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Abstract

Image Segmentation is an important process as it used to subdivide the different objects in an image to extract the Region of Interest (ROI). The objective of this research paper is to segment the left and right kidney regions from the abdominal Computed Tomography (CT) images and to extract its features. The first step is to apply the median filter for removing noise from the abdominal input image slices. For manual segmentation, contour points are selected for left and right kidney regions manually to extract the kidney regions. For automated segmentation, kidneys are extracted using the variation in pixel intensities between the region of interest and the background image. Then contour is initialized within the masked boundary region. The contour is growing by grouping the similar intensity pixels, and this process is repeated number of times for better segmentation. The computation time of manual and automated segmentation are compared. Automated segmentation produces better performance improvement over manual segmentation. Also, the computation time performance of proposed Active Contour with double mask method is improved 50% more than the Principle Component Analysis method.

Key Words: Segmentation, computed tomography, contour, pixel, region of interest.

1. Introduction

Image Segmentation is the process of dividing an image into regions with similar properties such as gray level, colour, texture, brightness, and contrast [24]. The main purpose of medical image segmentation is to study anatomical structure, surgical planning, identify region of interest to locate abnormalities, radiotherapy etc. Three major classifications of segmentation are manual segmentation, semi-automated segmentation and automated segmentation. Automated segmentation of medical images is a difficult task as the medical images are complex in nature. The segmented region of interest may not be accurate due to similarity in gray level of different organs [23].Computed Tomography (CT) is an imaging method which uses special equipment to generate specified pictures, or scans, of areas inside the body. Segmenting organs from abdominal CT images is a mandatory step for feature extraction. In the literature, various algorithms are used to segment the region of interest from the medical images. But the requirements for brain segmentation are different from those of kidney segmentation. Motion artifact is one of the key issues while segmenting the kidney regions. The other problems to be considered for abdominal CT medical images are ring artifacts, noise due to sensors and related electronic system [28]. Thus the selection of a segmentation methodology is more important for better accuracy. In this paper, the computation time of manual and automated segmentation of kidney regions are compared. Automated segmentation produces better performance improvement over manual segmentation [19].

The rest of the paper is organized as follows: In Section 2, work regarding kidney segmentation using various segmentation algorithms are discussed. In Section 3, methodologies for Active Contour Model and manual segmentation are introduced. In Section 4, experimental setup and results are discussed in detail. Then, in section 5 experimental findings and results are analyzed. Finally, Section 6 concludes the paper.

Nomenclatures	
E_s	Snake energy
E_i	Internal energy
E_c	Constraint energy
$E_{elastic}$	Elastic energy
$E_{bending}$	Bending energy
Abbreviations	
CT	Computed Tomography
ROI	Region of Interest
WHO	World Health Organization
PCA	Principle Component Analysis
AC	Active Contour
CT	Computed Tomography

2. Related Work

Several prior studies on kidney segmentation and extracting its abnormalities exist in the literature on different imaging modalities. Xinjian Chen et. al. [1] proposed an automated method for segmenting the kidneys on CT data slices.

Hossein Badakhshannoory and Parvaneh Saeedi [2] suggested a novel methodology for segmentation of kidney regions from the abdominal CT volumes. Kim et al. [3] combined region-growing, thresholding, thresholding, and histogram peak analysis to segment kidneys and kidney tumor tissue. Lin et al. [4] suggested an adaptive region growing method for finding kidneys using spine as a landmark and a model based approach for segmentation of kidney regions on CT images. Spiegel et al. [5] proposed an active shape model for segmentation on CT images. A seed point initialized this segmentation process. Kohlberger et al. [6] presented a level set method for organ segmentation that incorporates prior knowledge of shape and appearance for liver and kidney segmentation on CT data slices. P. R. Tamilselvi and P. Thangaraj [7] proposed a Computer aided diagnosis system for stone detection and early detection of kidney stones. Krishna Kant Singh and Akansha Singh [8] presented a study of Image Segmentation algorithms for different types of images. Lankton and Tannenbaum[9] proposed a framework using energy localized with region-based segmentation. Boying Wu and Yunyun Yang [10] suggested a methodology for image segmentation based on local and global-statistics Active Contour model.

