Morphological based technique for image segmentation

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Abstract

In this paper, a morphological image segmentation technique based on the watershed algorithm is proposed. New morphological based pre- and post-processing techniques are proposed to reduce over-segmentation, by means of merging and removing spurious segments. The preprocessing aims at removing trivial regions as well as background noise. The post-processing produces a more concise region representation of the watershed-segmented image, where a region adjacency list (RAL) is built for the region merging process. To control the merging, a similarity function is defined, whence the most similar neighboring regions are merged. The proposed technique produces effective and significant results in successfully segmenting various objects when tested on a series of well known test images, as shown in this paper.

Keywords: Morphological operations, watershed segmentation, region similarity function, region merging.

1. Introduction

Image segmentation is the division of an image into different regions, each possessing specific properties. In a segmented image, the elementary picture elements are no longer the individual pixels but connected sets of pixels belonging to the same region. Once the image has been segmented, measurements can be performed on each region and neighboring relationships between adjacent regions can be investigated. Image segmentation is therefore a key step towards the quantitative interpretation of image data.

Segmentation of intensity images usually involves five main approaches, namely threshold, boundary detection, region-based processing, pixel intensity and morphological methods.

The threshold techniques [1] are based on the postulate that all pixels whose values lie within a certain range belong to one class. Such methods neglect all of the spatial information of the image and do not cope well with noise or blurring at boundaries.

Boundary-based methods are sometimes called edge detection [2], because they assume that pixel values change rapidly at the boundary between two regions. The basic method is to apply a gradient filter to the image. High values of this filter provide candidates for region boundaries, which must then be modified to produce closed curves representing the boundaries between regions.

Region-based segmentation algorithms postulate that neighboring pixels within the same region have similar intensity values, of which the split-and-merge [3] technique is probably the most well known. The general procedure is to compare a pixel with its immediate surrounding neighbors. If a criterion of homogeneity is satisfied, the pixel can be classified into the same class as one or more of its neighbors. The choice of homogeneity criterion is therefore critical to the success of the segmentation.

In pixel intensity based methods, the intensity values of pixels are used to segment the image. The space continuity is not frequently considered in this type of methods. Within this group, there stands out a method of classification of pixels that uses statistical algorithms to assign pixel labels to the image [4].

A well known morphological approach to segmentation, the watershed algorithm, is generally applied to the gradients of the image. The gradient image can be considered as a topography with boundaries between regions, known as ridges. Over time, the watershed transformation has been established to be a very useful and powerful tool for image segmentation. It is the first algorithmic approach invented from the field of topography [5]. The watershed transformation is becoming more and more popular in areas such as biomedical and medical image processing [6], and computer vision [7]. The segments correspond to the individual regions identified in the image. Every pixel in the image is assigned to the catchment basin corresponding to a regional minimum.

Segmentation by morphological watershed normally suffers from the problem of over-segmentation, especially if the image is corrupted with different kinds of noises during acquisition, transmission and storage. In overcoming this problem, watershed preprocessing (noise filtering) and watershed post-processing (region merging) are proposed in this paper.

Linear filtering methods have been proposed by Haris [8], Gush [9] and Wang [10]. The disadvantages of these methods are that they destroy the location of boundaries and are generally computationally complex. When the SNR (signal-to-noise ratio) is low, Haris commented that the noise reduction stage did not perform well as the watershed technique is very noise sensitive, and as a result, produces false segments. If there are still too many regions after preprocessing, it would be computationally expensive for watershed segmentation and post-processing. Hernandez and Barner [11] proposed a non-linear filtering method to reduce over-segmentation. An integrated preprocessing system that combines linear, non-linear and thresholding filters is proposed in this paper. The algorithm preserves the location of boundaries, removes dark and bright spots, eliminates high frequency noise, eradicates background noise, and is computationally simple for watershed post-processing.

Most watershed segmented images still suffer from the problem of over-segmentation, even though they have been preprocessed. To overcome this problem, numerous region-merging methods have been proposed for watershed post-processing. A well known approach used to control over-segmentation is based on the concept of markers [12]. The difficulty of this method is that it does not work automatically. Wang [10] proposed an algorithm for eliminating irrelevant minima in the resulting gradient images. Shen [13] used a Just Noticeable Difference (JND) region based merging controller and the mean grey level measure for region merging. Haris [8] proposed a Region Adjacency Graph (RAG) based method for region merging. This method merges the most similar pairs of regions according to a dissimilarity function based on the homogeneity of regions. The problem of this method is that it only favors the merging of small regions as larger adjacent regions have higher dissimilarity. Tan [14] proposed another morphological method for region merging. The problem of this method is that the threshold parameters have to be properly tuned. In this paper, a morphological and graph based semi-automatic method is proposed for resolving the region merging problem, as an improved post-processing stage for watershed segmentation.

Numerous morphological watershed segmentation techniques have been proposed based on immersion, flooding and rainfalling. In this paper, the morphological rainfalling watershed technique [15] was chosen as it is computationally faster [16] than the other techniques.

In the next section the details of the proposed method is outlined and described. Section 3 discusses the significance of the algorithm as compared with other existing techniques. Section 4 presents sample results obtained through the application of the proposed algorithm. Finally, Section 5 draws the conclusions and provides suggestions for future work.

2. Methodology

Images are usually corrupted with different kinds of noises. As a result, the watershed algorithm frequently produces over-segmentation. To overcome this problem, watershed preprocessing and post-processing are proposed. Preprocessing prevents the generation of insignificant regions, while post-processing merges spurious regions. The proposed algorithm is detailed below.

2.1 Watershed preprocessing

In the proposed preprocessing technique, the image first undergoes morphological smoothing before it is convolved with a Gaussian kernel. This is followed by a global intensity thresholding with a low intensity value. The threshold is used to filter out background intensities in the image. Using this method, the intensities of the filtered image $T_i\,(x, y)$ are modified to be in the range of: $\mathrm{Max}\,(I) * th \leq T_i\,(x, y) \leq \mathrm{Max}\,(I)$, where Max (I) is the maximum intensity value of the convolution of the morphologically smoothed image, th is the thresholding percentage value based on histogram analysis of the images. The optimum threshold was experimentally obtained between the range: $0.1 \leq th \leq 0.15$ (between 10% to 15% of the maximum intensity value). Let, $\mathrm{Max}\,(G_{convol}) = 255$ and $th = 0.15$. Substituting the values into the previous equation, we obtain $255*0.15 \leq T_i\,(x, y) \leq 255$. For all values in $T_i\,(x, y)$ which are less than $0.15*\mathrm{Max}\,(G_{convol})$, set them to $0.15*\mathrm{Max}\,(G_{convol})$. After the thresholding process, all pixels would have intensities in the range of 38 to 255.

