

Survey on Kidney Segmentation using SKFCM and Improved GrowCut Algorithm

Digital Image Processing
18XDA3

Assignment Presentation

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Introduction

- Organ segmentation is an important step in computer-aided diagnosis and pathology detection.
- Accurate kidney segmentation in abdominal computed tomography (CT) sequences is an essential and crucial task for surgical planning and navigation in kidney tumor ablation.
- However, kidney segmentation in CT is a substantially challenging work because the intensity values of kidney parenchyma are similar to those of adjacent structures.

Image segmentation

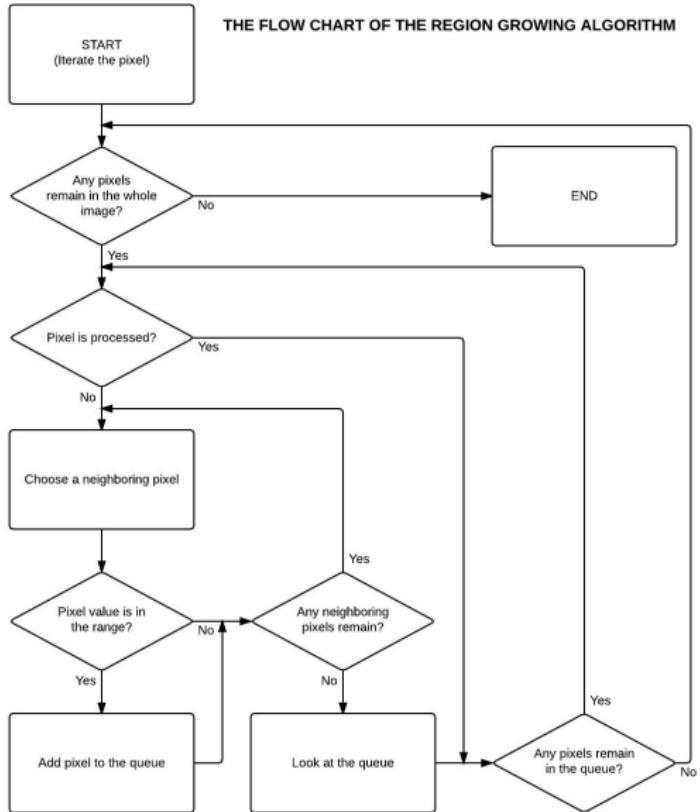
- Image segmentation divides an image into regions that are connected and have some similarity within the region and some difference between adjacent regions.
- The goal is usually to find individual objects in an image.
- For the most part there are fundamentally two kinds of approaches to segmentation: discontinuity and similarity.
- Similarity may be due to pixel intensity, color or texture.
- Differences are sudden changes (discontinuities) in any of these, but especially sudden changes in intensity along a boundary line, which is called an edge.
- Thresholding : the range of intensity levels covered by objects of interest is different from the background.

Region Growing

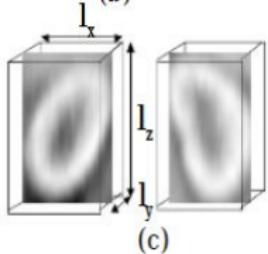
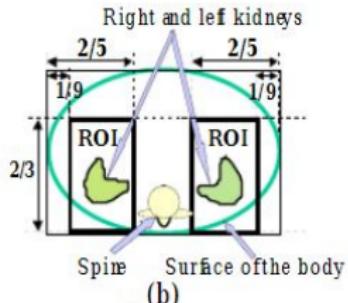
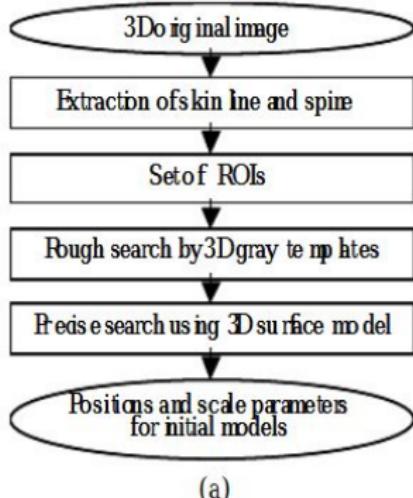
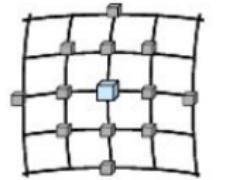
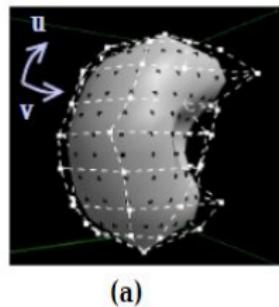
- Region growing algorithms works on principle of similarity . It states that a region is coherent if all the pixels of that region are homogeneous with respect to some characteristics such as colour, intensity, texture, or other statistical properties .
- Thus the idea is to pick a pixel inside a region of interest as a starting point (also known as a seed point) and allowing it to grow .
- Seed point is compared with its neighbours, and if the properties match (ROI) , they are merged together . This process is repeated till the regions converge to an extent that no further merging is possible

