INTERNATIONAL JOURNAL OF
NUMERICAL ANALYSIS AND MODELING
Volume 9, Number 2, Pages 378–384

AN EFFICIENT IMAGE SIMPLIFICATION ALGORITHM FOR BRAIN MRI SEGMENTATION BASED ON DOWNHILL FILTER

BOFENG ZHANG, HUI ZHU AND WU ZHANG

Abstract. Image simplification, which reduces the information content of an image to suppress undesired details such as noise, is a very important basic ingredient of a lot of practical applications. The simplification of human brain MRI (Magnetic Resonance Imaging) is one of essential pre-processing steps for medical researches and clinical applications. Usually, the process of image simplification requires multiple iterations of reconstruction. Therefore, the efficiency of the reconstruction algorithm is a key problem. This paper has proposed an efficient reconstruction algorithm for MRI brain image simplification based on downhill filter. The main contribution of this paper is to use the regional maxima concept to modify the initialization condition of downhill filter algorithm. Experimental results show that the efficiency of this algorithm is much better than that of fast hybrid reconstruction algorithm, and it can achieve good result when it is used to the contour extraction from the MRI of human brain.

Key words. MRI, Human Brain Image Simplification, Morphological Reconstruction, and Downhill Filter.

1. Introduction

The research on the segmentation of interest regions of medical image is the most important basis of the medical image analysis. Watershed transform is a common technique for image segmentation which has been widely used in many fields of image processing, including medical image segmentation. However, if the watershed transform is applied directly to image segmentation, the problem of over-segmentation caused by insignificant structures or noise will be very serious. So image segmentation is typically done by preprocessing, and then using the watershed transform[1]. The purpose of pre-processing is to remove the image details, which are not necessary to the segment and to produce flat zones. This process is usually called image simplification.

In recent years, several morphological reconstruction filters have been developed as tools for image simplification. These filters indeed produce flat zones while preserving the contour information. The classical filter is morphological reconstruction by dilation which is first proposed by Serra[2]. Then there are many varied instances of this kind filter, but there is a problem: the inefficiency of the 'iterate until convergence' approach. So a number of optimizations and algorithmic efficiencies have been detailed for this and similar procedures in both binary and grayscale morphology including structuring element decomposition [3] and manipulation[4, 5], flat zones [6], interval coding [7], and the use of ordered pixel queues [8]. These algorithms have a common drawback that is the procedure still remains computationally expensive and highly data dependant.

Received by the editors October 13, 2009 and, in revised form, August 22, 2010.
2000 *Mathematics Subject Classification.* 35R35, 49J40, 60G40.
This work was supported by Scientific and Technological Project of Science and Technology Commission of Shanghai (08511501702), Shanghai Leading Academic Discipline Project, Project Number (J501030), and the Graduates' Innovation Fund of Shanghai University (SHUCX102162). The part of this paper has been published previously in PHCA 2009.

In order to enhance the computing speed, Robinson proposed an efficient morphological reconstruction method which is called the downhill filter [9]. This is an improved algorithm based on the alternative reconstruction by dilation procedures. It can achieve the same filtering effect in a single pass through the data and as such is both fast and linear time in its execution. But the downhill filter usually remains brighter regions because this algorithm targets MRCP (Magnetic Resonance Cholangiopancreatography) data. Thus, in this paper, downhill filter algorithm will be improved to be better for the MRI brain image simplification.

2. Morphological Reconstruction

The reconstruction transformation[10] is relatively well-known in the binary case,where it simply extracts the connected components of an image which are "marked" by another image. However, reconstruction can be defined for grayscale images, where it turns out to be extremely useful for several image analysis tasks. It can be thought of conceptually as repeated dilations of an image, called the marker image, until the contour of the marker image fits under a second image, called the mask image. In morphological reconstruction, the peaks in the marker image "spread out," or dilate. Each successive dilation operation is forced to lie underneath the mask. When further dilations do not change the marker image any more, the processing is finished. The final dilation creates the reconstructed image. The most commonly used algorithm is alternative definition of grayscale reconstruction which is defined as follows:

Let J and I be two grayscale images defined on the same domain, taking their valuesin the discrete set $\{0, 1, \ldots, N-1\}$ and such that $J \leq I$ (i.e.,for each pixel $p \in D_1, J(p) \leq I(p)$). The elementary geodesic erosion ${\delta_I}^{(1)}$ of grayscale image $J \leq I$ above I is given by

$$\delta_I^{(1)}(J) = (J \oplus B) \wedge I \tag{1}$$

In this equation,$\wedge$ stands for the pointwise minimum and $J \oplus B$ is the dilation of J by flat structuring element B. These two notions are the direct extension to the grayscale case of respectively intersection and binary dilation by B. The grayscale geodesic dilation of size $n \geq 0$ is then given by

$$\delta_I^{(n)}(J) = \underbrace{\delta_I^{(1)} \circ \delta_I^{(1)} \circ \cdots \circ \delta_I^{(1)}(J)}_{n\ times} \tag{2}$$

