Diagnostic Accuracy Study

Medicine

OPEN

Improving segmentation accuracy of CT kidney cancer images using adaptive active contour model

Wei-Yen Hsu, PhD[a,b,c,*], Chih-Cheng Lu, MD[a,d], Yuan-Yu Hsu[a]

Abstract

In the present study, we retrospectively analyzed the records of surgical confirmed kidney cancer with renal cell carcinoma pathology in the database of the hospital. We evaluated the significance of cancer size by assessing the outcomes of proposed adaptive active contour model (ACM). The aim of our study was to develop an adaptive ACM method to measure the radiological size of kidney cancer on computed tomography in the hospital patients. This paper proposed a set of medical image processing, applying images provided by the hospital and select the more obvious cases by the doctors, after the first treatment to remove noise image, and the kidney cancer contour would be circled by using the proposed adaptive ACM method. The results showed that the experimental outcome has highly similarity with the medical professional manual contour. The accuracy rate is higher than 99%. We have developed a novel adaptive ACM approach that well combines a knowledge-based system to contour the kidney cancer size in computed tomography imaging to support the clinical decision.

Abbreviations: ACC = accuracy, ACM = active contour model, AJCC = American Joint Commission on Cancer, CT = computed tomography, FN = false negative, FP = false positive, RCC = renal cell carcinoma, TN = true negative, TP = true positive.

Keywords: active contour model, image segmentation, kidney cancers

1. Introduction

Kidney cancers account for 3% of all malignancies.[1] Most of them are sporadic and detected incidentally.[1] computed tomography (CT) imaging is considered as the better choice to detect the kidney cancer.[1,2] The size of renal cancer has critical role in planning for treatment.[3–5] Cancer size is determined to be one of the predicting factor for surviving.[6,7] However, discrepancy between radiological and pathological size of kidney cancer is noted.[8,9] Kidney cancer, which is the third most common urologic tumor,[1] with roughly 20% to 30% of quiet. After surgical resection, kidney cancer patients should be follow-up closely for survival. Now the most valuable determinant of kidney cancer classification is the tumor, lymph node, and metastasis organizing framework,[6] which gives basic data for cancer staging and prognosis.[10–12] The most recent American Joint Commission on Cancer (AJCC) 2017 tumor, lymph node, and metastasis framework, pathologic arrange T1 and T2 kidney cancers are classified depending exclusively on tumor estimate (<7 cm for T1 and >7 cm for T2). While many pathological types of kidney cancer were noted, the most common type of kidney cancer was renal cell carcinoma (RCC).[6]

Since the development of active contour models (ACM, a.k.a. snakes) in 1988,[13,14] they have been applied to many fields of imaging analysis.[15,16] In clinical imaging, ACM has been selected for analyzing hepatic[17] and lung[18] lesions. In studying renal lesions, ACM has been applied for renal traumatic staging in 2018.[19–21] No specific kidney cancer calculation on the tumor size from CT imaging was easily obtained from the CT imaging. Since the size of the tumor is important for planning of cancer treatment, preoperative imaging planning is important for good patient care.

In the present study, we retrospectively analyzed the records of surgical confirmed kidney cancer with RCC cancer pathology in the database of the hospital. We evaluated the significance of cancer size by assessing the outcomes of proposed ACM methods. The aim of our study was to develop an adaptive ACM method to measure the radiological size of kidney cancer on CT in the hospital patients.

2. Materials and methods

2.1. CT imaging collection

A retrospective chart review of confirmed kidney cancers in the hospital was performed. Inclusion criteria: abdominal CT with/

Editor: Chao Mao.

The authors have no funding and conflicts of interest to disclose.

The datasets generated during and/or analyzed during the current study are not publicly available, but are available from the corresponding author on reasonable request.

[a] Department of Information Management, [b] Advanced Institute of Manufacturing with High-Tech Innovations, [c] Center for Innovative Research on Aging Society, National Chung Cheng University, Chiayi, [d] Division of Urology, Department of Surgery, Chi Mei Medical Center, Liouying, Tainan, Taiwan.