Region Growing

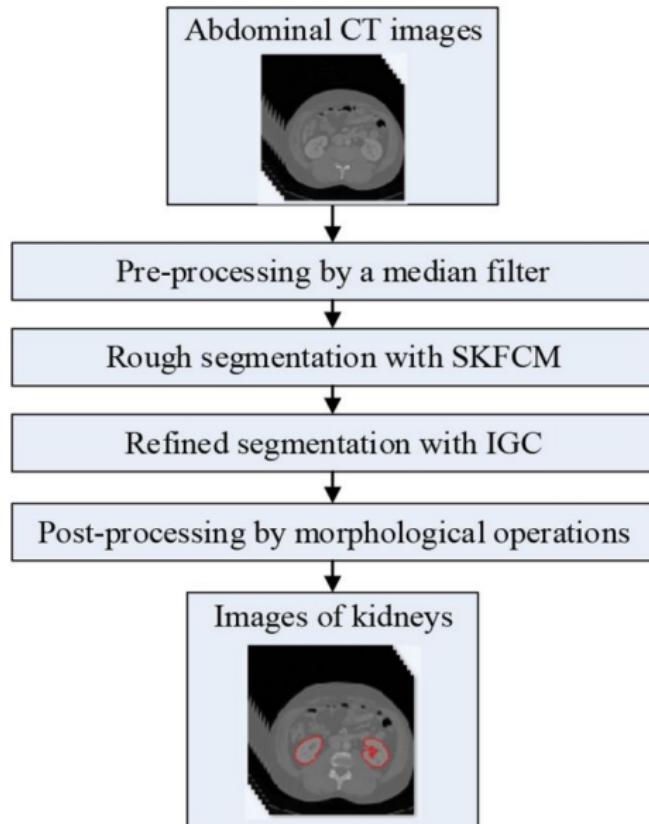
1	0	7	22	23
0	1	8	21	7
0	0	8	9	4
0	1	8	8	9
1	2	9	7	9



Approaches made in recent years



Framework Proposed



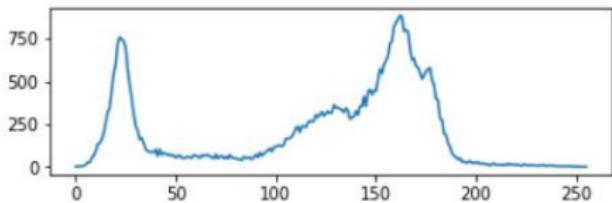
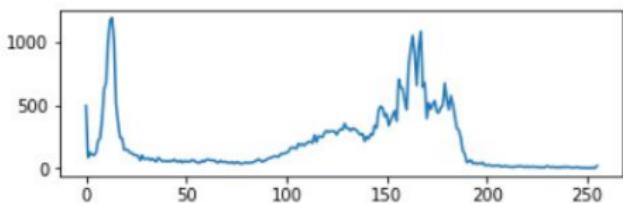
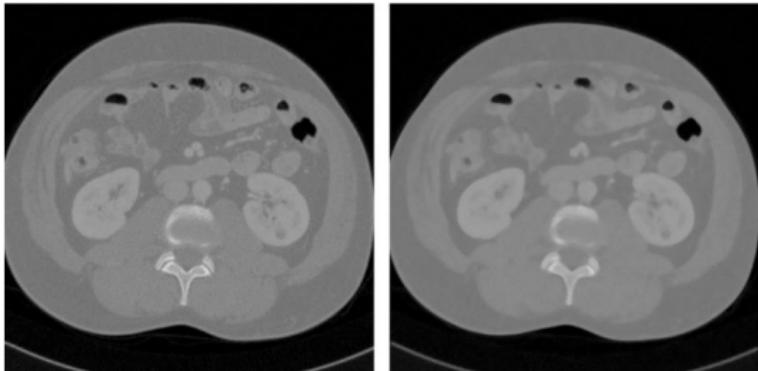
Pre-processing

