

Automatic Aorta and Heart Segmentation in Cardiac CTA using Hough Transform and Edge Map

Ho Chul Kang

School of Computer Science and Engineering, Sung Kong Hoe University,
08359 Seoul, Korea

Abstract: In this study, we propose an automatic segmentation method of aorta and heart in Computed Tomography Angiography (CTA) using Hough transform and edge map. First, we smooth the images by applying anisotropic diffusion filter to remove noise. Second, the Volume of Interest (VOI) is detected by using k-means clustering and edge map. Third, we detect the beginning of aorta using Hough transform. Finally, we extract the left and right heart with separating energy function which we proposed to split the heart. We tested our method in ten CT images and they were obtained from a different patient.

Key words: Image segmentation, heart segmentation, aorta segmentation, hough transform, edge map, CTA

INTRODUCTION

Image segmentation (Gonzalez and Woods, 2007; Yoo, 2016a, b; Gantuya *et al.*, 2015) is to detect specific region or divide areas in the image. In the field of medicine, it is necessary to detect some organs or tumors from medical images. Computed Tomography (CT) is an imaging procedure that uses X-ray technology to produce tomographic images of specific object. To produce CT volume of data, the patient is placed into a tube. This tube emits X-rays toward the center of the cylinder. The X-rays pass through the body and the intensity is measured on the other side. Then a reconstruction work is done to actually obtain a 3D image. CT distinguishes bones better than organic tissues. The muscle and the cavities of the specific organ are not well differentiated both appearing on close gray tones on the CT scan. CTA, CT angiography and one of medical images which have the information of the heart is widely used in image segmentation (Barandiaran *et al.*, 2009) because it provides more detailed anatomic information about the organ. The disorders of the heart of blood vessels often cause cardiovascular diseases (Anonymous, 2003) and heart segmentation from CTA has been used for cardiac diagnosis. Several approaches for the automatic heart segmentation have been proposed. Rousseau and Bourgault (2008) presented a heart segmentation method using an iterative Chan-Vese algorithm (Chan and Vese, 2001). They used L1 fidelity term for the computational efficiency instead of L2 fidelity which is classic term. However, this approach extracted only the whole heart. Ecabert *et al.* (2008) proposed automatic segmentation of four chambers by using statistical geometry model and

training meshes from cardiac CTA images. This method required well-defined training data sets, too much time and effort to generate a template mesh. In this study, we propose an automatic method to extract the aorta and heart region in CTA using Hough transform (Illingworth and Kittler, 1987) and edge map (Yoo, 2016a, b) which we develop without any training data sets and template meshes.

MATERIALS AND METHODS

Data sets: About 10 data sets of CTA are examined in this study. The numbers of images per scan ranged from 192-227. Each image had a matrix size of 512×512. The voxel size was 0.36.

Smoothing images: First, we smooth the input CTA. In general there is much noise in the cardiac CTA and it would not be vivid. So, image smoothing is essential to segment heart region. We use anisotropic diffusion filtering (Rudin *et al.*, 1992) which minimize Total Variation (TV) to preserve the edge while smoothing the original image and preserves finer detailed structures in images. The equation of anisotropic diffusion filter is as:

$$\min TV = \int_{\Omega} \sqrt{u_x^2 + u_y^2} dx dy \quad (1)$$

Where:

u = An image

u_x and u_y = The derivative of u w.r.t. x and y , respectively

To discretize and optimize this equation, Getreuer (2012) proposed a method to minimize using

gradient descent PDE. Through calculus of variations, the gradient descent PDE of the minimization is as:

$$\begin{aligned} \partial_t u &= \operatorname{div} \frac{\nabla u}{|\nabla u|} + \lambda (f - u) \\ \mathbf{v} \times \nabla u &= 0 \quad \text{on } \partial\Omega \end{aligned} \quad (2)$$

Since, this equation is convex, the steady state solution of the gradient descent is the global optimum. And gradient descent is performed by iterating (Eq. 3):

$$\begin{aligned} u_{i,j}^{n+1} &= u_{i,j}^n + dt \left[\nabla_x^- \left(\frac{\nabla_x^+ u_{i,j}^n}{\sqrt{(\nabla_x^+ u_{i,j}^n)^2 + (m(\nabla_y^+ u_{i,j}^n, \nabla_y^- u_{i,j}^n))^2}} \right) + \right. \\ &\quad \left. \nabla_y^- \left(\frac{\nabla_y^+ u_{i,j}^n}{\sqrt{(\nabla_y^+ u_{i,j}^n)^2 + (m(\nabla_x^+ u_{i,j}^n, \nabla_x^- u_{i,j}^n))^2}} \right) \right] + \\ &\quad dt \lambda (f_{i,j} - u_{i,j}^n), \quad i, j = 1, \dots, N-1 \end{aligned} \quad (3)$$

Extracting the whole heart: This step extracts the whole heart including the left and right heart region using thresholding, edge map (Yoo, 2016a, b) and k-means clustering (Kanungo *et al.*, 2002). And we expand the heart region by comparing the mean CT value of each cluster. So, the clusters are removed as cardiac muscles and the other clusters are merged. To extract the heart region exactly we use the edge map which has the information about the intensity difference between chambers (Fig. 1 and 2).