By combining these operations, the technique can remove dark and bright spots, filters noise in the outer parts of the spectrum and removes noise in the image background. By applying morphological watershed on gradient threshold images, we get greater reduction in the number of regions as the gradient threshold applied after the formation process is very effective in removing weak edges, resulting in further region reduction.

The definition of the notations used and pseudocode of the proposed algorithm are as follows:

Notations

1) $I(x, y)$: input image
2) $S_e = \{(x\text{-}1, y\text{-}1), (x\text{-}1, y\text{+}1), (x, y), (x\text{+}1, y\text{-}1), (x\text{+}1, y\text{+}1)\}$: morphological structuring element
3) $D = \text{Max}\ [\{I(x\text{-}i, y\text{+}j) + S_e(i, j)\}]$: morphological greyscale dilation
4) $E = \text{Min}\ [\{I(x\text{+}i, y\text{+}j) - S_e(i, j)\}]$: morphological greyscale erosion
5) $SM = CL(OP(I, S_e))$: morphological smoothing
6) $G_d(x, y)$: gradient image
7) W_{pre} : watershed preprocessing
8) $W(x, y)$: watershed function
9) W_L: watershed labeled image
10) $T_i(x, y)$: threshold image
11) T_g: gradient thresholding
12) Gd_{Tg} : gradient thresholding image
13) G_u: exp $(-(x^2 + y^2))/ 4\pi\sigma^4$: Gaussian kernel
14) *Convol*: convolve an array with a kernel

Algorithm: *watershed preprocessing*

Step 1: read grey level image, $I(x, y)$
Step 2: $W_{pre} = Convol(SM(I, S_e)), G_u) > T_i$
Step 3: $G_d = 0.5*(D(W_{pre}) - E(W_{pre}))$
Step 4: $Gd_{Tg} = G_d > T_g$
Step 5: $W_L = W(Gd_{Tg})$
<u>OUTPUT</u>: Watershed labeled image, W_L

Step 1 reads the image, Step 2 performs image filtering, Step 3 determines the gradient image, Step 4 applies gradient thresholding and Step 5 produces the watershed labeled image.

The effect of preprocessing on a watershed labeled image is shown in Fig. 1, where Fig. 1(a) shows the original test image, Fig. 1(b) shows the watershed segmented image without preprocessing and Fig. 1(c) shows the watershed segmented image applied with the proposed preprocessing. As observed, the preprocessing reduces the number of spurious regions significantly.

2.2 Watershed post-processing

Reduction in the number of regions in preprocessing is computationally more efficient. However, even with the preprocessing, there are still too many regions after watershed segmentation. If more concise region representation is required, post-processing by means of region merging can be applied.

In this paper, we propose a morphological algorithm for region merging based on the region adjacency list (RAL). The region-merging algorithm consists of the region similarity function, RAL, and region merging and updating, as described below.

2.2.1 Region similarity function

A similarity function for region merging is proposed based on two criteria: region homogeneity (R^H) and border homogeneity (B^H). These are defined as

$$R^H = \begin{cases} 1, & \text{if } |\, L_i - L_j \,| \le T_R \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where
R^H = 1 indicates that both regions are similar,
R^H = 0 indicates that both regions are dissimilar,
T_R is the region homogeneity threshold, and
L_i and L_j are the mean intensity values of two adjacent regions, R_i and R_j.

$$B^H = \begin{cases} 1, & \text{if } |\, B_i - B_j \,| \le T_B \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where
B^H = 1 indicates spurious border,
B^H = 0 indicates genuine border
T_B is the border homogeneity threshold, and
B_i and B_j are the mean intensity values at the border between regions R_i and R_j.

The region homogeneity threshold and border homogeneity threshold are related, and experimentally, satisfactory results were obtained when the border homogeneity threshold was set to 6% of the region homogeneity threshold. Thus, a single parameter, C (the merge-controlling factor), can be used in both criteria: if T_R is set to C, T_B can be set to 0.06*C. A pair of adjacent regions is merged only if the difference of L_i and L_j is not more than C and the difference of B_i and B_j is not more than 0.06*C. The borders B_i and B_j are determined using morphological dilation of the regions R_i and R_j , as shown in Fig. 2.

Four possible cases between a pair of adjacent regions are considered as shown in Fig. 3:

Case 1: Two regions with dissimilar average intensity.
Case 2: Two regions with similar average intensity but large difference in average border intensity.
Case 3: Two regions with similar average intensity and small difference in average border intensity.
Case 4: Two regions with similar average intensity and average border intensity.

Using the similarity function, a pair of regions (R_i and R_j) will be merged only when both criteria are fulfilled. This would prevent the merging of legitimate regions, as shown in Fig. 3, where the regions in Case 1 and 2 are not merged. It is clear that the regions in Case 2 are legitimate and should not be merged albeit their average intensities being similar. This could be prevented if their average border intensities are also taken into consideration. Consequently, only illegitimate regions that fulfilled both criteria are merged, such as those in Case 3 and 4.

For each pair of regions that satisfy the merging criteria, a merging cost is calculated using the following function:

$$M(R_i, R_j) = |L_i - L_j| + |B_i - B_j| \tag{3}$$

where $M(R_i, R_j)$ is the merging cost of regions R_i and R_j, L_i and L_j are the mean intensity values of regions R_i and R_j, and B_i and B_j are the mean intensity values at the border between R_i and R_j. The most similar pair of adjacent regions corresponds to the pair with the minimum merging cost. At each merging step, the region pair with the minimum merging cost is merged.