- CT image has inhomogeneity, noise which affect the continuity and accuracy of the images segmentation.
- Therefore, a 3×3 median filter is used to reduce the noise. The equation of median filter is defined as:

$$g(x, y) = \text{Median } f_s(x, y)$$

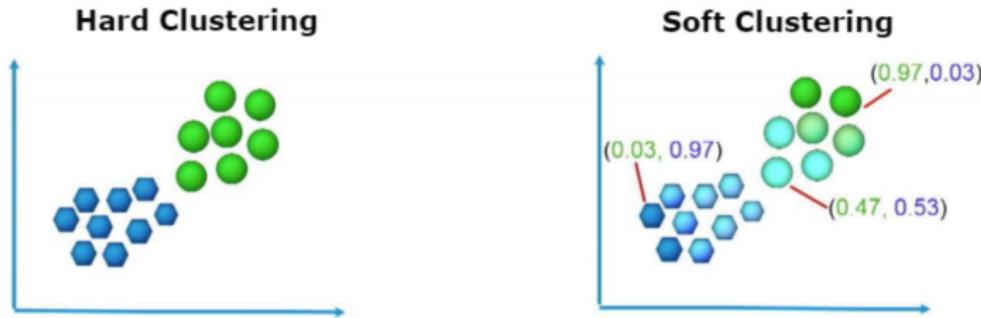
where S represents the template window with a 3×3 surrounding neighborhood, $f_s(x, y)$ represents the intensity value of each pixel in the S, Median $f_s(x, y)$ represents the middle value of all the values of the pixels in the neighborhood.

Denoised Image



FCM

- Fuzzy logic is an approach to computing based on "degrees of truth" rather than the usual "true or false" (1 or 0) Boolean logic
- Fuzzy C-Means clustering is a soft clustering approach, where each data point is assigned a likelihood or probability score to belong to that cluster.



FCM : Steps

Algorithm goes as follows ,

Step 1: Initialize the data points into desired number of clusters randomly.

Step 2: Find out the centroid.

$$V_{ij} = \left(\sum_1^n (\gamma_{ik}^m * x_k) \right) / \sum_1^n \gamma_{ik}^m$$

Where, γ is fuzzy membership value of the data point, m is the fuzziness parameter (generally taken as 2), and x_k is the data point.

FCM

Step 3: Find out the distance of each point from centroid.(By the euclidean distance formula)

Step 4: Updating membership values.

$$\gamma = \sum_1^n (d_{ki}^2/d_{kj}^2)^{1/m-1}]^{-1}$$

Step 5: Repeat the steps(2-4) until the constant values are obtained for the membership values or the difference is less than the threshold value .

Step 6: Defuzzify the obtained membership values.