The grayscale reconstruction $\rho_I(J)$ of I from J is given by

$$\rho_I(J) = \bigvee_{n \geq 1} \delta_I^{(n)}(J) \tag{3}$$

There are four algorithms described in [10] for the two dimensional eight connected and three dimensional six connected cases:

A Standard Technique: this algorithm works by iterating elementary dilation followed by pointwise minimum until stability. It is not suited to conventional computers, because the image pixels can be scanned in an arbitrary order. It requires the iteration of numerous complete image scanning, sometimes several hundreds.

Its execution time is often minutes.

B Sequential Reconstruction Algorithm: this algorithm first propagate the information in a raster scanning and then upwards in an anti-raster scanning, so it usually requires only a few image scanning (typically a dozen) until stability is reached, but it does not deal well with "rolled-up structures" like several other sequential algorithms.

C Reconstruction Using a Queue of Pixels: in this algorithm the boundary pixels of the marker image are loaded into a FIFO (first-in-first-out) queue at the initialization. Then pixels are removed, their neighbors examined, changed, and added to the queue as required. Processing continues repeating until the queue is empty. However, this algorithm may be slowed down by the initial determination of the boundary pixels.

D Fast Hybrid Reconstruction Algorithm: this algorithm takes advantage of the strong points of the previous two algorithms described in the last two sections without retaining their drawbacks.

3. Downhill Filter Algorithm and Improvement

3.1. Downhill Filter. The downhill filter algorithm is an optimal implementation of the reconstruction by dilation procedure. As with the third and fourth algorithms above, the downhill filter operates on a pixel queue. Folded or rolled up structures in the input image for instance seriously compromise the execution speeds achieved by all four approaches so that no guarantees can be given as to the processing time required in the general case. This algorithm exhibits no such level of variability in its execution speed.

The downhill filter can be presented in two stages. In the first algorithm restrict the marker image in order to make computing easier. Initialization methods state as follows: each pixel in the marker is either equal to the corresponding pixel in the mask or it is equal to zero.Eq.4.

$$\forall p : D \cdot ((J[p] = I[p]) \vee (J[p] = 0)) \tag{4}$$

Then the reconstruction will be determined directly in the marker image J. Let m be the maximum value of the pixels in J and maintain m lists which from L[1] to L[m]. So each pixel is set to its final value will be placed in the list corresponding to that value. While the current list is not empty the next element is removed and its neighborhood is examined. For each neighbor pixel which has not already been finalized, J is set equal to the lesser of the current list number and the value in I at this location and the neighbor is added to the corresponding list. If it was already in a list it is also removed from that location.

The process above ensures the scanning from a high gray value to a low gray value pixel by pixel after initialization, and then gets the final reconstruction image. Because a random access queue is implemented instead of a FIFO queue in order to allow the processing of pixels in an optimal order, every pixel is addressed only once in the course of the algorithms execution. Specific operations can be referenced in [9].

3.2. Improvement of Downhill Filter Algorithm. The downhill filter algorithm is much faster than the four techniques mentioned above .But it is not suitable for all kind of medical images, because it is improved just for data like MRCP and usually remains the brighter regions. The purpose of the simplification of MRI brain image is to produce flat zones to separate the skull, brain and other structures. So when it is used for the MRI brain image simplification, much important boundary information will be lost except cerebrospinal fluid (CSF). Thus, this paper improves the downhill filter algorithm for the MRI brain image simplification. The drawback occurs in the initialization cause the progress starting from the maximum pixel, so this paper introduces a concept of regional maxima to solve this problem.

A regional maximum M of a grayscale image I is a connected components of pixels with a given value h (plateau at altitude h), such that every pixel in the neighborhood of M has a strictly lower value. It can be defined as follows: A regional maximum at altitude h of grayscale image I is a connected component C of $T_h(I)$ such that $C \cap T_{(h+1)}(I) = \emptyset(T_h(I)$ is threshold of I at level h.). $R(I)$ is used to denote the regional maxima:

$$R(I)(p) = \begin{cases} I(p), & \textit{if p belongs to a maximum} \\ 0, & \textit{otherwise} \end{cases} \quad \forall p \in D_I \tag{5}$$

In practice, the process of initialization after introducing regional maxima method is described as follows: First, let the marker image value equals the mask image value, or equals zero. Then, find the regional maxima at the region of non-zero pixels, and modify pixels values in accordance with the Eq.5. The final image J will include more important pixels related to different part of image. Each of the regional pixels is added to the corresponding list, then use the part of the downhill filter algorithm to reconstruct image.