Detecting the aorta: To extract the heart region more exactly we detect the beginning of the aorta and remove upper region of the aorta using Hough transform (Illingworth and Kittler, 1987). Hough transform is a feature extraction method for detecting lines and circles. The purpose of this method is to find several circles in an image. The circle candidates are proposed by voting in the parameter space. The circle equation is as:

$$(x-a)^2 + (y-b)^2 = r^2 \quad (4)$$

where, a, b is the position of the center of the circle. To calculate this center we use the Hough parameters equation and find the position (a, b) using accumulator matrix:

$$\begin{aligned} a &= x - r \cos \theta \\ b &= y - r \sin \theta \end{aligned} \quad (5)$$

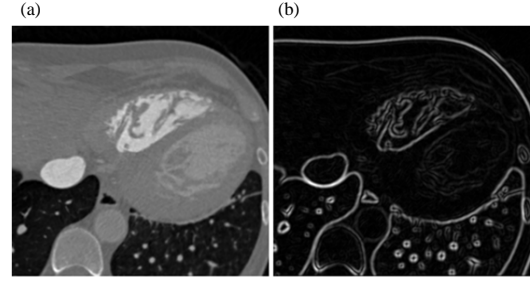


Fig. 1: The edge map of the heart: a) The input image and the edge map which has the information about the intensity difference between left ventricle and b) Right ventricle

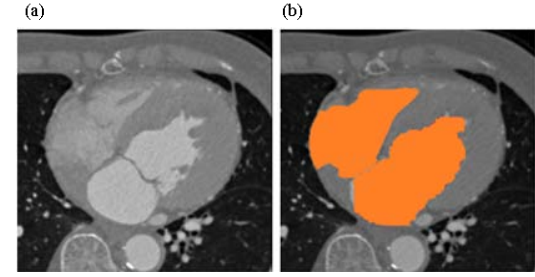


Fig. 2: The result of the whole heart extraction: a) The input image and b) The result of segmentation

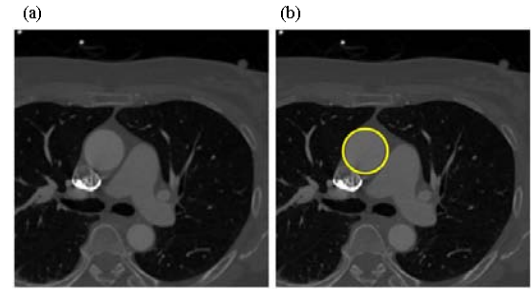


Fig. 3: The result of the aorta detection using hough transform: a) The input image and the result of segmentation and b) yellow circle is the aorta

The result of the aorta detection is in Fig. 3. We remove upper region of this aorta in heart region from previous step and we obtain more precise region.

Separating the left and right heart from the whole heart: In this step, we split the heart into the left and the right heart from the clustered mask volume, the output of the previous extracting the heart region step. It is hard to divide the heart into the left and the right heart

automatically because there is ambiguity in the boundaries or difference between them. So, we minimize the separating energy function for splitting the heart into the left and right heart. We propose the separating energy function as:

$$E = \alpha \times \text{Area energy} + \beta \times \text{Intensity energy} \quad (6)$$

where, α and β is weights of the area energy and intensity energy, respectively the area energy is the area of intersection with the separating plane and heart region and the intensity energy is the bright value of the intersection plane:

$$\text{Area energy} = \int_{\Omega_M} H(\text{mask}(x)) dx \quad (7)$$

$$\text{where } H(t) = \begin{cases} 1, & t \neq 0 \\ 0, & \text{otherwise} \end{cases}$$

Where:

$\text{mask}(x)$ = The function of mask function from the heart extraction

$H(t)$ = The binary function w.r.t t value

$$\text{Intensity energy} = \text{The mean value of bright values in the heart region} \quad (8)$$

To split the heart into left and right heart, we minimize the separating energy function E . We obtain the minimum by calculating using Powell's method (Powell, 1964) iteratively.

RESULTS AND DISCUSSION

We tested our method using the system which has the Intel® Core™2 Quad 3.4 GHz processor, 16 GB of main memory and Windows 10. We extract the left and right heart from ten CT images and they were obtained from a different patient. The numbers of images per scan ranged from 192-227. Each image had a matrix size of 512×512 . The voxel size was 0.36. Figure 3 shows the result of the left and right heart segmentation and Table 1 shows the computational time for each step. For the evaluation of the computational performance of the proposed method we measured the total processing time. The average of total processing time from first step to third step was 14.5 ± 1.63 sec. In Fig. 4, the area of blue is the region of right heart, and the area of red is the region of left heart. In addition, we extract an iso-surface from the result of the segmentation and rendered it.