<https://www.geeksforgeeks.org/ml-fuzzy-clustering/>

KFCM

A kernel can be represented as a function K below:

$$K(x, y) = \langle \Phi(x), \Phi(y) \rangle$$

Commonly used kernel functions are:

$$K(x, y) = \exp\left(\frac{-||x - y||^2}{\sigma^2}\right)$$

$$K(x, y) = (1 + \langle x, y \rangle)^d$$

$$K(x, y) = \tanh(\alpha \langle x, y \rangle + \beta)$$

KFCM : Algorithm

The standard FCM objective function for partitioning a dataset $\{x_k\}_{k=1}^N$ into c clusters is given by

$$J_m = \sum_{i=1}^c \sum_{k=1}^N u_{ik}^m \|x_k - v_i\|^2$$

where $\{v_i\}_{i=1}^c$ are the centers or prototypes of the clusters and the array $\{u_{ik}\}$ ($=U$) represents a partition matrix satisfying

$$U \in \left\{ u_{ik} \in [0, 1] \middle| \begin{array}{l} \sum_{i=1}^c u_{ik} = 1, \quad \forall k \quad \text{and} \\ 0 < \sum_{k=1}^N u_{ik} < N, \quad \forall i \end{array} \right\}$$

The parameter m is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification. In image clustering, the most commonly used feature is the gray-level value, or intensity of image pixel.

KFCM : Algorithm

$$J_m = \sum_{i=1}^c \sum_{k=1}^N u_{ik}^m \|\Phi(\mathbf{x}_k) - \Phi(\mathbf{v}_i)\|^2$$

where Φ is an implicit nonlinear map.

$$J_m = 2 \sum_{i=1}^c \sum_{k=1}^N u_{ik}^m (1 - K(\mathbf{x}_k, \mathbf{v}_i))$$

$$u_{ik} = \frac{(1 - K(\mathbf{x}_k, \mathbf{v}_i))^{-1/(m-1)}}{\sum_{j=1}^c (1 - K(\mathbf{x}_k, \mathbf{v}_j))^{-1/(m-1)}}$$

$$\mathbf{v}_i = \frac{\sum_{k=1}^n u_{ik}^m K(\mathbf{x}_k, \mathbf{v}_i) \mathbf{x}_k}{\sum_{k=1}^n u_{ik}^m K(\mathbf{x}_k, \mathbf{v}_i)}$$

$$\begin{aligned} \|\Phi(\mathbf{x}_k) - \Phi(\mathbf{v}_i)\|^2 &= (\Phi(\mathbf{x}_k) - \Phi(\mathbf{v}_i))^T (\Phi(\mathbf{x}_k) - \Phi(\mathbf{v}_i)) \\ &= \Phi(\mathbf{x}_k)^T \Phi(\mathbf{x}_k) - \Phi(\mathbf{v}_i)^T \Phi(\mathbf{x}_k) \\ &\quad - \Phi(\mathbf{x}_k)^T \Phi(\mathbf{v}_i) + \Phi(\mathbf{v}_i)^T \Phi(\mathbf{v}_i) \\ &= K(\mathbf{x}_k, \mathbf{x}_k) + K(\mathbf{v}_i, \mathbf{v}_i) - 2K(\mathbf{x}_k, \mathbf{v}_i) \end{aligned}$$

SKFCM : Algorithm

Although KFCM can be directly applied to image segmentation like FCM, it would be helpful to consider some spatial constraints on the objective function.

A modification to the objective function of KFCM by introducing a penalty term containing spatial neighborhood information.

Such regularization is helpful in segmenting images corrupted by noise.