[*] Correspondence: Wei-Yen Hsu, National Chung Cheng University, Chiayi County 621, Taiwan (e-mail: shenswy@gmail.com).

How to cite this article: Hsu W-Y, Lu C-C, Hsu Y-Y. Improving segmentation accuracy of CT kidney cancer images using adaptive active contour model. Medicine 2020;99:47(e23083).

Received: 11 June 2020 / Received in final form: 8 October 2020 / Accepted: 13 October 2020

http://dx.doi.org/10.1097/MD.0000000000023083

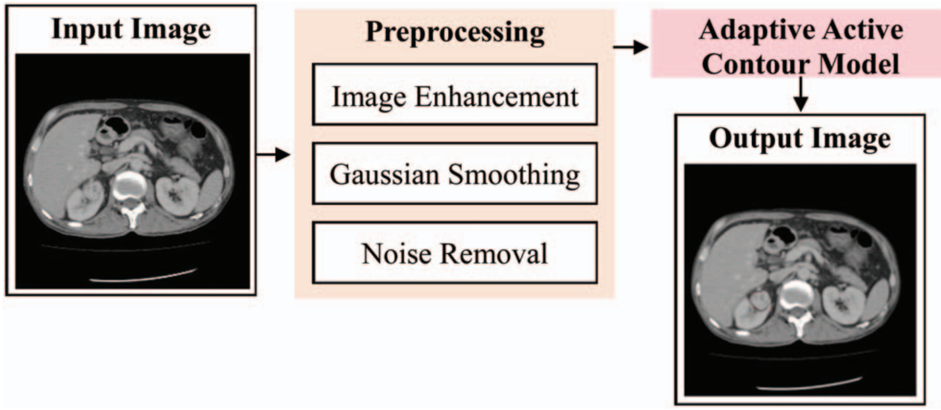

Figure 1. Flow chart of computed tomography imaging segmentation and analysis.

without contrast showed kidney tumor and pathological confirmation of RCC from radical surgery or biopsy. Exclusion criteria: kidney cancer without pathology report or surgery. The segmentation from sectional cuts of abdominal CT imaging (64-slice, 0.5 mm) before surgical treatment was obtained.

Radiological tumor size was defined as from the smallest to largest transverse diameter in the axial plane on the CT imaging. Each section of tumor site, the region of interest, was circled and reported by the urologist and radiologist as ground truth. The ground truth was not revealed until the present adaptive ACM outcome for comparison.

2.2. Preprocessing

The noise signals were managed first. As CT imaging produces a little noise, in order to avoid the division of the error occurred when the need to remove the noise. Compared to other fuzzy filters, the Gaussian smoothing combined with bilateral filter can effectively smooth the image while maintaining the edge of the image to some extent. In addition, in order to enhance the edge of images, image enhancement is performed to further sharp the edge of images to aid the edge detection prior to ACM.

2.3. ACM

Further adaptive ACM was present. There were 2 major steps. Step 1: Create an initial curve in the image manually, the shape of the informal, but the need to target the outline o"f the object wrapped in the inside. Step 2: Establish the "energy equation (E)" internal energy to standardize the curve shape "elastic energy (α)" and ensure the smooth continuous "bending energy (β)" of the curve and the "outside" of the gauge curve close to the target object contour Energy (γ). In the process of operation, minimizing the internal energy can make the curve to the internal tightening and smooth; and minimize the external energy can make the curve close to the target object contour. The formula was listed as follow:

$$\mathrm{E} = \int_0^1 \left\{ \alpha(s)\left|\frac{\partial}{\partial s}\upsilon(s)\right| + \beta(s)\left|\frac{\partial^2}{\partial s^2}\upsilon(s)\right| + \gamma \right\} ds \qquad (1)$$

The working flow chart is shown in detail in Figure 1.