P.V.V. Kishore et al. [11] proposed a technique for Tumor Identification in CT Medical Images using Semi Automatic Active Contour Models. Gao Yan and Boliang Wang [12] addressed the problem of accurately identifying kidneys automatically from abdominal 2D computed tomography images (CT). Xinjian Chen [13] proposed a novel method based on the Active Appearance Model, Live Wire, and Graph Cuts for abdominal 3-D organ segmentation. Moe Moe Myint [14] presented an efficient gradient based segmentation method for 2D abdominal Computed Tomography (CT) images of the human kidneys. Hong Song et. al. [15] proposed a coarse-to-fine method to segment kidney regions from CT images, which consists two stages including rough segmentation based on FCM and refined segmentation based on IGC.

Manjori Rao et. al. [16] compared a method for automatic image segmentation with conventional user-guided segmentation of right and left kidneys from Computerized Tomographic (CT) images. Gao-Yuan Dai et. al. [17] proposed a fast GrowCut (FGC) algorithm and applies the new algorithm in three-dimensional (3D) kidney segmentation from computed tomography (CT) volume data. Mahmoud Saleh Jawarneh [18] introduced a medical knowledge based system to automate medical image segmentation through active contour methods. Sanjay Saxena et. al. [19] proposed a method for kidney segmentation from an abdominal image, and it suggests the idea about the segmentation of multiple regions like Spine, Kidney, Liver.

3. Metodology

First, the abdominal CT image is pre-processed using the median filter. Then contour points were selected manually from the abdominal CT images for segmenting left and right kidney portions. The original abdominal CT images are considered for masking to find the variation in pixel intensities between the region of interest and the background of the image. Kidney regions are extracted after executing the masking module. The active contour is initialized within the masked boundary region for segmenting the region of interest. This algorithm is iterated number of times to extract the region of interest with higher accuracy.

Pre-processing

Pre-processing is an important factor to be considered for medical image processing and computer-aided diagnostic systems. The pre-processing is the first step to be done for the CT images because labels present can interfere during segmentation. To improve the quality of the image and to remove the noise the median filter is applied. The median filter is a conventional filter which replaces each pixel by the median of the gray levels in the neighbourhood of that pixel, and it is efficient to reduce the intensity of noise. Also, the median filter enhances the edges of the image.

Manual Segmentation

The contour points are chosen manually for segmenting the region of interest. The contour points must be selected carefully for accurate segmentation. Also, the accuracy of segmentation depends on the number of contour points.

Masking

For automated segmentation, kidneys are extracted using the variation in pixel intensities between the region of interest and the background image.

Active Contour Model

A contour represents an object boundary or a curve. An energy function E is associated with the curve. Then the object boundary will be traced by defining an energy minimization function as the final position of the contour will have a minimum energy E_{min} A contour can be defined in the plane (x,y) of an image as a parametric curve

$$V(s) = (x(s),y(s)) \qquad (1)$$

The contour holds an energy which can be defined as the sum of the three energy terms

$$E_s = E_i + E_e + E_c \qquad (2)$$

where s represents snake, i represents internal, e represents elastic and c represents constraint.