Comparisons

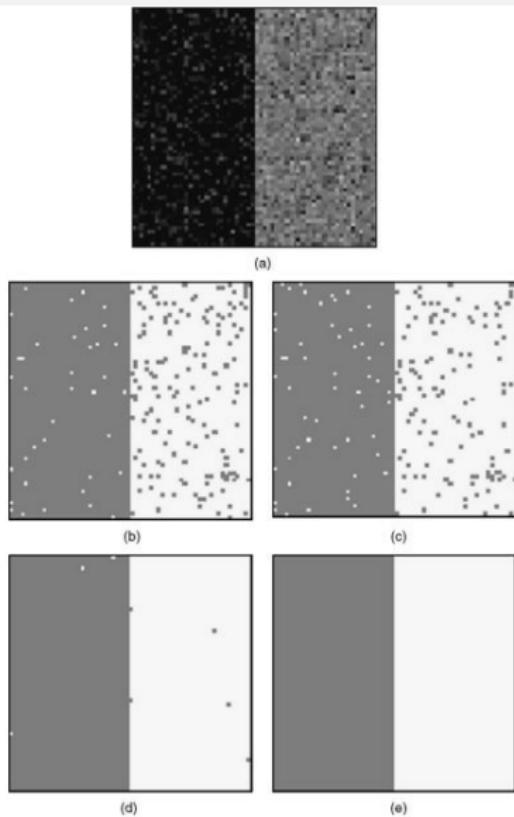
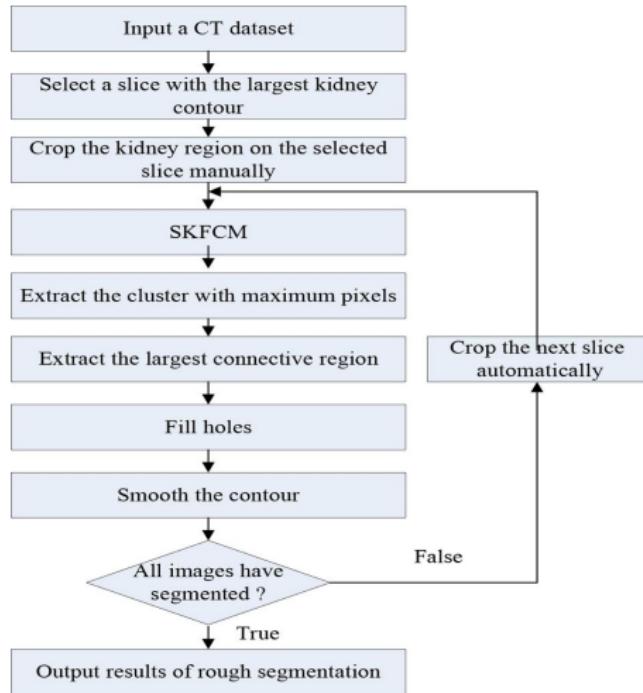


Figure 1 Comparison of segmentation results on a synthetic image corrupted by 5% Gaussian noise. (a) The original image, (b) using FCM, (c) using KFCM, (d) using SFCM, and (e) using SKFMC.

Rough Segmentation overview



Rough Segmentation with SKFCM

- SKFCM algorithm introduces a kernel function and spatial constraint into the FCM algorithm, which can reduce the effect of noise and improve the clustering ability.

$$J_m = \sum_{i=1}^c \sum_{k=1}^N u_{ik}^m (1 - K(x_k, v_i)) + \alpha \sum_{i=1}^c \sum_{k=1}^N u_{ik}^m (1 - K(\bar{x}_k, v_i))$$



Objective function

$$J_m = \sum_{i=1}^c \sum_{k=1}^N u_{ik}^m (1 - K(x_k, v_i)) + \alpha \sum_{i=1}^c \sum_{k=1}^N u_{ik}^m (1 - K(\bar{x}_k, v_i))$$

- c is the number of clusters of the dataset $\{x_k\}_{k=1}^N$
- N is the number of pixels
- m is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification
- $\{v_i\}_{i=1}^c$ are the centers and the array $\{u_{ik}\}$ ($= U$) represents a partition matrix
- α in the second term controls the effect of the penalty
- $K(\cdot, \cdot)$ is the Gaussian kernel function

The objective function is to be minimized using the alternate iterations of the fuzzy partition matrix (1) and the centroids of clusters (2).

$$u_{ik} = \frac{\frac{-1}{((1 - K(x_k, v_i)) + \alpha(1 - K(\bar{x}_k, v_i)))^{(m-1)}}}{\sum_{j=1}^c \frac{-1}{((1 - K(x_k, v_i)) + \alpha(1 - K(\bar{x}_k, v_i)))^{(m-1)}}} \longrightarrow (1)$$

$$v_i = \frac{\sum_{k=1}^n u_{ik}^m (K(x_k, v_i)x_k + \alpha K(\bar{x}_k, v_i)\bar{x}_k)}{\sum_{k=1}^n u_{ik}^m (K(x_k, v_i) + \alpha K(\bar{x}_k, v_i))} \longrightarrow (2)$$

SKFCM

The SKFCM algorithm can be summarized in the following steps:

Step 1: Fix the number c of these centroids and select initial class centroids and set $\varepsilon > 0$ to a very small value.