2.4. Analysis

For further interpretation of the accuracy (ACC), compared the output imaging with the ground truth data. The focused kidney cancer in the CT imaging (5 mm separation) was collected. Each segmentation of the cancer region was the region of interest. Each segmented CT imaging after further adaptive ACM analysis was compared with the ground truth data. The metrics of sensitivity, specificity, and ACC were calculated as:

Sensitivity = true positive (TP)/(TP + false negative (FN))
Specificity = true negative (TN)/(TN + false positive (FP))
ACC = (TP + TN)/(TP + TN + FP + FN)
Recall = TP/(TP + FN)
Precision = TP/(TP + FP)
F1 = 2TP/(2TP + FN + FP) = 2*Precision*Recall/(Precision + Recall)

2.5. Ethical approval

The protocol was approved by the Ethics Committee of the institutional review board of the hospital. (IRB serial No: 10603-L04)

3. Results

A total 277 files of CT imaging from 10 patients with kidney cancers were collected for analysis. The demographic data was shown as Table 1. There were 5 male and 5 female patients with mean age 47.3 years (ranged from 39 to 68 years). Six were left side kidney cancer and 4 were right side. Cancer pathology was documented clear cell carcinoma (RCC). The estimated largest diameter of the kidney cancer in CT imaging report ranged from 2.5 to 14.4 cm (mean 7.2 cm). The measurement of cancer size by the pathology with the largest diameter ranged from 2.3 to 19 cm (mean 6.8 cm). Adaptive ACM was applied to each segmentation of CT imaging of kidney cancer.

The sample results were shown in Table 2, Table 3 and Figure 2. Each file in Tables 2 and 3 represented 1 CT segmentation. The performance matrices, including TP, FN, FP, TN, ACC, Recall, Precision, and F1 are estimated between the results of Ground truth and adaptive ACM Method. They are used to measure the performance. The experimental results of

Table 1

Demographic data of clinical cases with kidney cancers.

Gender	Age (yr)	Diagnosis	Side	Largest diameter in CT (cm)	Largest diameter from Pathology (cm)	CT files
Male	42	RCC	right	2.5	2.5	20
Male	40	RCC	right	14.4	19	31
Male	54	RCC	left	5.4	4.8	20
Male	39	RCC	left	8.8	7.8	51
Male	55	RCC	right	3.7	2.3	23
Female	68	RCC	left	5.1	4.7	18
Female	50	RCC	left	7.4	7.5	32
Female	43	RCC	left	3.8	3.8	18
Female	40	RCC	right	10.7	9	46
Female	42	RCC	left	5.7	5.4	18

CT = computed tomography, RCC = renal cell carcinoma.

the proposed method (the blue area in Fig. 2) were compared with the tumor area manually selected by the doctor (the hollow red line in Fig. 2). More specifically, the ground truth was circled by urologists (including Dr Chih-Cheng Lu), and they were also measured by the same doctors after adaptive ACM. According to the experimental results, the results of this research method were very similar to the size and shape of the cancer judgment made by the doctor, and the semi-automatic operation of adaptive ACM was adopted. The ACC rate was higher than 99%. When the image interpretation was performed, it was proposed to be used as a second opinion to help the doctors in diagnosis and evaluation.

4. Discussion

This paper proposes an innovative region-based adaptive ACM for image segmentation by semi-automatic function to improve local kidney cancer CT imaging. CT images have been used as a tool of chose and focused on the cancer region. The main contribution of this paper is the formulation of a new energy functional from adaptive ACM models for kidney oncological planning for patient care. Qualitative and quantitative analysis showed that the proposed method produced comparable segmentation results and correction of homogeneous regions for supporting professional work.

The semi-automatic kidney segmentation is particularly innovative by other organs such as liver, brain or lungs. Although many methods have been proposed for the accurate lung, brain, and liver segmentation, sparse algorithms functioned well for the kidney were noted. Only kidney trauma adaptive ACM was noted.[19]

We have developed a novel adaptive ACM approach that combines a knowledge-based system for contouring the kidney cancer size in CT imaging. Visual inspection of the preliminary results suggests that the performance of the algorithm is comparable to that of ground truth by the clinical doctors contouring methods. In the diagnosis and staging of cancer size, the adaptive ACM is supporting and feasible for the clinical situation. It may provide a feasible supporting method for the doctors to evaluate the 2 dimensional size for the cancer area and further critical to surgical planning.

