

An Improved Canny Algorithm Based on Median Filtering and Adaptive Threshold in Robot Training System

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Abstract. The system of robot virtual operation training requires effective soft-tissue organ models, of which the shape and size shall be obtained according to patients' medical image. The way of cutting required organ image from CT scans with noise background is essentially important. This paper proposes a kind of improved algorithm that can effectively reduce salt-and-pepper noise in image, according to traditional Canny edge detection algorithm's weak effect in reduction of salt-and-pepper noise in image and disadvantage of manual selection of double thresholds. Firstly, improved Gaussian weighted median filtering is applied by the algorithm on smooth processing of medical images, well reducing salt-and-pepper noise and effectively protecting edge detail information of medical images. Secondly, modified adaptive OTSU algorithm is used to acquire appropriate threshold value, according to the interclass variance value between the object and the background in medical image, so as to accurately locate medical image edge. The simulation result reveals the improved algorithm's detection effect under background of salt-and-pepper noise is better than traditional canny edge detection algorithm and the published literature methods, thus the effectiveness of the algorithm are proved.

Introduction

In virtual operation training system, the foundation of the entire training process is to establish models of operation organs. In operation training system, there have to establish operation models consistent with diseased organs of patients. At first, the particular organ image is separated from the CT image by image filtering and segmentation technique. Secondly, corresponding 3D organ model is established according to organ image. At last, the model would be loaded to virtual training system, while utilizing force-feedback hand equipment to manipulate virtual operative instrument and completing virtual training process before actual operation, to improve success rate of operation.

Medical image edge detection is one of key techniques of separating CT image, and its objective is to confirm edge of objects in image with noise background. Its role in confirming position and size of liver nidus is significant [1]. In addition, medical image edge detection must have corresponding evaluation system, which would be applied as one basis to judge image segmentation algorithm [2].

There are many different edge detection algorithms, such as Sobel algorithm, Prewitt algorithm, Roberts algorithm, LoG algorithm. Although these algorithms are quick in computing, their antijamming capability or edge effect processing is not good. The detection method based on traditional canny operator can improve these shortcomings to a large extent, but even canny

operator has its deficiencies. At present, there are quite a number of edge detection methods based on canny operator. Medical image segmentation method that combines FCM algorithm and GPU technique is brought up by Shehab [3]. In literature [4], there proposes to improve canny operator edge detection algorithm basing on adaptive dual-threshold. Some technical applications related to other medical fields are derived from research on medical image detection technology. Segmentation of brain medical image is applied by Lubis[5] to detect disease. Asymmetric Gaussian function segmentation technology is defined by Haksoo[6] to test position and organizational characteristics of medical organs. Graphic segmentation and contour filling algorithm is utilized by El-said [7] to put forward a kind of 3D medical image segmentation technology, which uses feature vector of the smallest characteristic value to solve image segmentation problem.

Based on above analysis on medical image segmentation technology, combing with model characteristics of virtual operation training system, according to limitation of manual selection of dual threshold and sensitivity to salt-and-pepper noise, this paper brings forward an improved median filter and adaptive threshold canny algorithm (IMACA), to further improve segmentation effect of medical image, especially edge blur position. The simulation result reveals the improved algorithm's detection effect under background of salt-and-pepper noise is better than traditional canny algorithm (TCA) and adaptive statistical filtering double thresholds canny algorithm (ADTCA) [4], thus the effectiveness of the algorithm are proved.

The improved canny algorithm

An improved median filter of Gaussian weighted

In literature [4], it puts forward improvement suggestion to canny operator. This algorithm avoids Gaussian filter's shortcoming of identifying edge point as noise during smooth processing, but its effect in filtering salt-and-pepper noise is not good. According to this issue, in this paper, the bilateral filter in literature [4] is changed to Gaussian weighted median filter. The Gaussian weighted median filter effectively reduces interference of salt-and-pepper noise to image information, and Gaussian weighting is involved in square median filter with $N \times N$ size. On the basis of literature [8], the parameter m is added, and it can change weight of pixel points, so as to enhance intensity of information points in the image. The implementation steps are as following.

Step 1: the pixel gray value in filter is sorted in order of size, to obtain median and pixel gray value of pixel points $(N-1)/2$ before and after the median. The total number is N .

$$f_n(x, y) = \text{median}(n) \{g(i, j), (i, j \in W)\} \quad (1)$$

$n \in (-(N-1)/2, \dots, -1, 0, 1, \dots, (N-1)/2)$, N is the side of filter windows. W represents two-dimensional space which size is $N \times N$. The size of is usually 3×3 or 5×5 region, $g(i, j)$ is the grey level of pixel. $f_n(x, y)$ is the grey level of the $(N \times N + 1)/2 + n$ th pixel after sort.

Step 2: to calculate corresponding Gaussian weighted values of the N pixel points.

$$h(n) = m \frac{\exp\left[-\frac{n^2}{2d^2}\right]}{\sqrt{2pd}} \quad (2)$$

d is standard deviation, m is parameter variables, $h(n)$ is the Gaussian weight of the

$(N \times N + 1) / 2 + n$ th pixel.

Step 3: to perform convolution operation on the sorted N grey values and Gaussian weighted values of each point.