E_i depends on the intrinsic properties of the curve which are the sum of elastic energy and bending energy.

$$E_{elastic} = 0.5 \int_s \alpha(s)\, |v_s|^2\, ds \qquad v_s = \frac{dv(s)}{ds} \qquad (3)$$

$$E_{bending} = 0.5 \int_s \beta(s)\, |v_{ss}|^2\, ds \qquad (4)$$

where the elastic energy is controlled by the weight $\alpha(s)$ and $\beta(s)$ along different parts of the contour. The internal energy of the snake can be defined as

$$E_{snake} = \int_s 0.5(\alpha(s)|v_s|^2 + \beta(s)|v_{ss}|^2 + E_{image}(v(s))ds \quad (5)$$

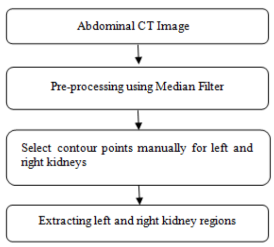
The external energy of the contour E_{ext} is derived from the image. The function $E_{image}(x,y)$ takes smaller values for the features of interest such as boundaries.

$$E_{ext} = \int_s E_{image}(v(s))ds \quad (6)$$

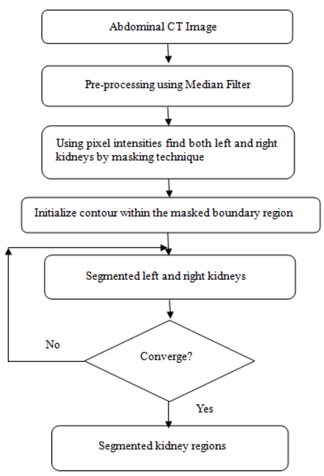
To find a contour v(s) that minimizes the energy functional

$$E_{snake} = \int_s 0.5(\alpha(s)|v_s|^2 + \beta(s)|v_{ss}|^2 + E_{image}(v(s))ds \quad (7)$$

The contour is initialized within the masked boundary region. The contour is growing by grouping the similar intensity pixels. That is the pixel features inside the initially drawn contour is compared with the pixels outside the contour and this process is repeated number of times for better segmentation. The computation time of manual and automated segmentation are compared. Automated segmentation produces better performance improvement over manual segmentation.



(a)