2.2.2 Constructing the Morphological Region Adjacency List (RAL)

Let, $R = \{R_1, R_2 \ldots R_M\}$ be M partitions (regions) of the watershed labeled image W_L. The resulting M-partition image is used for construction of the RAG that will be used in the region merging procedure. The RAG of the M partitions is represented by graph nodes. Two regions (nodes) are adjacent if they have a common edge (border). An example of an 8-partition image is shown in Fig. 4 and the corresponding region adjacency list (RAL) is presented in Table 1. A cost is assigned to each region pair, expressing the homogeneity between two adjacent regions.

Binary morphological dilation is used to determine the neighboring regions. An example to determine adjacent regions is shown in Fig. 5. The following algorithm is implemented using binary morphological dilation.

Notations

1) $W_L(x, y) = \{R_1, R_2 \ldots R_M\}$: watershed labeled image
2) D_b: binary dilation function
3) D_L: dilated image
4) *adjReg*: adjacent region
5) B_r: border region
6) *UNIQUE*: identify the unique elements of each group of elements
7) $S_e = \{(x\text{-}1, y\text{-}1), (x\text{-}1, y\text{+}1), (x, y), (x\text{+}1, y\text{-}1), (x\text{+}1, y\text{+}1)\}$: morphological structuring element

Algorithm*: *Construction of RAL

<u>INPUT</u>: watershed labeled image, $W_L(x, y) = \{R_1, R_2 \ldots R_M\}$
Step 1: iteration, For $i = 1$ to M
Step 2: $D_L = D_b(R_i, S_e)$
Step 3: $B_r = D_L - R_i$
Step 4: $tempReg = W_L[B_r]$

Step 5: *adjReg* [R_i] = *UNIQUE(tempReg*)
Step 6: End for
OUTPUT: *adjReg* [R_i] : represents the RAL where $i = \{1,2,3\ldots M\}$, and each *adjReg* [R_i] holds N_i number of regions that are adjacent to region R_i.

2.2.3 Region merging and updating

Once the RAL has been constructed, the adjacent regions of R_i are determined by scanning the RAL. The region R_i and adjacent region R_j will be merged if they satisfy equations (1) and (2). After merging these two regions, the watershed labeled image and RAL are updated. This process is repeated until no more merging is possible. The algorithm for this stage is given below:

Algorithm: *Calculate merging cost table*

INPUT: RAL
Step 1: For i = 1 to M
Step 2: For j = 1 to N_i
Step 3: If (R^H (*adjReg*[i] [j]) ==1) AND (B^H (*adjReg*[i] [j]) ==1))
Step 4: Calculate merging cost for R_i, R_{ij} /* R_{ij} *is the* j^{th} *neighbor of* R_i */
Step 5: Add R_i, R_{ij} and their merging cost in the cost table
Step 6: End If
Step 7: End For
Step 8: End For
OUTPUT: Merging cost table (CT)

Algorithm: *Region merging and updating*

INPUT: RAL, watershed labeled image *(W_L)*
Step 1: REPEAT
Step 2: Calculate merging cost
Step 3: Find the pair of regions with minimum merging cost from the CT
Step 4: Merge the corresponding pair of regions
Step 5: Update RAL and W_L
Step 6: UNTIL no more merging
OUTPUT: Watershed labeled image (W_L)

An example of the output result of the proposed algorithm with C = 25 (determined experimentally for best results), is given in Fig. 6. As observed in the result, the proposed algorithm improved the overall segmentation.

3. Discussion and Comparison

In this section, we compare our watershed preprocessing and post-processing technique with other existing watershed preprocessing and post-processing techniques. Firstly, the proposed preprocessing technique is compared with the preprocessing technique by Hernandez and Barner [11]. The comparison results, obtained for 3 test images are shown in Fig. 7.

Visually comparing the results obtained in Fig. 7 (the original images are shown in Fig. 9), it is obvious that the proposed algorithm achieved the more accurate segmentation of the objects in the test images. Comparing the total number of regions obtained on the experimental images in Fig. 7, the proposed preprocessing technique produced an average of 647 regions, while Hernandez's technique produced an average of 1452 regions. Thus, the proposed preprocessing is also computationally simpler for post-processing (region-merging) as compared to Hernandez's technique.

Secondly, we compare the proposed post-processing method (region merging) with the popular Haris [8] and Tan [13] region merging techniques. The preprocessed image used is given in Fig. 1(c). Fig. 8 shows the comparison results of Haris's, Tan's and the proposed methods, which are applied after the same preprocessing technique (i.e. the proposed preprocessing). From the observation in Fig. 8(a), it can be seen that Haris's method favors the merging of small regions, leaving larger regions unmerged. Fig. 8(b) shows that some objects are over-merged with the background. The problem of Tan's method is that the thresholding parameters have to be tuned optimally. The proposed merging technique produces better segmentation results than both the Haris's and Tan's methods. Fig. 8(c) shows that most of the objects in the Cameraman image are well segmented using the proposed merging method. However, the quality of regions depends on the controlling factor, where the result in Fig. 8(c) appears slightly over- merged as compared with the result in Fig. 6 (with $C = 25$).

4. Experimental Results

The proposed algorithm was tested on a series of abdominal MRI medical and well-known real world test images, as listed in Table 2. All the test images used were of size 256×256 pixels with, 8 bits per pixel (bpp) resolution. The proposed preprocessing technique presented in Section 2.1 is first applied on all the test images. Morphological watershed is then applied on the resulting gradient images. Finally, the proposed post-processing technique is used to yield the final region representation.

The results of the proposed segmentation algorithm, tested on various well known test images are given in Fig. 9. Four parameters are used in the experimental work. We set $\sigma = 1$ for the Gaussian kernel that removes noise in the outer parts of the spectrum, $T_i = 15$ for intensity thresholding that removes image background noise and $T_g = 0.5$ for gradient thresholding that prevents false regions. The merging criterion using the merge control factor, C, was described in Section 2. Selecting $C = 25$ means that the normalized average intensity difference between the two neighboring regions is less than or equal to 25. As C depends on the range of grey levels of the images, different values of C were found to be best for the different test images, as shown in Fig. 10.

The segment boundaries of the results in Fig. 9 verify the successful segmentation abilities of the proposed algorithm. As shown in the results, the proposed morphological segmentation scheme comprising of the preprocessing, watershed segmentation and post-processing was able to segment the various objects of the images with good accuracy. The success rates of the proposed algorithms for the test of abdominal MRI and real world images, as shown in Fig. 10, are summarized in Table 2. It can be seen that the proposed segmentation algorithm successfully segmented 56 out of the 60 test images. The other 4 images were not segmented accurately due to over-merging during the post-processing, excessive blurring in the preprocessing or low intensity difference between the objects of interest and surrounding objects. Another problem faced in the segmentation was when the object was dilated too much, wrong edges would be produced and resulted in the wrong object boundary. The merging criteria chosen may also not be optimal.