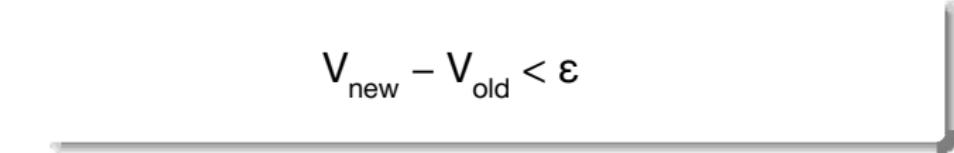
Step 2: Compute the mean filtered image.

Step 3: Update the partition matrix using (1).

Step 4: Update the centroids using (2)

Repeat steps 3-4 until the following termination criterion (5) is satisfied:

$$V_{\text{new}} - V_{\text{old}} < \varepsilon$$



The rough segmentation includes six steps

Step 1: The cropped image is the input of SKFCM algorithm, and then each pixel in the cropped region is clustered into different clusters.

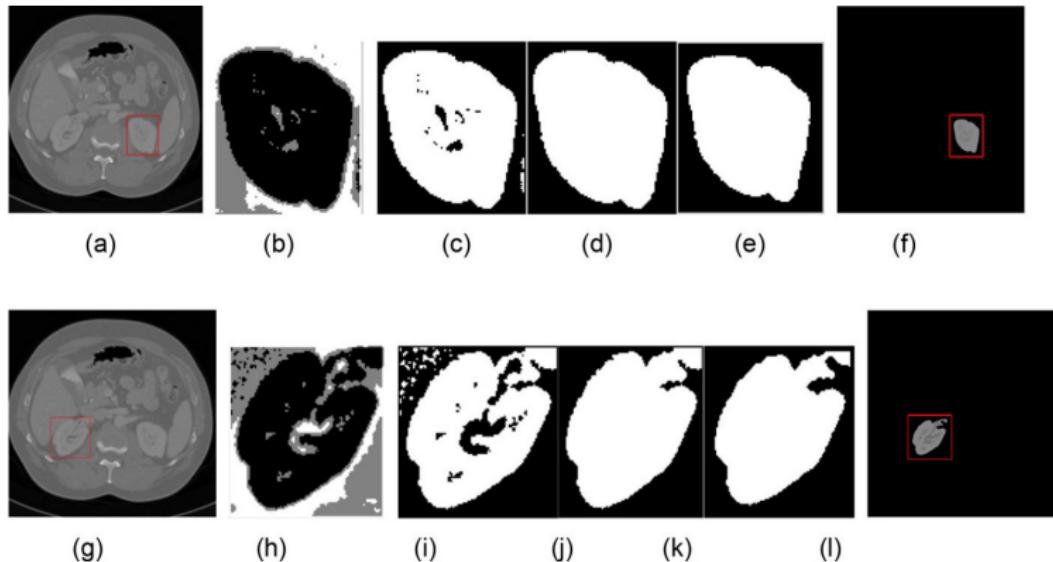
Step 2: The number of pixels in each cluster is calculated and the cluster which contains maximum pixels is extracted.

Step 3: The largest connected region is extracted to be the candidate kidney region.

Step 4: There are some holes inside the kidney because some vessels are rejected in the processing of fuzzy clustering. Therefore this step is to fill holes.

Step 5: The kidney contour is smoothed by morphological operations.

Step 6: Through the above steps, the mask of candidate kidney region is gotten. In order to realize the continuous segmentation, the minimum bounding rectangle(MBR) of the mask is calculated. Then the MBR is extended about 10 pixels so that we can get a new rectangle. This new rectangle is used to crop the next slice of CT sequences.