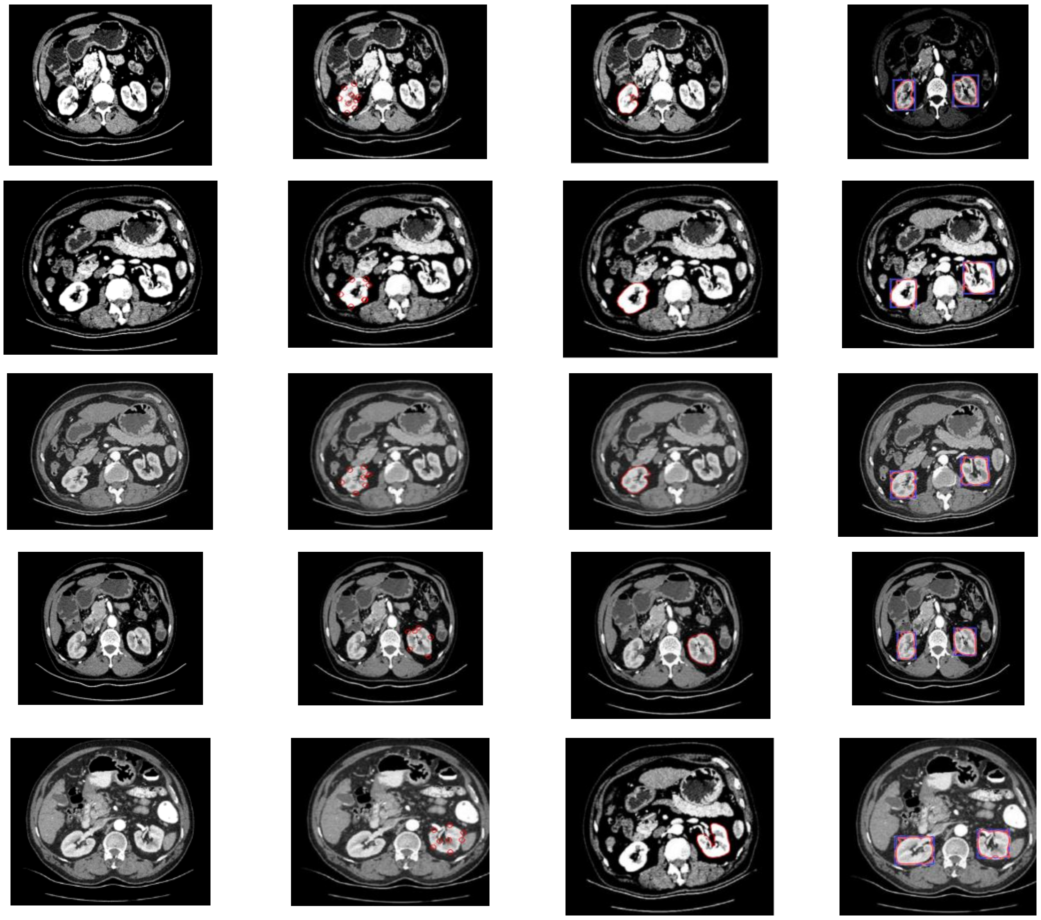


(b)

Figure 1: System Model (a) Manual Segmentation (b) Automated Segmentation

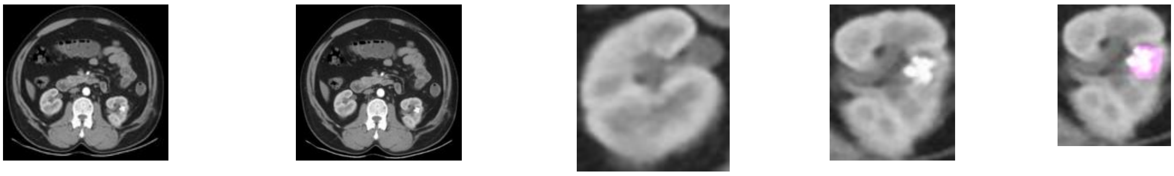
4. Experimental Setup and Results

Initially, the abdominal CT datasets were taken from Radiological Society of North America (www.rsna.org) for implementing the methodology. Then the 2D abdominal CT images acquired on optima CT machine were provided by Metro Scans, Trivandrum, India. A total of 100 CT slices of several patients has been considered for the study. The abdominal CT images are of 0.6mm thickness in which all the organs such as liver, kidneys, spine, spleen, etc. appear. This segmentation methodology was implemented on MATLAB R2016b. All experiments were implemented with Intel i5 - Core CPU at 1.8 GHz and 6 GB RAM memory.



(a) Input Image (b) Selecting Contour Points (c) Manual Segmentation (d) Automated Segmentation Masked (blue) & Segmented ROI (red)

Figure 2: Manual and Automated Segmentation of Kidney Regions



(a) Input Image (b)Pre-processed Image (c)Segmented Right Kidney (d)Segmented Left Kidney (e) Segmenting Abnormal ROI

Figure 3: Extracting Region of Interest

Table 1: Execution Speedup

Input Image	Execution time(s) Manual (t1) sec	Execution Time(s) Automated (t2) sec	Speedup (t1/t2) sec
1	50.10	21.22	2.36
2	53.71	20.40	2.63
3	50.16	19.77	2.54
4	57.05	22.97	2.48
5	57.07	21.54	2.65
6	51.09	19.23	2.66
7	50.83	20.41	2.49
8	50.66	19.87	2.55
9	56.57	18.99	2.98
10	52.97	23.56	2.25
11	50.01	18.23	2.74
12	55.97	22.07	2.54
13	56.02	17.37	3.23
14	56.55	19.65	2.88
15	53.24	22.51	2.37

