A Novel Watershed Method Using Reslice and Resample Image

Shengcai Peng, Lixu Gu

Computer Science, Shanghai Jiao Tong University, 1954 Huashan Road, Shanghai, P.R.China 200030
tsai@sjtu.edu.cn, gu-lx@cs.sjtu.edu.cn

Abstract. A novel Watershed segmentation approach is proposed in this paper. Firstly a review of medical image segmentation was presented where the advantages and drawbacks of the traditional watershed method are discussed. To resolve the existing problem, the proposed algorithm employs a threshold operation according to the range determined by the region of interest (ROI) and the modality of the medical image. And a "reslice" operation was employed to shrink the intensity of the image into a smaller range. Finally a resample operation is introduced to reduce the resolution of the image and this make watershed transform run in shorter time and less memory. The results indicated that the proposed method is efficient in solving the over segmentation problem and faster than classic watershed.

Keyword. segmentation, watershed, resample, reslice

1 Introduction

Image segmentation is one of the most critical tasks in automatic image analysis. For example, segmentation is a prerequisite for quantification of morphological disease manifestations and for radiation treatment planning, for construction of anatomical models, for definitions of flight paths in virtual endoscope, for content-based retrieval by structure, and for volume visualization of individual objects. The application that provided the incentive for our work was manifestations of disease from CT/MRI data.

Many different algorithms have been proposed to address the segmentation, which may fall to two major streams: model based and region-based methods. The model based method such as Snake or Level set is relatively faster but sometimes can't achieve satisfactory accuracy, especially at the narrow sharp boundary area. The region based method like Watershed [1],[2] or Morphological operations may get more accurate results but more costly. However, Watershed can be parallelized easily to improve its performance, and has been widely used in medical image segmentation.

G. Hommel and Sheng Huanye (eds.), Human Interaction with Machines, 99-106.

Since S. Beucher and F.Mever firstly proposed Watershed algorithm [6], many scientists have addressed their efforts to improve it [3]. Some researchers employed diffusion algorithms before running the watershed transform because watershed is very sensitive to noises [8]. Some researchers use probability theory to compute the landscape of the image or use different strategy to compute the saliency of merge to merge the watershed images [7]. But the over-segmentation problem has still not been effectively resolved.

In this paper the traditional watershed was introduced (see Section 2.1) at first. Then it discusses an improved watershed method using reslice image to resist over-segmentation problem and resample image to lower the cost from traditional watershed algorithm (see Section 2.2). The method is especially designed for medical image analysis by using the preknowledge of medical imaging phenomenon. For the sake of clarity, a comparison between classical watershed and our method is also presented (See Section 3). A conclusion about our method was drawn at the end of this paper (See Section 4).

2 Methods

2.1 Traditional Watershed

A widely used implementation of traditional watershed is a method by simulating immersion [4] where an image is regarded as a (topographic) surface. Suppose this surface was immersed into a lake, the water will progressively fill up the different catchment basins of the image. Then, at each pixel where the water coming from two different minima would merge, we build a “dam”. At the end of this immersion procedure, each minimum is completely surrounded by dams, which delimit its associated catchment basin. The whole set of dams which has been built thus provides a tessellation of the image in its different catchment basins and these dams correspond to the watersheds of our image. (See Fig. 1).

This method was quite efficient but without thinking about the over-segmentation problem. Over-segmentation is a quite common problem as watershed is very sensitive to noise and gives segmentation even to low contrast region, which may belong to the same object. We will employ traditional watershed as a base of the proposed method.

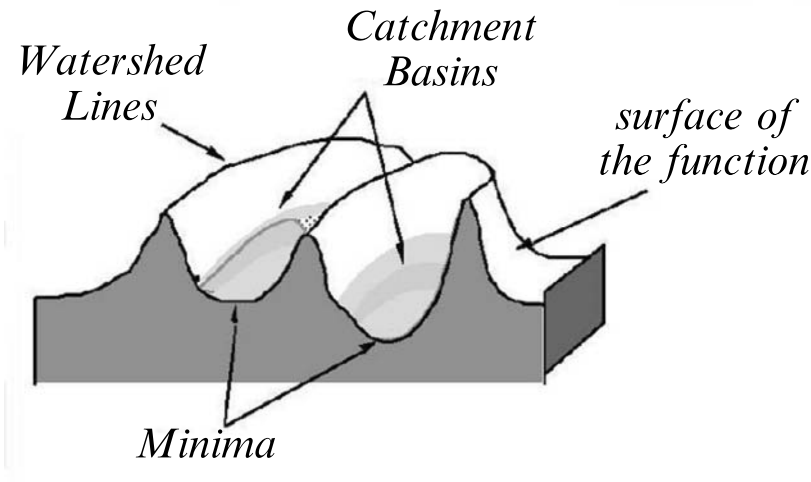


Fig. 1. Minima, catchment basins and watersheds.

