $K = 4$, since the medical images of human bones are regularly made up of bones, soft tissues, fats, and background. The effect is shown in Figure 3. Computer hardware environment: the CPU model is Intel Core i7-4510, the main frequency of the computer is 2 GHz, and the memory is 16G.

The algorithm proposed was applied to segment the images of human bones. First, Figure 3 was converted into a greyscale image, shown in Figure 4. The greyscale image was then converted by Otsu thresholding into a binary image, shown as Figure 5. Next, Figure 6 was processed by morphological close operations to remove the noise after by morphological open operations, where a $7 \times 7$ structure unit was selected as the morphological operation structural unit. By the morphological open operations, the human bones were cut off from the connection with other human tissues, and the background noises of a smaller area were also removed. Meanwhile, the morphological close operations flattened the edges of the bone zones, bridged the narrower disconnections, eliminated the smaller hollows, and patched the fractures in the contour line [12]. The results are shown in Figure 7. The watershed transformation in Figure 7 was segmented. Corresponding results were shown in Figure 8. The connectivity of watershed transformation was set to 4.

Since excessive segmentation is the most critical problem of the original watershed algorithm, the number of segments was used as the index for comparison. 100 human bone images were selected to carry out the target segmentation experiment; the numbers of segments made by the original watershed algorithm, the improved watershed algorithm, and the proposed algorithm were compared. The results are shown in Figure 9.

5. Conclusion

We come up with an image segmentation algorithm by combining K-means clustering and an improved watershed algorithm in order to crack the excessive segmentation and the noise sensitivity that result from the original watershed algorithm. First of all, K-means initial clustering was carried out upon the removal of gauss noise from images, followed by threshold division using the Otsu method. Then, morphological open and close operations were employed to eliminate human body noises and thereby to extract human bone zones. On the basis of watershed transformation, next, the similarity was computed for segment integration and precise segmentation of human bone zones. After the application of our proposed algorithm to medical segmentation of bone zones, the experimental results demonstrate the good viability of this algorithm in solving the excessive segmentation of the original watershed algorithm and in segmenting the bone zones from other human tissues. Our research findings are of practical significance to medical image segmentation, providing a reliable means to both computer auxiliary therapy and clinical diagnoses. In this article, however, we experimented only on the medical images of human bones. Therefore, further in-depth explorations are required for the ways of applying our algorithm to a wider range of medical images of other tissues, organs, and so forth. Since the target to be segmented in the image is constantly changing, but the number of targets’ classification needs to be known when using the K-means algorithm for initial segmentation, the proposed image segmentation algorithm is still not ideal in the number of image blocks generated after image segmentation. All these aspects should be studied in depth. At the same time, the algorithm proposed in the article may be useful for brain
imaging detection of mental illness, and further research is needed.

Data Availability

The data included in this paper are available without any restriction.

Disclosure

The same title was presented in the “2021 International Conference on Intelligent Computing Automation and Applications” (ICAA) [25].

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Figure 9: Comparison of the number of image segmentation blocks.
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