For kidney pre-segmentation of CT imaging by ACM has been studied.[22] The prognosis of the cancer patient depends on multiple tumor parameters, and size is only 1 consideration. The present study explores the possible role of adaptive ACM in detecting cancer in the kidney. It is more practical than normal

Table 2

Distribution of prediction of region of interest.

	TP	FN	FP	TN	ACC
FILE0			No tumor		
FILE1	1093	522	31	117454	99.53%
FILE2	1622	509	53	115697	99.41%
FILE3	1839	560	17	114303	99.50%
FILE4	1457	700	15	113470	99.38%
FILE5	1684	301	133	112497	99.62%
FILE6	976	503	16	112117	99.54%
FILE7			No tumor		
FILE8	840	594	0	117817	99.50%
FILE9	1488	506	27	116192	99.54%
FILE10	1587	656	1	114997	99.44%
FILE11	1899	437	151	113827	99.49%
FILE12	1500	449	73	113393	99.54%
FILE13	1238	625	37	112638	99.42%
Average	1435.25	530.16	46.16	114533.5	99.49%

ACC = accuracy, FN = false negative rate, FP = false positive rate, TN = true negative rate, TP = true positive rate.

Table 3

Distribution of prediction of region of interest (continued).

	Precision	Recall	F1
FILE0			
FILE1	97.24%	67.68%	79.81%
FILE2	96.84%	76.11%	85.23%
FILE3	99.08%	76.66%	86.44%
FILE4	98.98%	67.55%	80.30%
FILE5	92.68%	84.84%	88.58%
FILE6	98.39%	65.99%	79.00%
FILE7			
FILE8	100.00%	58.58%	73.88%
FILE9	98.22%	74.62%	84.81%
FILE10	99.94%	70.75%	82.85%
FILE11	92.63%	81.29%	86.59%
FILE12	95.36%	76.96%	85.18%
FILE13	97.10%	66.45%	78.90%
Average	97.20%	72.29%	82.63%

imaging segmentation[22] in cancer treatment fields. The innovative methods of adaptive ACM of our study is not going to replace the present staging system of kidney cancers based on AJCC system. Medicine is a changing science. Besides AJCC system, other staging improving scoring or quality assuring methods for the kidney cancer are undergoing.[23] Our methods may provide a linchpin of further machine learning of kidney cancer staging which is critical for treatment planning in the future.

Some limitations the adaptive ACM methods were noted in the study. First, it was a retrospective imaging comparison, not a prospective method. A prospective randomized study is further encouraging in the future. Second, Clinical imaging may have difficulty for caner size measurement when cancer metastases to adjacent organs. Although the kidney is surrounded by adipose tissue which is a good contrast to the cancer, advanced stage of the cancer still a challenge to contour the cancer margin. Third, it was a 2 dimensional method. Three dimensional imaging contour method will be better for clinical usefulness professionally. Further a larger scale study is required to determine whether the proposed algorithm is indeed capable of providing consistently superior segmentation.

We have proposed a novel kidney contour extraction algorithm capable of detecting kidney cancers. The algorithm is based on the adaptive ACM model to detect cancer region after eliminate FPs through noise points detection. It is promising that our proposed method enhances the ACC of kidney segmentation and can assist doctors in the interpretation of CT images, particularly for kidney cancer related analysis.