Algorithm: improved reconstruction algorithm by downhill filtering:

I:grayscale mask image
J:grayscale marker image, defined on domain D_I, $J \leq I$.
Reconstruction is determined directly in J
  Compute regional maxima of $J : J \leftarrow R(J)$,
  Initialization of the queue with pixels of maxima:
    For every pixel $p \in D_I$:
      If $J(p) \neq 0$ textsland $p \notin R(J), J(p) = 0$
  Find m,the maximum pixel value in image J
  Place each non-zero pixel in J into its appropriate list
    For every pixel $p \in R(J)$:
      If $J(p) \neq 0$, $L[J[p]] \leftarrow L[J[p]]^p$
  Process the m lists from high to low:
      For $n = m \cdots 1$
        While $L[n]_{emptey()} = false$
          $p \leftarrow L[n]_{first()}$
            For every pixel $q \in N_G(p)$
              If $J(q) < min(n, I[q])$
                If $J(q) \neq 0$
                  $L[J[q]] \leftarrow squash(L[J[q]] \triangleright \{q\})$
                $J(q) \leftarrow min(n, I[q])$
                $L[J[q]]_{add()} \leftarrow L[J[q]]^p$

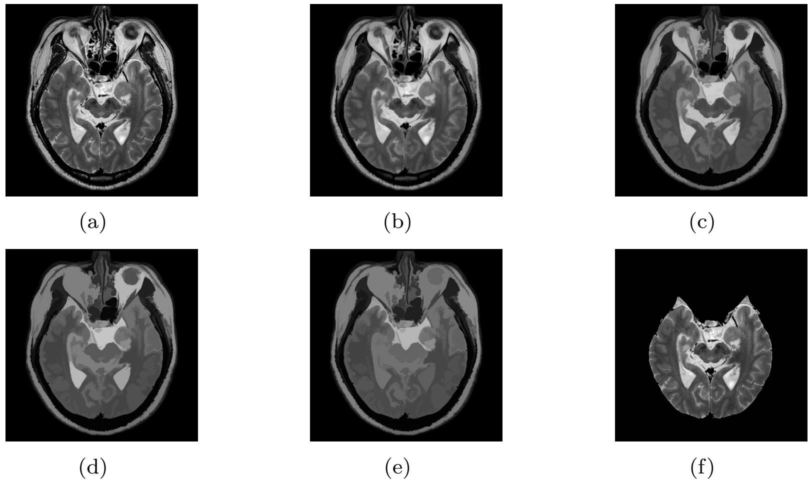

FIGURE 1. MRI brain image simplification

Symbol definitions.

$N_G(p)$	—	The neighbours of pixel p on the grid G
$I[p]$	—	The p^{th} pixel in image I
$\leftarrow$	—	Assignment (to differentiate from = for equality)
$\triangleright$	—	Range subtraction: removes a specified element from a list
squash	—	Closes up holes in a list (e.g. left by range subtraction)

4. Experiments

In order to demonstrate the efficiency of the proposed method, it has been implemented and tested on the MRI brain image data from the Shanghai Renji hospital. The scanning apparatus is Philips MR scanner and slice thickness is 1.5mm. In all cases the image size is 512 × 512 pixels, and the data is eight bit (256 grey value levels). Two experiments have been carried out on the images with different characteristics.

The first experiment is to perform a series of the validation test to confirm the improved algorithm could be correctly implemented. So this paper designed an experiment about the MRI brain image contour extraction. First, this paper use multi-scale alternating sequential filtering reconstruction to simplify the input image, here using the improved reconstruction algorithm, then use the marking extraction technology to get the gradient image, at last the watershed transform algorithm is applied to the marked gradient images to get the contour of brain.

The results are shown in Fig.1. Fig.1(a) is the original image. For the purpose of comparison, the simplified images obtained by multi-scale alternating sequential filtering reconstruction are showed in Fig.1(b)∼(e) respectively. The results show that simplification process can transform homogenous regions into flat zones and preserve the contours of skull and brain well according the images. In Fig. 1(b) the structure element (SE) size is 5 × 5. In Fig.1(c) the SE size is 20 × 20. In Fig.1(d) the SE size is 25 × 25. In Fig.1(e) the SE size is 30 × 30. Fig.1(f) is the final result of contour extraction after using mark extraction watershed transformation. Obviously, the experiment could obtain good segmentation results, thus confirmed that the algorithms performed correctly.