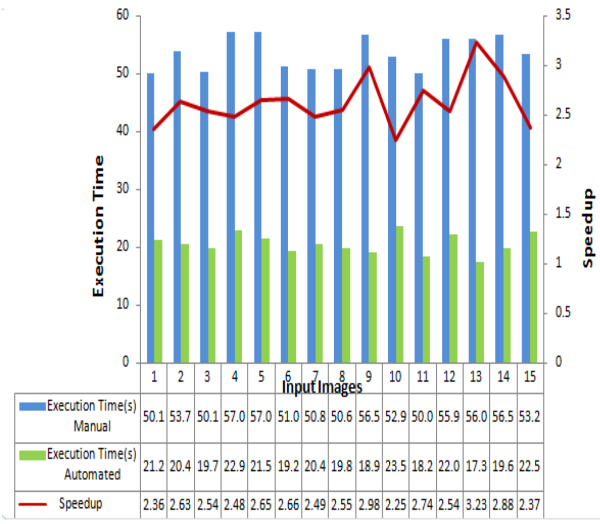


Figure 4: Comparison of Manual and Automated Execution Time, Speedup

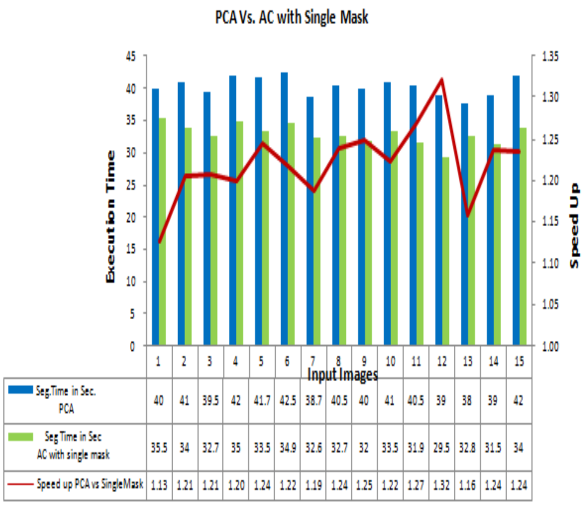
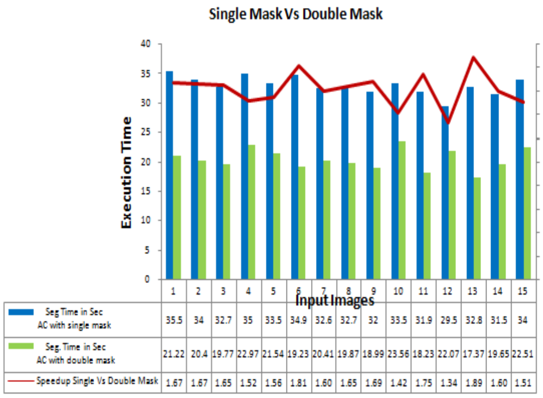
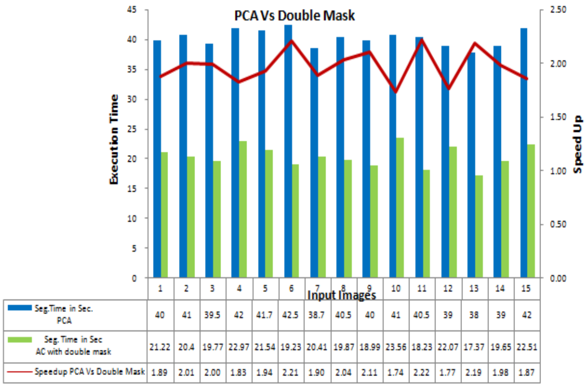