It is difficult to segment the heart because the chambers of the heart have weak edge or no edge. This

Table 1: Computational time for each segmentation step (sec)

	Smoothing	Extracting	Detecting	Separating	
Data	image	heart	aorta	heart	Total
1	5.3	1.6	0.7	5.3	12.9
2	6.1	1.9	0.9	5.7	14.6
3	5.4	1.3	0.7	5.2	12.6
4	7.0	2.0	0.8	6.5	16.3
5	5.8	1.5	0.6	6.1	14.0
6	7.1	2.5	1.6	6.2	17.4
7	5.0	1.9	0.7	5.5	13.1
8	6.2	1.8	0.7	5.7	14.4
9	6.8	2.3	0.9	6.2	16.2
10	5.9	1.2	0.5	5.9	13.5

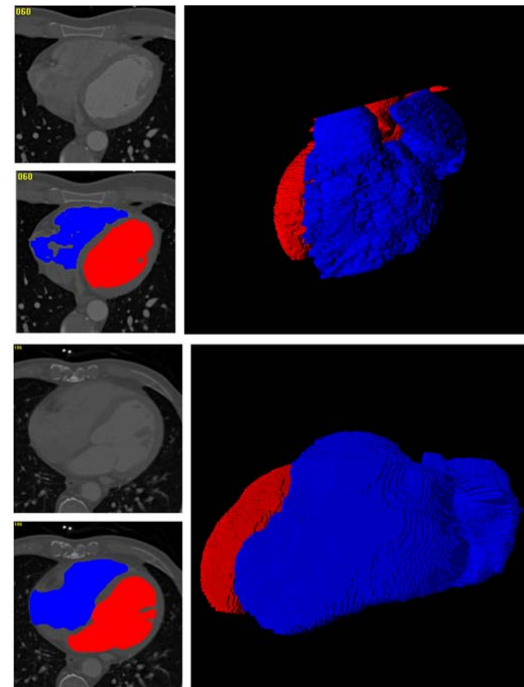


Fig. 4: The result of the left and right heart segmentation. The input image (left top), the result of segmentation (left bottom) and the iso-surface extraction (right)

study presented a segmentation method of the left and right heart region using k-means clustering and separating energy function. This method is expected to be used in cardiac diagnosis.

CONCLUSION

For the evaluation of the computational performance of the proposed method we measured the total processing time. The average of total processing time from first step to third step was 14.5 ± 1.63 sec. We expect for our method to be used in cardiac diagnosis for cardiologist.

ACKNOWLEDGEMENTS

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT and Future Planning (NRF-2017R1C1B5017738) in 2017.

REFERENCES

- Anonymous, 2003. The world health report: Report of the director-general. World Health Organization, Geneva, Switzerland.
- Barandiaran, I., I. Macia, E. Berckmann, D. Wald and M.P. Dupillier *et al.*, 2009. An Automatic Segmentation and Reconstruction of Mandibular Structures from CT-Data. In: Intelligent Data Engineering and Automated Learning, Corchado, E. and H. Yin (Eds.). Springer, Berlin, Germany, pp: 649-655.
- Chan, T.F. and L.A. Vese, 2001. Active contours without edges. *IEEE Trans. Image Process.*, 10: 266-277.
- Ecabert, O., J. Peters, H. Schramm, C. Lorenz and J.V. Berg *et al.*, 2008. Automatic model-based segmentation of the heart in CT images. *IEEE. Trans. Med. Imaging*, 27: 1189-1201.
- Gantuya, P., B. Mungunshagai and B. Suvdaa, 2015. Mongolian traditional stamp recognition using scalable KNN. *Intl. J. Adv. Smart Convergence*, 4: 170-176.
- Getreuer, P., 2012. Rudin-Osher-Fatemi total variation denoising using split Bregman. *Image Process. Line*, 2: 74-95.
- Gonzalez, R.C. and R.E. Woods, 2007. Digital Image Processing. 3rd Edn., Prentice Hall, New York, USA.
- Illingworth, J. and J. Kittler, 1987. The adaptive hough transform. *IEEE. Trans. Pattern Anal. Mach. Intell.*, 5: 690-698.
- Kanungo, T., D.M. Mount, N.S. Netanyahu, C.D. Piatko and R. Silverman *et al.*, 2002. An efficient K-means clustering algorithm: Analysis and implementation. *IEEE. Trans. Pattern Anal. Machine Intell.*, 24: 881-892.
- Powell, M.J.D., 1964. An efficient method for finding the minimum of a function of several variables without calculating derivatives. *Comput. J.*, 7: 155-162.
- Rousseau, O. and Y. Bourgault, 2008. Heart segmentation with an iterative Chan-Vese algorithm. University of Ottawa, Ottawa, Ontario. <https://hal.archives-ouvertes.fr/hal-00403627/>
- Rudin, L.I., S. Osher and E. Fatemi, 1992. Nonlinear total variation based noise removal algorithms. *Physica D Nonlinear Phenomena*, 60: 259-268.
- Yoo, S.W., 2016a. Adaptive thinning algorithm for external boundary extraction. *Intl. J. Adv. Culture Technol.*, 4: 75-80.
- Yoo, S.W., 2016b. Digital image enhancement algorithm. *Intl. J. Adv. Culture Technol.*, 4: 48-55.