2.2 Watershed Using Reslice and Resample Image

There are three preprocessing steps in our method. Firstly the threshold operation is applied according to the range determined by the region of interest (ROI) and the modality of the medical image. As we know, different organs are presented in different intensity ranges in a medical image because of their different physical features (Fig. 2). After the modality of the input medical image data was defined, the intensity range of a specified organ can also be roughly determined. Based on this pre-knowledge, the regions with the intensity out of this range can be ignored. The processing makes the image simpler and reduces the complexity of the whole procedure.

Secondly we make a reslice of the image. Here reslice means presenting the image with a smaller intensity range. For example, if we use one byte to present one pixel, as one byte consists of 8 bits, each pixel has one of the 2^8=256 grey levels. Usually a medical image uses four bytes for every pixel, but after the first step of our method, only the tissue with the intensity in a specified range was left, so it is possible to present the image with shorter bytes. And more importantly, this operation merges the pixels with small differences together, and the over segmentation problem can be resisted. The original image and the resliced image are shown in Fig. 3. It must be emphasized that we can only reduce the grey levels to a proper number; otherwise the detail of the image may be lost.

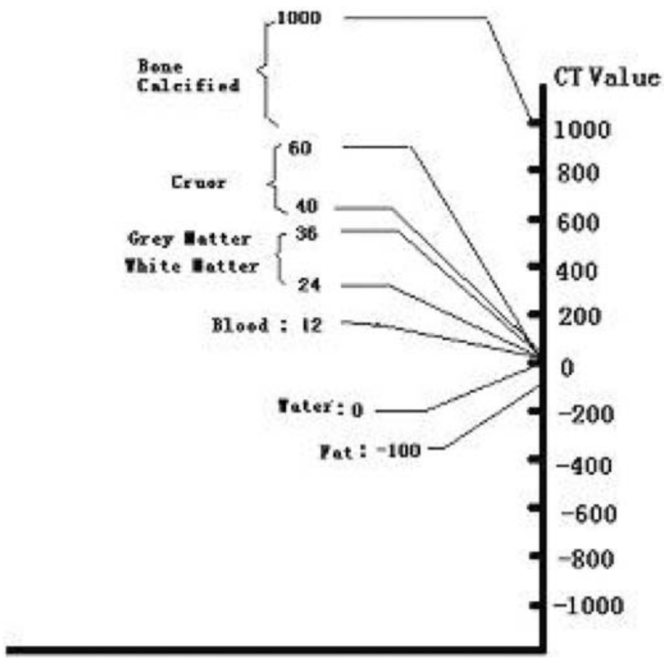


Fig. 2. Different organs are presented in different intensity ranges in a CT image.

Finally, the preprocessed image is sent to a resample procedure. The resample produces an output with different spacing (and extent) than the input. Linear interpolation can be used to resample the data. Here the resample is used to reduce the resolution of the image, so that the watershed transform requires less memory and run faster. Furthermore, the resample operation helps to resist the over segmentation problem because the small regions are ignored and reduced during this operation. A comparison of a brain image and its resample image (In every dimension the resample rate is 0.8) are shown in Fig. 4.

3 Results and Discussions

We implemented our experiment in a normal PC with Pentium 2.4G CPU and 1G DDR RAM, where the program was written in Python + VTK environment and run on a Windows platform. Two datasets were used in this experiment: One is a brain MRI data [5] downloaded from BrainWeb[1] . It is a 181*217*181 voxel volume, with isotropic 1 mm3 voxels. Another one is a real clinical canine cardiac CT data, which is a 512*512*86 voxel volume with isotropic 0.35*0.35*1.25 mm3 voxels.