Figure 5: Comparison of Segmentation Speedup between PCA and AC with Single Mask



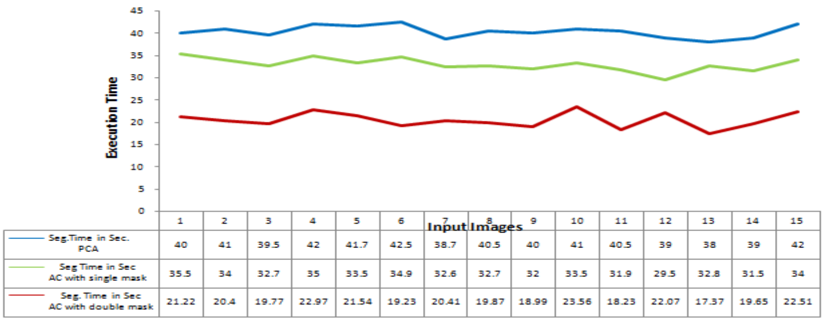
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Seg Time in Sec AC with single mask	35.5	34	32.7	35	33.5	34.9	32.6	32.7	32	33.5	31.9	29.5	32.8	31.5	34
Seg. Time in Sec AC with double mask	21.22	20.4	19.77	22.97	21.54	19.23	20.41	19.87	18.99	23.56	18.23	22.07	17.37	19.65	22.51
Speedup Single Vs Double Mask	1.67	1.67	1.65	1.52	1.56	1.81	1.60	1.65	1.69	1.42	1.75	1.34	1.89	1.60	1.51

Figure 6: Comparison of Segmentation Speedup between AC with Single Mask and Double Mask



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Seg.Time in Sec. PCA	40	41	39.5	42	41.7	42.5	38.7	40.5	40	41	40.5	39	38	39	42
Seg. Time in Sec AC with double mask	21.22	20.4	19.77	22.97	21.54	19.23	20.41	19.87	18.99	23.56	18.23	22.07	17.37	19.65	22.51
Speedup PCA Vs Double Mask	1.89	2.01	2.00	1.83	1.94	2.21	1.90	2.04	2.11	1.74	2.22	1.77	2.19	1.98	1.87

Figure 7: Comparison of Segmentation Speedup between PCA and AC with Double Mask



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Seg.Time in Sec. PCA	40	41	39.5	42	41.7	42.5	38.7	40.5	40	41	40.5	39	38	39	42
Seg Time in Sec AC with single mask	35.5	34	32.7	35	33.5	34.9	32.6	32.7	32	33.5	31.9	29.5	32.8	31.5	34
Seg. Time in Sec AC with double mask	21.22	20.4	19.77	22.97	21.54	19.23	20.41	19.87	18.99	23.56	18.23	22.07	17.37	19.65	22.51

Figure 8: Comparison of Segmentation Time between PCA, AC with Single Mask and Double Mask

5. Findings

The manual and automated methodologies were tested on different slices of clinically acquired images, and promising results were obtained. This automated algorithm eliminates the problems in manual segmentation such as improper selection of control points, segmentation inaccuracy and higher computation time. This methodology is more robust to noise and retains computational simplicity.

If the contour is initialized too far from the object boundary, it is possible that the contour may not be able to converge onto object boundary. The segmentation accuracy is good for manual segmentation but the computation time is two or three times greater than the automated segmentation. The efficiency of the automated segmentation is improved when the number of iterations of masking is increased. Also speedup is improved in automated segmentation. This automated segmentation process gives better visualization of kidney regions and its abnormalities for abdominal CT datasets. This methodology provides greater accuracy and efficiency in identification of kidney regions and abnormalities. For the identification of kidneys and their abnormalities, the system is well performed with a mean accuracy of 99.9% and 95%, respectively.

Also, the computation time performance of Active Contour with double mask methodology is compared with Active Contour with single mask methodology and Principle Component Analysis. The computation speedup performance of Active Contour with double mask is improved 50% more than the Principle Component Analysis method.

6. Conclusion

This automated algorithm eliminates the problems in manual segmentation. In this paper, we have focused on a construction of automated image segmentation method that deals with multi-modal medical images. This algorithm is more robust to noise and retains computational simplicity. The methodologies for both manual and automated segmentation were implemented to enhance the performance of segmentation process by improving the speed of segmentation process. In terms of speedup, automated implementation was about three times faster than manual implementation.

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