The second experiment is the comparisons about execution times for two reconstruction algorithms tests. These methods are: (1) Fast hybrid reconstruction algorithm; (2) The proposed algorithm of this paper. All tests were performed on a 2.8GHz Duo CPU with 2GB of RAM.

Table1 indicates the computing timings with a same structure element (disk-shaped, size 3×3). In Table1 the execution times are presented in milliseconds for each of the algorithm as applied to each of four test slices. The rate of reduction is 77.64% based on 4 slices.

Table 1. Timings in milliseconds for the two reconstruction algorithms to four test images

Methods	Slice1	Slice2	Slice3	Slice4	Average
Fast hybrid reconstruction	97.65	101.72	89.22	95.31	95.975
This paper method	21.35	26.86	17.49	20.56	21.565
Rate of reduction	78.14%	73.59%	80.40%	78.43%	77.64%

Table2 indicates the computing timings or the two reconstruction algorithms applied to four test volumes. These four test volumes data come from four persons' MRI images and each volumes is of the same size ($512 \times 512 \times 40$). After tested on almost 160 slices (four persons), the mean reduction of the execution time is about 75.65% compared to the fast hybrid reconstruction algorithm. It means that the execution times are reduced significantly.

Table 2. Timings in seconds for the two reconstruction algorithms to four test volumes

Methods	Person1	Person2	Person3	Person4	Average
Fast hybrid reconstruction	45.28	69.37	31.26	38.93	46.21
This paper method	10.65	17.26	7.85	9.24	11.25
Rate of reduction	76.48%	75.12%	74.49%	68.62%	75.65%

5. Conclusions

Image simplification, which reduces the information content of an image to suppress undesired details such as noise, is a very important basic ingredient of a lot of practic-al applications. The simplification of human brain MRI is one of essential pre-processing steps for medical researches and clinical applications. Usually, the fast hybrid reconstruction algorithm, one of the common algorithms of image simplifica-tion, requires multiple iterations of reconstruction, so the time complexity is high. A downhill filter was presented to overcome this shortage, but it usually remains brighter regions because this algorithm targets MRCP data. In response to the characteristics of brain MRI simplification, this paper pro-poses an efficient morphological reconstruction algorithm. The contributions of this paper are as follow.

(1) Firstly, regional maxima concept is introduced to modify the initialization condition.

(2) Then an improved downhill filter algorithm is applied to reconstruct image.

(3) Experimental results show that the mean reduction of the execution time is

about 75.65% compared to the fast hybrid reconstruction algorithm.

(4)The algorithm can achieve good result when it is used to the contour extraction from the brain MRI.

Further works on automatic selection of structure element and times of iteration aim at achieve the simplified image more effectively.

References

[1] Dougherty,E.R., Mathematical morphology in image processing, CRC Press Control Ser.,Boca Raton, 1992.
[2] Serra,J., Image analysis and mathematical morphology,Academic Press,Inc.,Orlando, 1983.
[3] H. Park,J. Yoo, Structuring element decomposition for efficient implementation of morphological filters. IEE Proceedings-Vision,Image and Signal Processing, 148:32-35,2001.
[4] K. Sivakumar,M. J. Patel,N. Kehatamavaz, Y. Balagurunathan, and E. R. Dougherty, A constant-time algorithm for erosions/dilations with applications to morphological texture feature computation, Real-Time Imaging, 6:223-239,2000.
[5] M. Van. Droogenbroeck and H. Talbot, Fast computation of morphological operations with arbitrary structuring elements, Pattern Recognition Letters, 17:1451-1460,1996.
[6] P. Salembier and J. Serra Flat zones filtering, connected operators, and filters byreconstruction, IEEE Trans. Image Process, 4:1153-1160,1995.
[7] L. Ji, J. Piper, and J. Y. Tang, Erosion and dilation of binary images by arbitrary structuring elements using interval coding, Pattern Recognition Letters, 9:201-209,1989.
[8] L. J. van Vliet and B. J. H. Verwer, A contour processing method for fast binary neighbourhood operations, Pattern Recognition Letters, 7:27-36,1988.
[9] K. Robinson and P. F. Whelan, Efficient morphological reconstruction: A downhill filter, Pattern Recognition Letters, 25:1759-1767,2004.
[10] Vincent, Morphological grayscale reconstruction in image analysis: Applications and efficient algorithms, IEEE Trans. Image Process, 2:176-201,1993.

School of Engineering and Science, Shanghai University, Shanghai, 200072, China
E-mail: bfzhang@shu.edu.cn