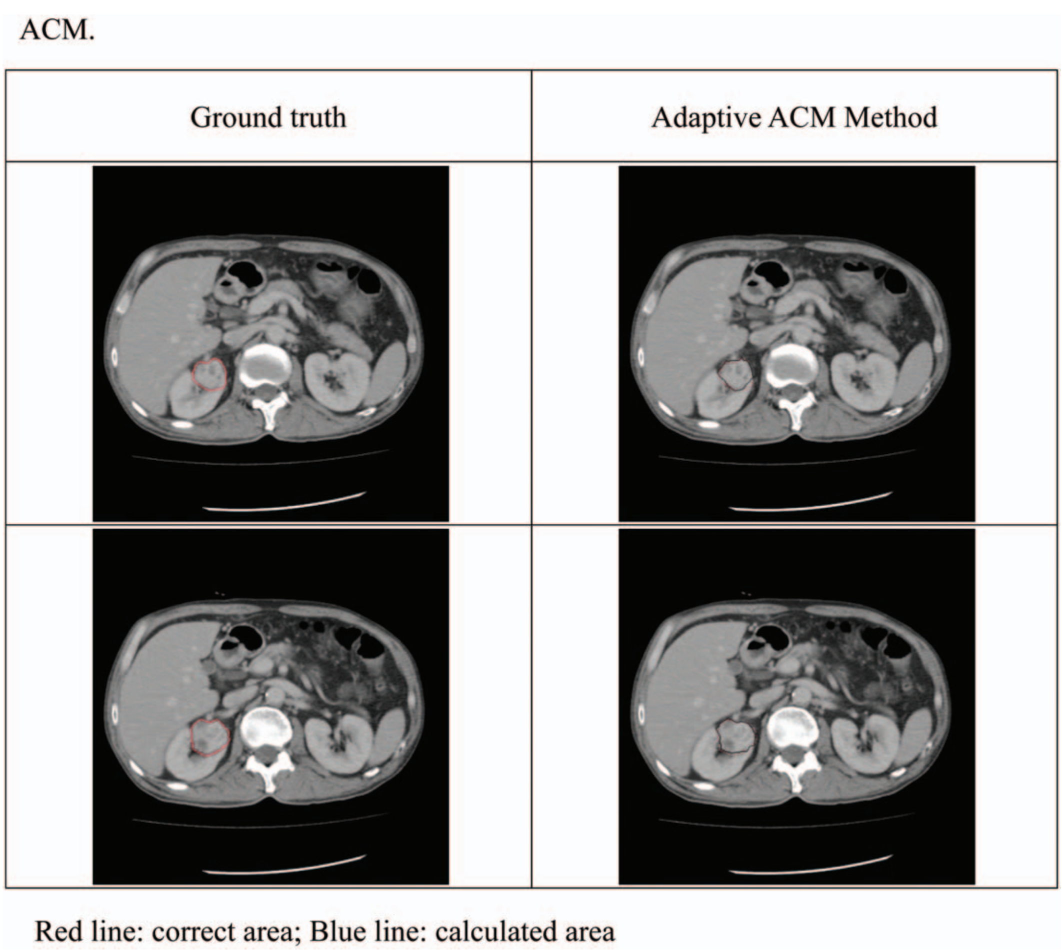

Figure 2. Tumor contour by computed tomography. Left side is ground truth, and right side from adaptive active contour model.

Acknowledgment

The authors would like to thank for grant (Prof Wei-Yen Hsu) partially from MOST105-2410-H-194-059-MY3 and MOST108-2410-H-194-088-MY3, Ministry of Science and Technology, Taiwan.

Author contributions

Conceptualization: Wei-Yen Hsu.
Data curation: Chih-Cheng Lu.
Formal analysis: Yuan-Yu Hsu, Chih-Cheng Lu.
Funding acquisition: Wei-Yen Hsu.
Investigation: Wei-Yen Hsu.
Methodology: Wei-Yen Hsu.
Project administration: Wei-Yen Hsu.
Resources: Wei-Yen Hsu.
Software: Yuan-Yu Hsu.
Supervision: Wei-Yen Hsu.
Validation: Yuan-Yu Hsu.
Visualization: Yuan-Yu Hsu.
Writing – original draft: Chih-Cheng Lu, Yuan-Yu Hsu.
Writing – review & editing: Wei-Yen Hsu.