5. Conclusion

In this paper, we have proposed a morphological based preprocessing and post-processing technique for watershed segmentation. The pre-processing technique composes of morphological smoothing with Gaussian filtering and a global thresholding value. It effectively reduces over-segmentation. In addition, a morphological RAL based region merging technique was developed for the merging of spurious segments. Although developed for general images, the proposed algorithm has also shown good performance when extended to other types of images such as medical images. The proposed algorithm allows for better object recognition, as shown in this paper.

There are some limitations of the proposed system. Firstly, the parameter for region merge control (C) differs from image to image and optimal selection produces the best results. Secondly, the proposed region-merging technique is computationally more expensive than the Haris [8] technique. Nonetheless, there are possibilities for optimization and parallel implementation of the proposed region merging technique. It is also possible to adjust the threshold value dynamically for C, thus enabling the best results. Further work on automatic parameter selection may be undertaken to improve the usability of the algorithm.

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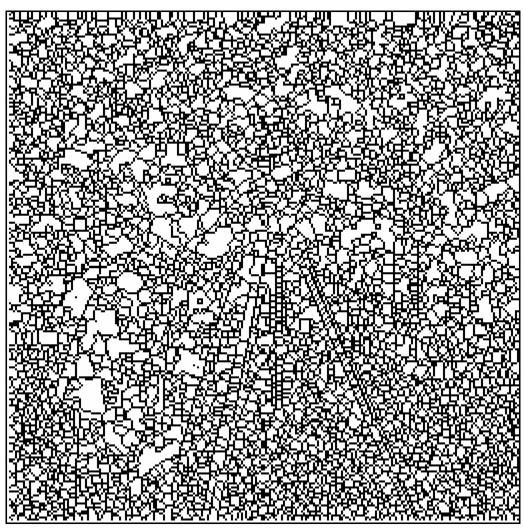
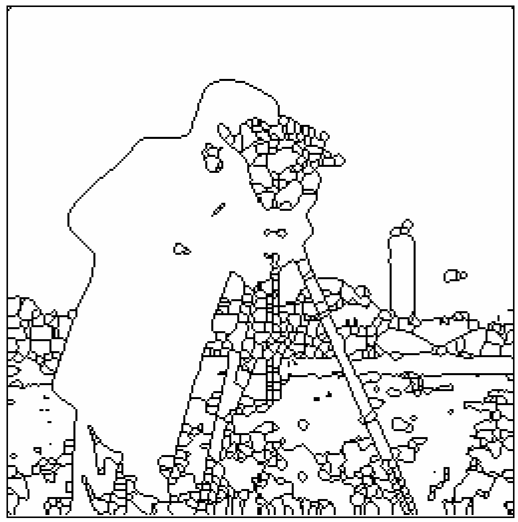
(a) Original image (256x 256 Cameraman image).

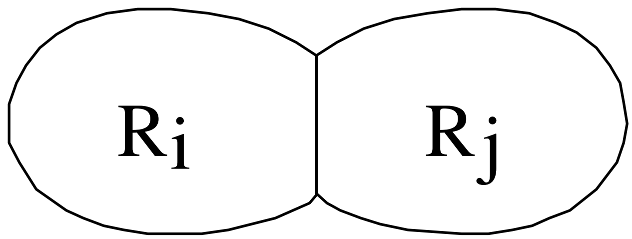


(b) Watershed segments with no preprocessing (regions = 4864).

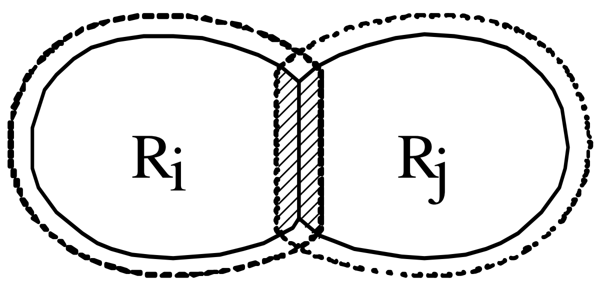


(c) Watershed segments with proposed preprocessing (regions = 665).

Fig. 1. The effect of watershed preprocessing.

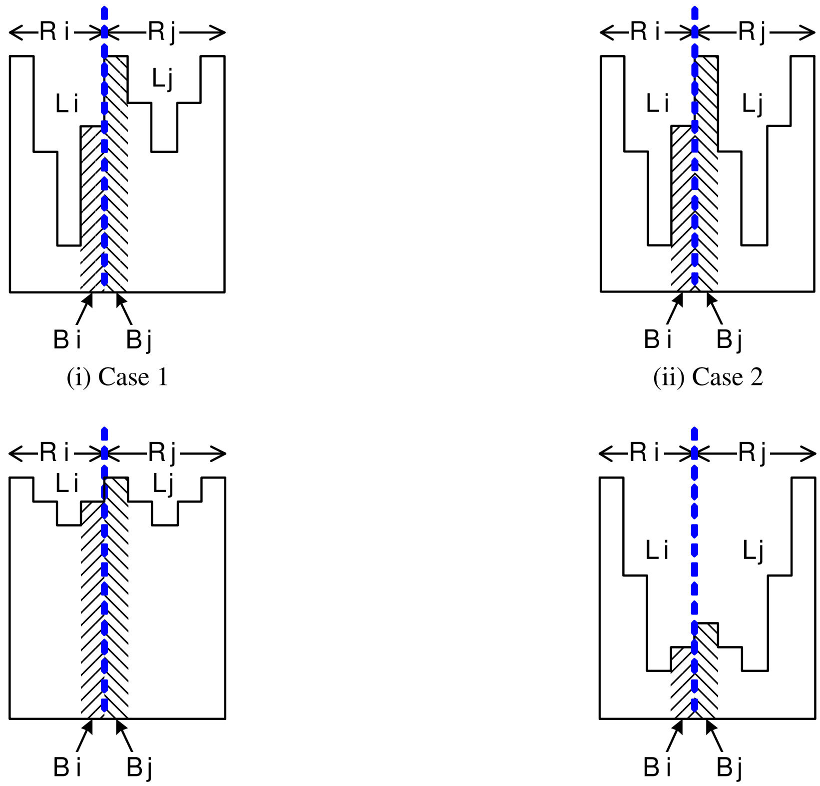


(a) A pair of adjacent regions.