Examples of rough segmentation. (a) and (g) are original images with cropping rectangle; (b) and (d) are clustering results; (c) and (i) are the extracted clusters with maximum pixels; (d) and (g) are the largest connective regions with filled holes; (e) and (k) are the smooth results; (f) and (l) are the rough segmentation results and the red rectangles are used to crop next slice.

Why grow cut algorithm?



a



b



c

Segmentation of a color image. (a) Source image, (b) user-specified seeds, (c) segmentation results

Traditional GrowCut Algorithm for refined segmentation

- GrowCut algorithm is an interactive segmentation method and solves pixel labeling task based on cellular Automaton.
- A cellular automaton (CA) is defined as a triplet $A = (S, N, \delta)$, where S is a set of non-empty state, N is the neighborhood system and $\delta : S^N \rightarrow S$ defines the state transition rule of cells at time $t+1$ based on the states of neighbor cells at time t . The Moore von (8-connected) and Neumann (4-connected) neighborhoods are two commonly used neighbor systems. The state of each cell is also a triplet $S_p = (l_p, \theta_p, C_p)$, where l_p is the label of this cell, θ_p is the strength of this cell which ranges from 0 to 1, and C_p is the feature vector that its value is image intensity.

A two-dimensional medical image (P) is a matrix of $m \times n$ pixels. Each pixel (p) in the image is a “cell” with a certain type, and it may be background, foreground or undefined. The initial state for $\forall p \in P$ is set to

$$I_p = 0; \theta_p = 0; C_p = I_p$$

Before starting the segmentation, user should input an initial label matrix manually. The label matrix has a same size with the original image. In the label matrix, there are two kinds of marked points, one is foreground seed point whose label is $I_p = 1$, and the other is background seed point whose label is $I_p = -1$. The original strength of these two kinds of marked points is $\theta_p = 1$. Apart from these two kinds of marked points, the label of the remainder of points is $I_p = 0$.

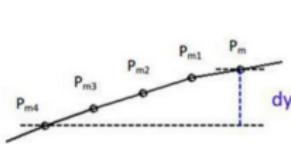
Improved GrowCut for refined segmentation

- In order to avoid multi-interaction between foreground and background pixel, we propose an improved GrowCut algorithm which can generate seed labels automatically.
- The rough segmentation results are continuous in space series and about half of them do not need refined segmentation. Therefore, the initial label matrix can be generated automatically using the result of rough segmentation (denoted as “a seed template image”). The seed template image must meet two conditions. One is that it does not need refined segmentation, and the other is that it is adjacent to the slice which needs refined segmentation.

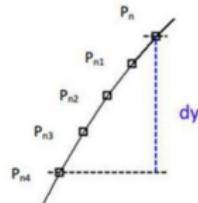
The process of generating both foreground and background seed points is described below



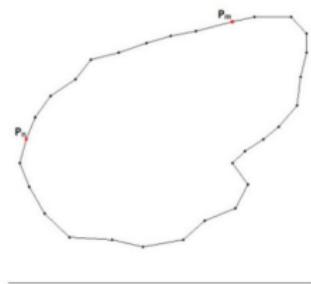
(a)



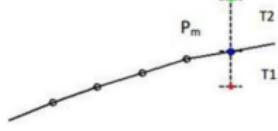
(b)



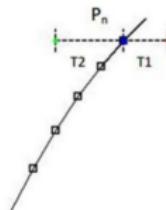
(c)



(d)

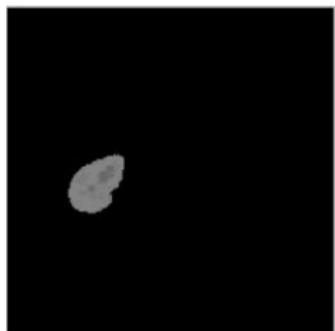


(e)

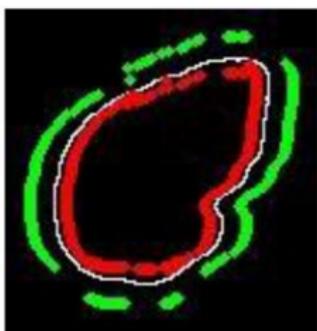


(f)