References

[1] Amin MB, Edge S, Greene F, Byrd DR, et al. AJCC Cancer Staging Manual. 8th ed. Springer International Publishing: American Joint Commission on Cancer:2017;740–744.
[2] Wein A, Kavoussi L, Partin A, Peters C. Malignant renal tumors. Campbell-Walsh Urology 11th ed. Philadelphia, PA: Elsevier; 2016.
[3] Hsu WY. Automatic left ventricle recognition, segmentation and tracking in cardiac ultrasound image sequences. IEEE Access 2019;7:140524–33.
[4] Hsu WY. A customer-oriented skin detection and care system in telemedicine applications. Electron Libr 2019;37:1007–21.
[5] Hsu WY. A decision-making mechanism for assessing risk factor significance in cardiovascular diseases. Decis Support Syst 2018;115: 64–77.
[6] Seçil M, Çullu N, Aslan G, et al. The effect of tumor volume on survival in patients with renal cell carcinoma. Diagn Interv Radiol 2012;18:480–7.
[7] Hsu WY. Automatic atrium contour tracking in ultrasound imaging. Integr Comput Aided Eng 2016;23:401–11.
[8] Hsu WY. A hybrid approach for brain image registration with local constraints. Integr Comput Aided Eng 2017;24:73–85.
[9] Jeffery NN, Douek N, Guo DY, et al. Discrepancy between radiological and pathological size of renal masses. BMC Urol 2011;11:1–9.
[10] Hsu WY. Enhancing the performance of motor imagery EEG classification using phase features. Clin EEG Neurosci 2015;46:113–8.
[11] Hsu WY. Assembling a multi-feature EEG Classifier for left-right motor data using wavelet-based fuzzy approximate entropy for improved accuracy. Int J Neural Syst 2015;25:1550037.
[12] Hsu WY. EEG-based motor imagery classification using neuro-fuzzy prediction and wavelet fractal features. J Neurosci Methods 2010; 189:295–302.
[13] Kass M, Witkin A, Terzopoulos D. Snakes: active contour models. Int J Comput Vision 1988;l:321–31.
[14] Maksimovic R, Stankovic S, Milovanovic D, et al. Computed tomography image analyzer: segmentation applying active contour models—“snakes”. Stud Health Technol Inform 1999;68:395–9.
[15] Hsu WY. Continuous EEG signal analysis for asynchronous BCI application. Int J Neural Syst 2011;21:335–50.
[16] Hsu WY. Clustering-based compression connected to cloud databases in telemedicine and long-term care applications. Telemat Inform 2017; 34:299–310.
[17] Esfandiarkhani M, Foruzan AH. A generalized active shape model for segmentation of liver in low-contrast CT volumes. Comput Biol Med 2017;82:59–70.
[18] Alilou M, Beig N, Orooji M, et al. An integrated segmentation and shape-based classification scheme for distinguishing adenocarcinomas from granulomas on lung CT. Med Phys 2017;44:3556–69.
[19] Farzaneh N, Reza Soroushmehr SM, Patel H, et al. Automated kidney segmentation for traumatic injured patients through ensemble learning and active contour modeling. Conf Proc IEEE Eng Med Biol Soc 2018;3418–21.
[20] Hsu WY. Improving the classification accuracy of motor imagery EEG using a genetic feature selection method. Clin EEG Neurosci 2014; 45:163–8.
[21] Hsu WY, Sun YN. EEG-based motor imagery analysis using weighted wavelet transform features. J Neurosci Methods 2009;167:310–8.
[22] Zhang P, Liang Y, Chang S, et al. Kidney segmentation in CT sequences using graph cuts based active contours model and contextual continuity. Med Phys 2013;40:081905.
[23] Hou X, Li M, He W, et al. Quality assessment of kidney cancer clinical practice guidelines using AGREE II instrument: a critical review. Medicine (Baltimore) 2019;98:e17132.