(b) Dilating the regions to obtain their borders (shaded area).

Fig. 2. Dilation and merging of adjacent regions in the proposed algorithm.



(i) Case 1

(ii) Case 2

(ii) Case 3

(iv) Case 4

Fig. 3. Cross-sectional view of 4 possible cases for a pair of adjacent regions.

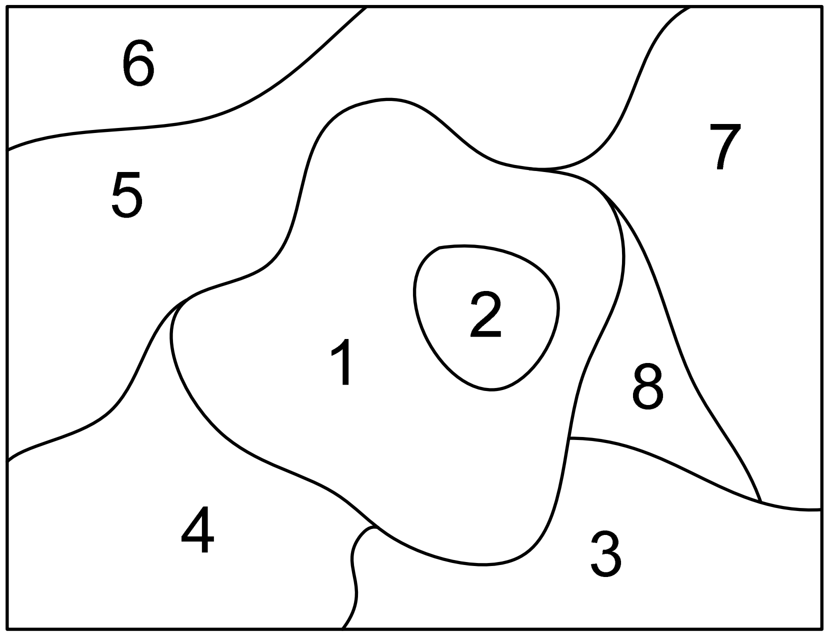


Fig. 4. An image with 8 regions.

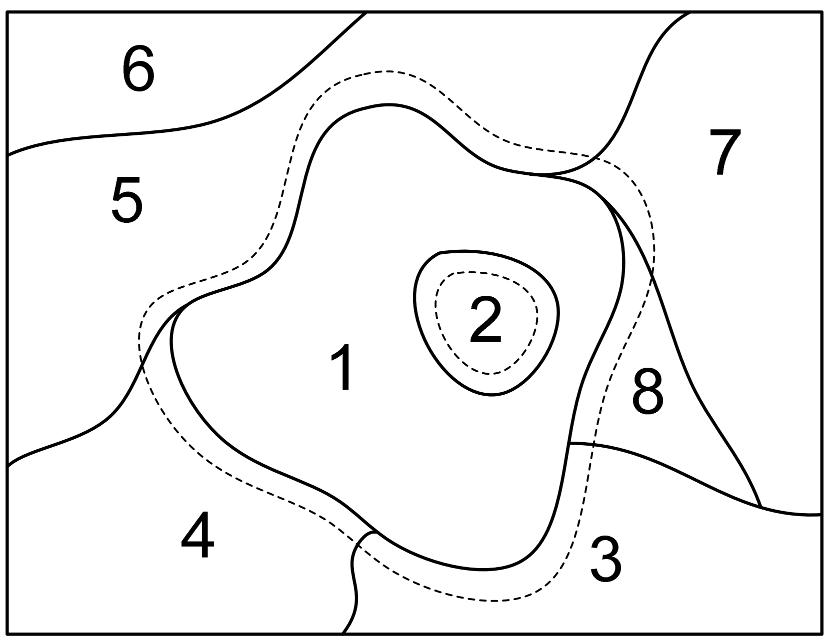


Fig. 5. Dilating Region 1 (dilation given by dotted region) to determine its adjacent regions.

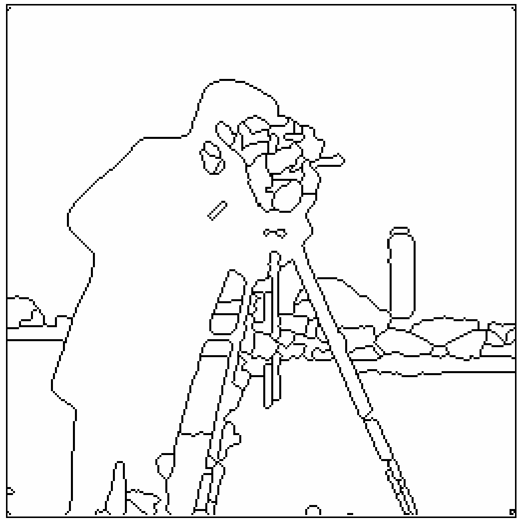
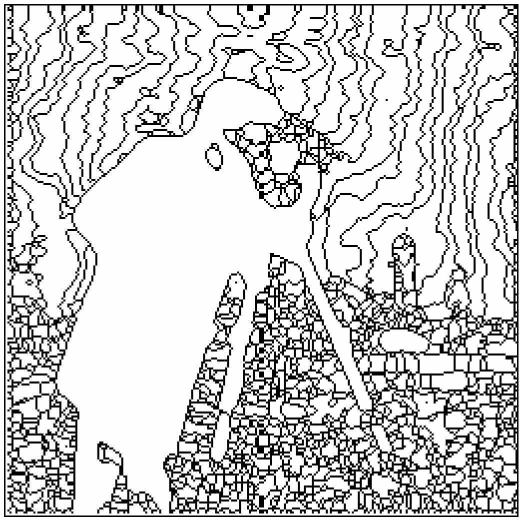


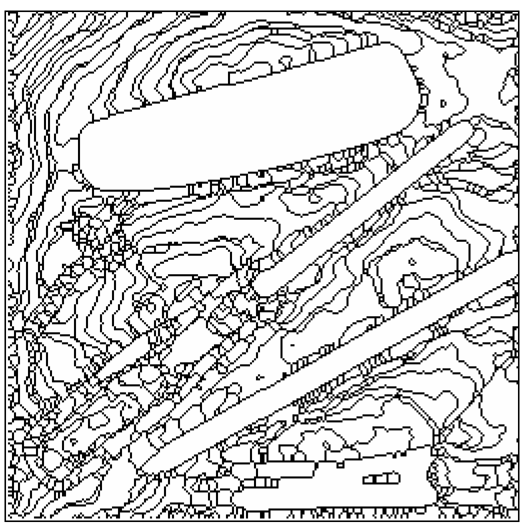
Fig. 6. Result after region merging (regions = 96).