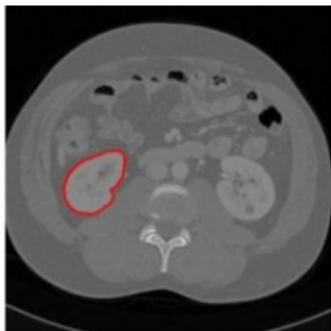
The example of generating the seed template automatically. (a) an original image of template; (b) altitude difference of point P_m ; (c) altitude difference of point P_n ; (d) the contour of template (e)the foreground seed point (red) and background seed point (green) of point P_m ; (f) the foreground seed point (red) and background seed point (green) of point P_n .



(a)



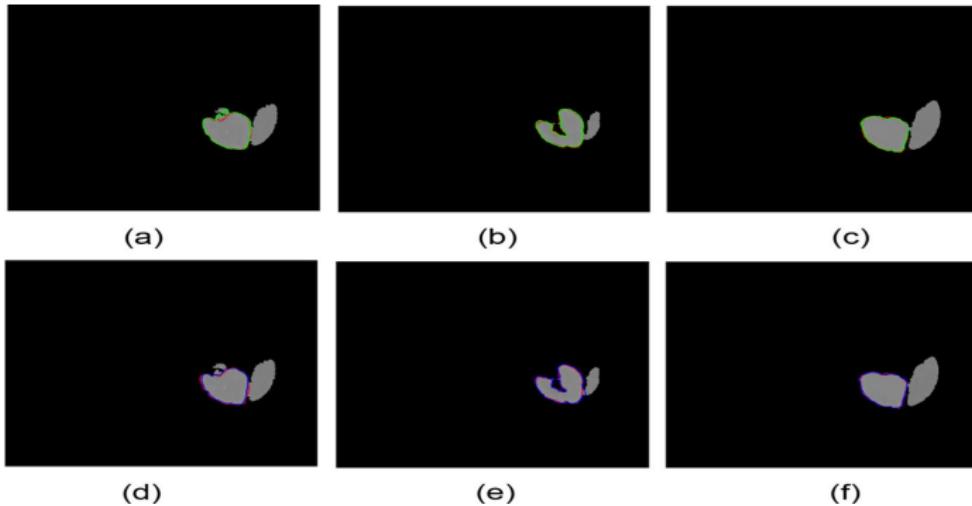
(b)



(c)

The refined kidney segmentation based on IGC algorithm. (a) the seed template image; (b) the seed label image which is generated automatically by IGC, the red points are foreground seed points and the green points are background seed points; (c) result by IGC algorithm.

TGC vs IGC



(a)(b)(c) show the refined segmentation results of TGC algorithm; (d)(e)(f) show results of IGC algorithm; the red line denotes the manual segmentation result; the green line denotes the result of TGC algorithm; the blue line denotes the result of IGC algorithm.

Results and evaluation

Accuracy is a common criterion that it is used to evaluate performance of segmentation methods widely. Overlap shows the degree of overlap between segmentation results by computer algorithm and manual segmentation results. The closer overlap is to 1, the better segmentation result will be. The accuracy and overlap are defined as follows:

$$\text{accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

$$\text{overlap} = \frac{TP}{FN + TP + FP}$$

$$\text{sensitivity} = \frac{TP + TN}{TP + FP + TN + FN}$$

$$\text{specificity} = \frac{TP}{FN + TP + FP}$$

The evaluation of different algorithms

	Methods	Accuracy (%)	Overlap (%)	NOI	TOGSP (s)
Data 1	TGC	99.69	86.61	1	29.14
	IGC	99.64	85.11	0	0.50
Data 2	TGC	99.59	80.71	2	25.23
	IGC	99.62	82.57	0	0.51
Data 3	TGC	99.69	86.59	1	38.28
	IGC	99.72	88.08	0	0.50

Conclusion

- In this paper, we proposed a new coarse-to-fine method that combines SKFCM and the improved GrowCut.
- The segmentation results of our method can be used to diagnose the kidney diseases and make treatment planning. They are also the foundation of 3D visualization.

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THANK YOU!