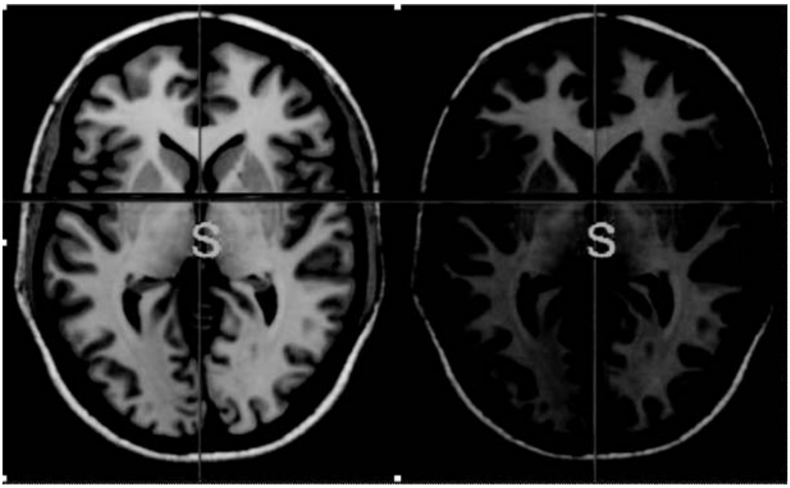


Fig. 3. (Left) The source image. (Right) The image after reslices operation.

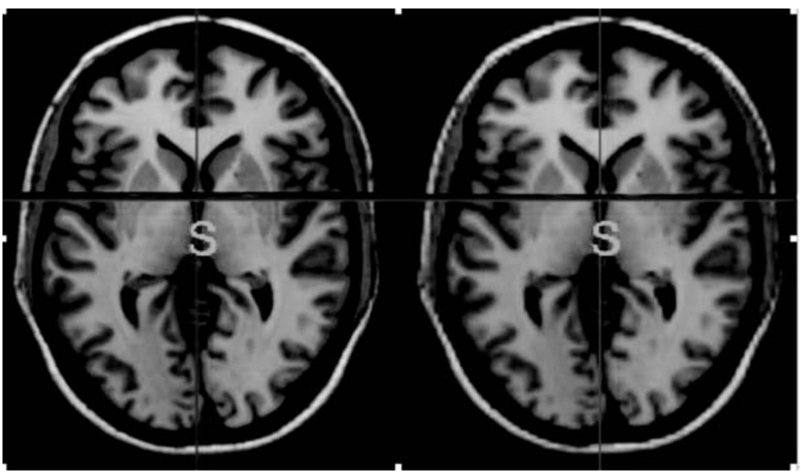
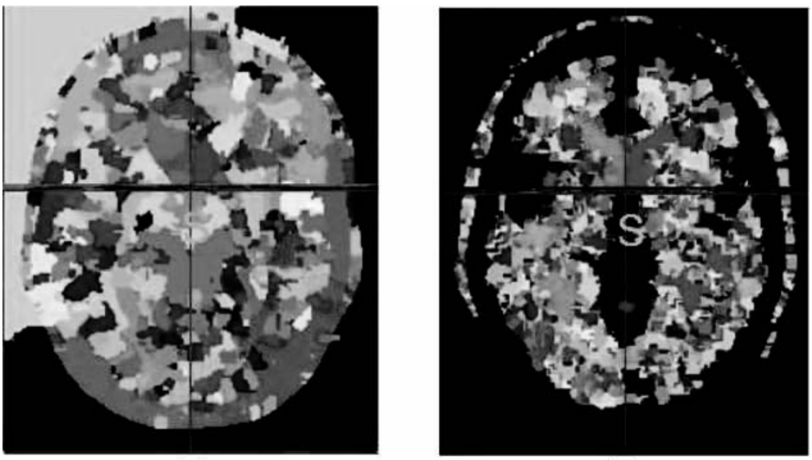


Fig. 4. (Left) A brain image. (Right) The resample image (with resample sample rate 0.8 in every dimension)·

Three comparisons to demonstrate the effect of every step of our method was conducted. Fig. 5 indicates that when the threshold operation is