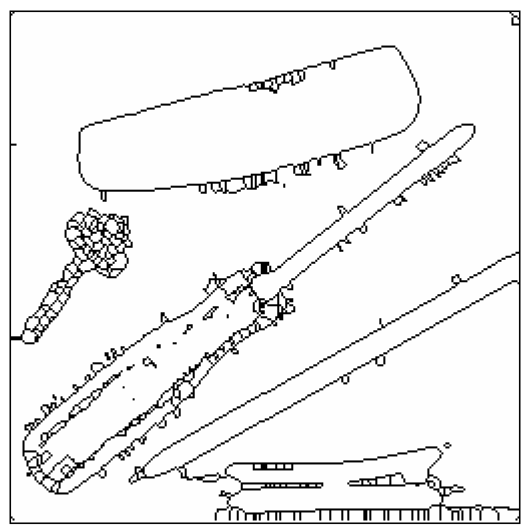
(i) Hernandez's technique (regions = 1500).

(ii) Proposed technique (regions = 665).

(a) Cameraman test image.

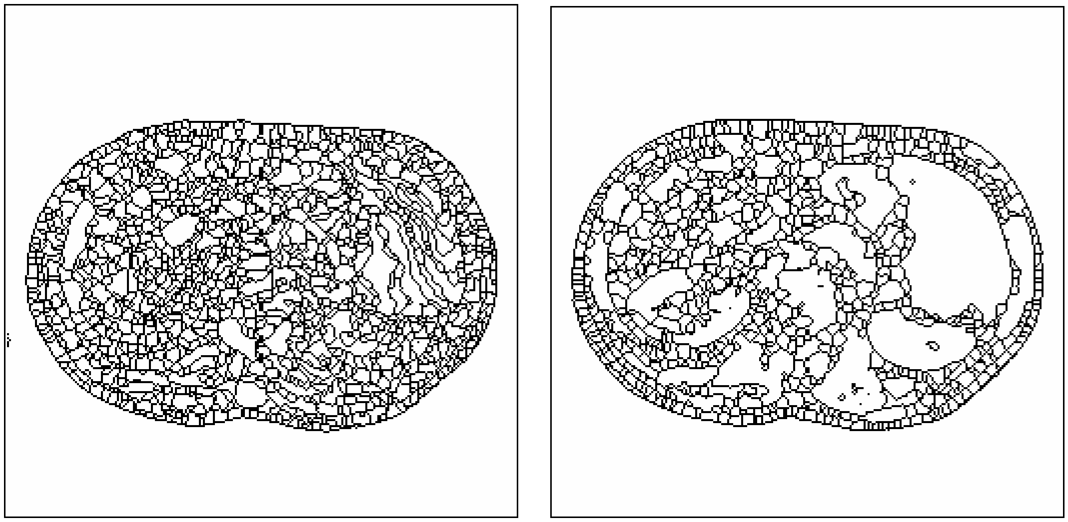


(i) Hernandez's technique, regions=1300.



(ii) Proposed technique, regions = 348.

(b) Object test image.



(i) Hernandez's technique, regions = 1558.

(ii) Proposed technique, regions = 926.

(c) MRI test image.

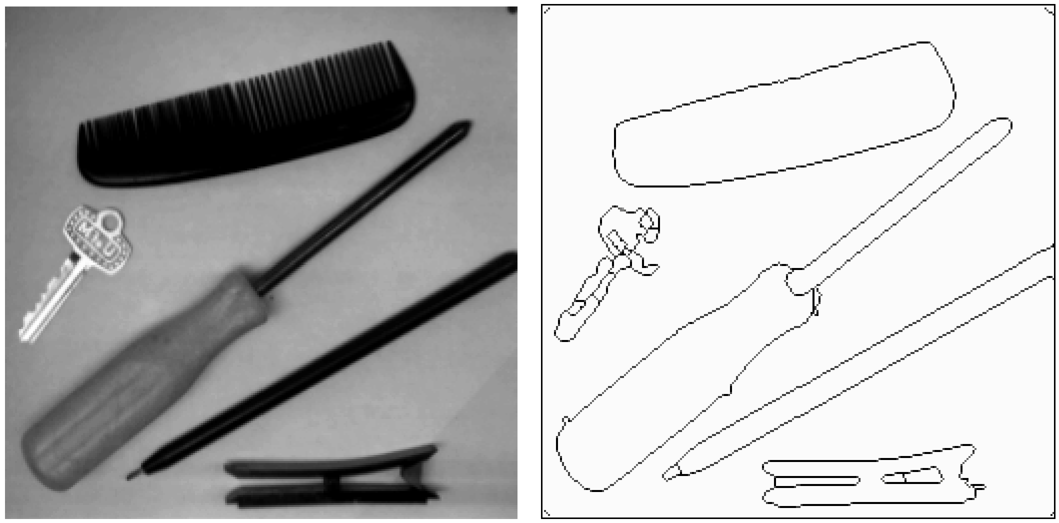
Fig. 7. Comparison result of proposed preprocessing with Hernandez & Barner [11] preprocessing technique.

(a) Merged by Haris's approach.

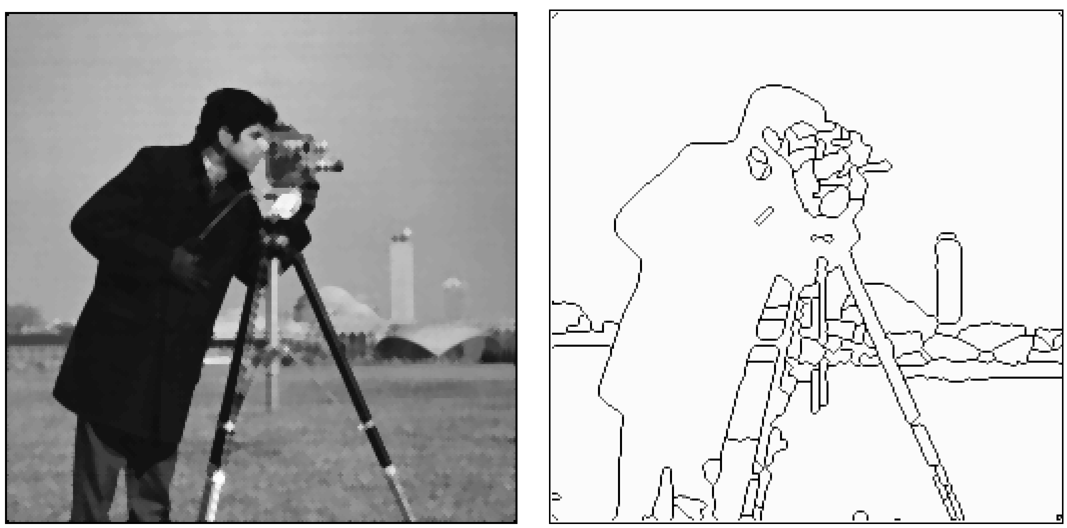
(b) Merged by Tan's approach.

(c) Merged by the proposed approach

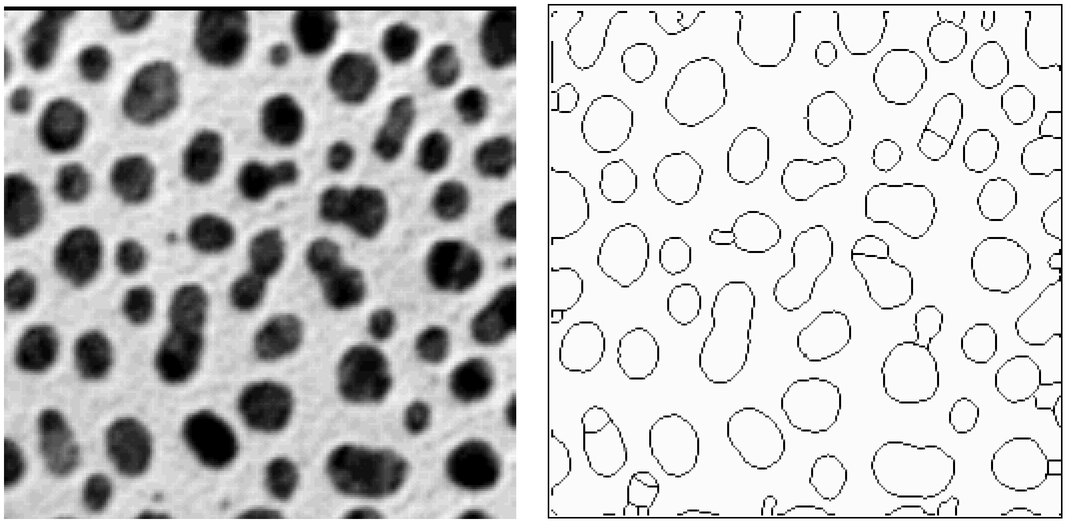
Fig. 8. Comparison result of Haris [8] and proposed region merging technique.



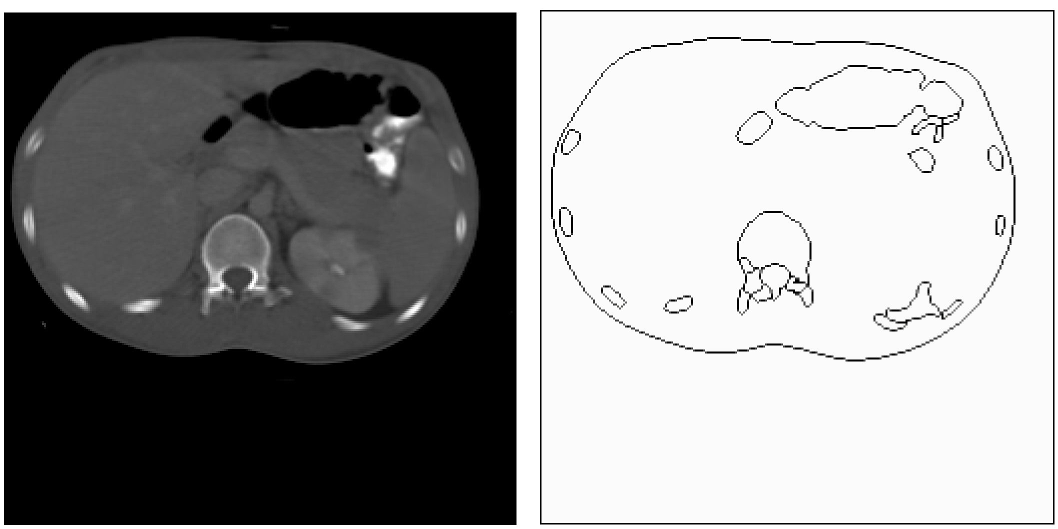
(a) 256 × 256 Object image.



(b) 256 × 256 Cameraman image.