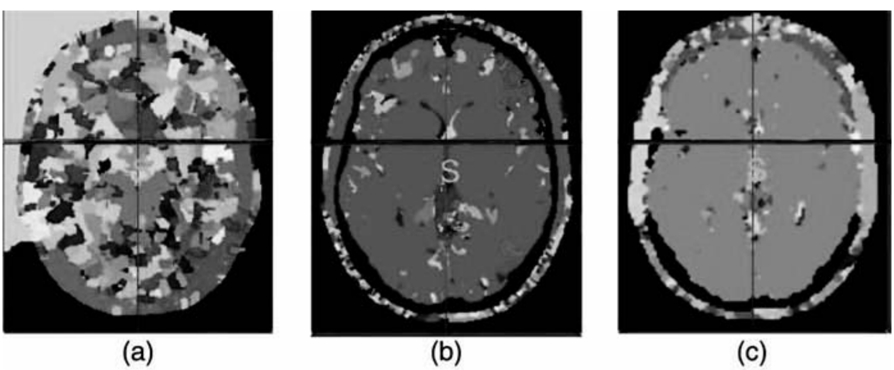
[1] http://www.bic.mni.mcgill.ca/brainweb/

applied (Fig. 5(b)) at first, the regions out of the brain are resolved into background. Fig.6 shows the results of the watershed transform applied to original image (a), reslice (b) and resample (c) images, respectively. The amount of the watershed regions is decreased apparently. From Fig. 5, we also found that some part of the ROI is merged to background unexpectedly. This is often caused by connections between the ROI and the surrounding structures. For better results, the morphological opening operation was employed to deal with this problem by breaking the connections.



(a) (b)

Fig. 5. Comparison between the normal Watershed and the Watershed on the threshold image (a) Normal Watershed (b) Watershed with threshold operation.



(a) (b) (c)

Fig. 6. The results of the watershed transform applied to original image (a), reslice (b) and resample (c) images, respectively.

The comparison reveals that proposed approach can significantly resist the over-segmentation problem. The average amount of watershed regions in ROI is described as Table 1:

- Classical watershed generated 244 regions (Fig. 6(a)) of ROI;
- Watershed using reslice image generated 84 regions (Fig. 6(b)) of ROI;
- Watershed using reslice and resample image generated 32 regions (Fig. 6(c)) of ROI.

The efficiency of the proposed method has also been evaluated with the classical one. The proposed watershed cost 95s to process the brain data, when the classical Watershed required 90s.

Table 1. Comparison between the traditional watershed and our method in generated areas and time consuming.

	Generated regions of ROI	Time consuming
Traditional Watershed (Fig. 6(a))	244	90s
Watershed using reslice image (Fig. 6(b))	84	95s
Watershed using reslice and resample image (Fig. 6(c))	32	95s

4 Conclusion

In this paper, an improved watershed method using reslice and resample image was proposed. The reslice operation significantly decreased the amount of the watershed regions in ROI to 34%. And resample operation can further decrease this amount to 38%. It means that the over-segmentation problem was resisted efficiently. But the computing cost has not been improved. To save the cost, it is recommended to implement the method with parallel strategy in the future.

References

[1] J.B.T.M. Roerdink, A. Meijster, "The Watershed Transform:Definitions, Algorithms and Parallelization Strategies", Fundamenta Informaticae, vol. 41, pp.187-228, 2000.

[2] Kari Saarinen, "Color Image Segmentation By A Watershed Algorithm And Region Adjacency Graph Processing", IEEE International Conference Image Processing, Proceedings, ICIP-94, pp.1021-1025, 1994.

[3] L.Shafarenko, M.Petrou, J.Kittler, "Histogram-Based Segmentation in a Perceptually Uniform Color Space", IEEE Transactions On Image Processing, vol. 7. No.9, 1998.

[4] Luc Vincent, Pierre Soille, "Watersheds in Digital Spaces: An Efficient Algorithm Based on Immersion Simulations", IEEE Transactions On Pattern Analysis And Machine Intelligence, vol. 13, No.6, 1991.

[5] R.K.S. Kwan, A.C. Evans, G.B. Pike, "MRI simulation-based evaluation of image processing and classification methods", IEEE Trans. Med. Imag., vol.18-11, pp.1085-1097, Nov. 1999.

[6] S.Beucher, F.Meyer, "The morphological approach to segmentation: The watershed transformation", Mathematical Morphology in Image Processing, New York, pp. 443-481, 1993.

[7] V.Grau, A.U.J. Mewes, M. Alcaniz, "Improved Watershed Transform for Medical Image Segmentation Using Prior Information", IEEE Transactions On Medical Imaging, vol. 23, No. 4, 2004.

[8] Zhao Jianwei, Wang Peng, Liu Chongqing, "Watershed Image Segmentation Based on Wavelet Transform", Acta Photonica Sinica vol. 32, No. 5, China, 2003.