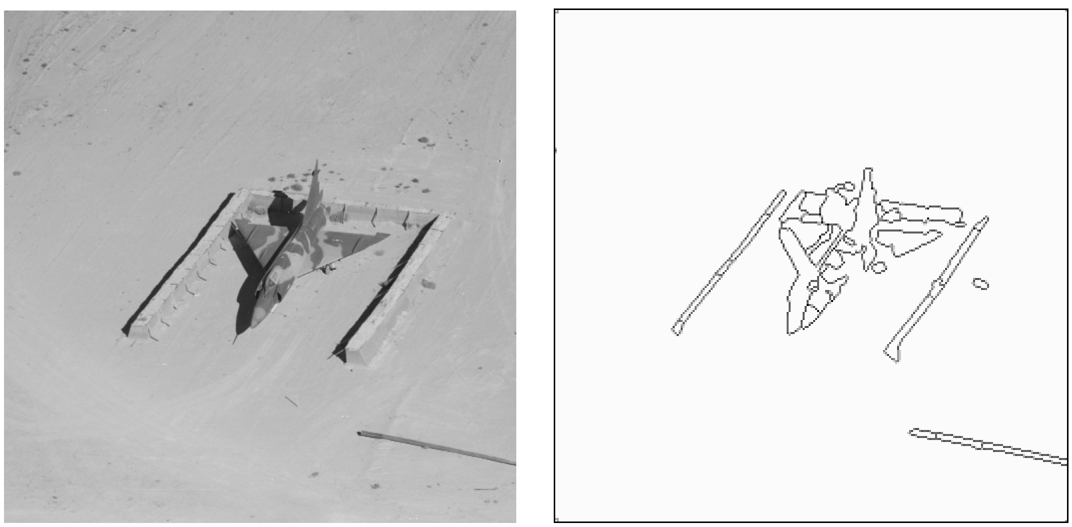


(c) 256 × 256 Blobs image.

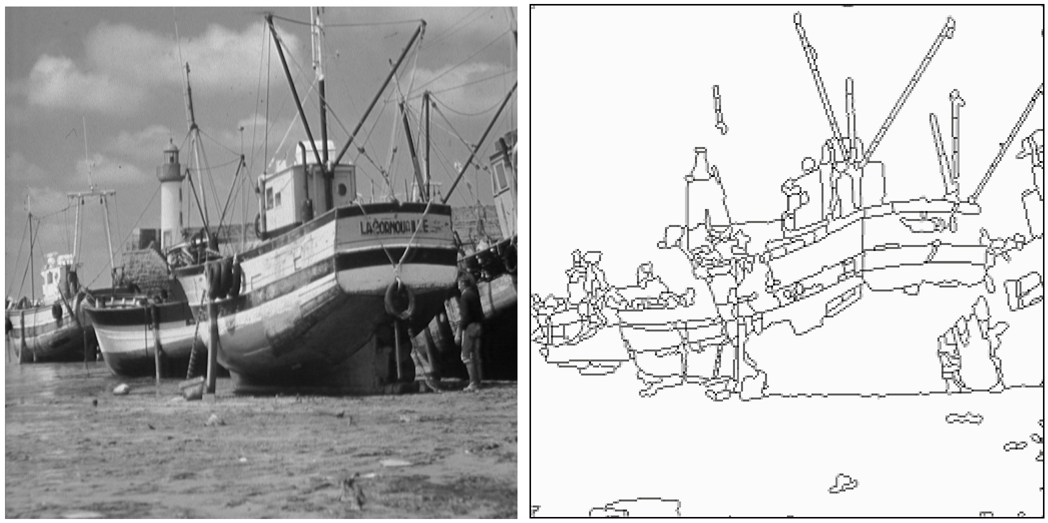


(d) 256 × 256 sample CT image.

(e) 256 × 256 Lena image.



(f) 512 × 512 Airplane image.



(g) 512 × 512 Boat image.

Fig.9. Region representation (segment boundary) results on well known test images by applying proposed algorithm.

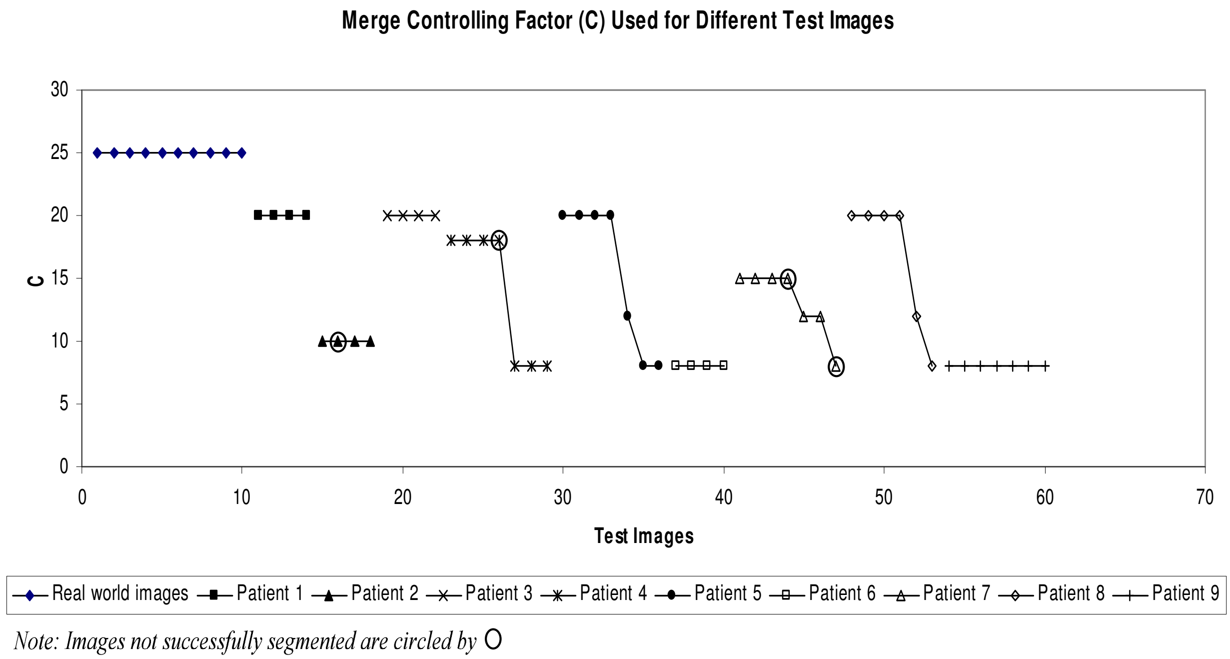


Fig. 10. Range of values for merge control factor (*C*) used with different test images.

Table. 1 List of adjacent regions (RAL) of region R_i

Region No	Adjacent regions
1	2,3,4,5,7,8
2	1
3	1,4,7,8
4	1,3,5
5	1, 4, 6,7
6	5
7	1,3,5,8
8	1,3,7

Table.2 Success rate of the proposed algorithm

Image Type	Test images[Failed]	Success rate
Real world image	10[0]	100%
Medical image	50[4]	92%

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