Step 4 : we set $F(x, y)$ as the pixel gray value of center position of filter.

The improved Otsu self-adaptive threshold method

Otsu algorithm is regarded as the optimal algorithm of manual selection of threshold. In this method, selection of threshold is based on interclass variance value between the object and the background. According to grey information of image and interclass variance, the image information is classified. The way of applying Otsu to adaptively select high and low threshold according to grey values of image avoid traditional canny operator's disadvantage of manual set of the thresholds. On the basis of literature [9], some improvement on low threshold calculation methods are conducted. The implementation procedures are as following.

In a size $A \times B$ of image, we supposed that M different gray levels can express as $\{0, 1, 2, \dots, L, M-1\}$, n_i means the number of pixel that the gray level is i . $i \in \{0, 1, 2, \dots, L, M-1\}$. Then, we have

$$A \times B = n_0 + n_1 + n_2 + \dots + L + n_{M-1} \quad (3)$$

The percentage of pixel which the gray level is i can be write as

$$P_i = \frac{n_i}{A \times B} \quad (4)$$

Assume that a threshold $T \in (0, M-1)$ is selected. Based on T , images are classified into two classes, C and D . The pixels with grey value within $[0, T]$ range compose C , when all pixels with grey value within $[T+1, M-1]$ range compose D .

P_C and P_D are the probability of Pixel distribution of C and D respectively, it can be write as

$$P_C = \sum_{i=0}^T P_i \quad (5)$$

$$P_D = 1 - P_C \quad (6)$$

q_C means the percent of pixel which belong the pixel points of C in entire image, it can be write as

$$q_C = \sum_{i=0}^T i P\left(\frac{i}{C}\right) = \sum_{i=0}^T i \frac{P\left(\frac{C}{i}\right) \times P(i)}{P_C} = \frac{1}{P_C} \sum_{i=0}^T i P_i \quad (7)$$

Similarly, q_D means the percent of pixel which belong the pixel points of D in entire image.

d^2 is interclass variance, it can be write as

$$d^2 = P_C (q_C - q)^2 + P_D (q_D - q)^2 = P_C P_D (q_C - q_D)^2 = \frac{(q P_C - q_D)^2}{P_C (1 - P_C)} \quad (8)$$

T value obtained when the interclass value is the maximum is the optimal threshold. In case

that T value is more than one when d^2 is the max value, then the average value of T values at the maximum interclass value is taken as the optimal threshold. The optimal threshold is regarded as high threshold T_{high} .

$$T_{low} = \frac{T_{high}}{k} \quad (9)$$

For $\{k \in (1, 2, 3, \dots, 10)\}$, many groups of dual thresholds can be confirmed according to K value. After comparing and analyzing edge information figures obtained through different dual thresholds, the result shows that the image edge information is the most accurate when $k=5$. Therefore, the optimal dual threshold ratio is confirmed as $T_{high}:T_{low}=6:1$.

Experiment results

The experimental process performs image edge detection and contrast test on TCA, ADTCA [4] and IMACA in non-noise and noisy environments. In addition, the noisy environment is divided into environment with 0.01 variance salt-and-pepper noise and environment with 0.1 variance salt-and-pepper noise. Fig.1 and Fig.3 are filtering and segmentation results of liver CT scans with different algorithms respectively. Fig. 1(a) is the original liver image with 0.1 noise. Fig. 1(b) and Fig. 3(b) are the filtering and segmentation results of liver CT scans with 0.1 noise by TCA method respectively. Fig. 1(c) and Fig. 3(b) are the filtering and segmentation results of liver CT scans with 0.1 noise by TCA method respectively. Fig. 1(d) and Fig. 3(d) are the filtering and segmentation results of liver CT scans with 0.1 noise by TCA method respectively. Similarly, Fig.2 and Fig.4 are filtering and segmentation results of kidney CT scans adding 0.01 variance salt-and pepper noise with different algorithms respectively. From these figures, it can be obviously seen that the de-noised image applying improved Gaussian weighted median filter is clearer and has better effect.

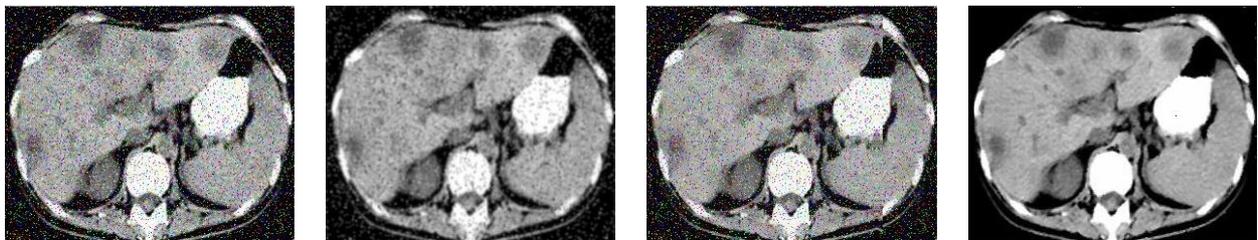


Figure.1 (a) Original Liver image (0.1 noise) (b) TCA filtering results (0.1 noise) (c) ADTCA filtering results (0.1 noise) (d) IMACA filtering results (0.1 noise)

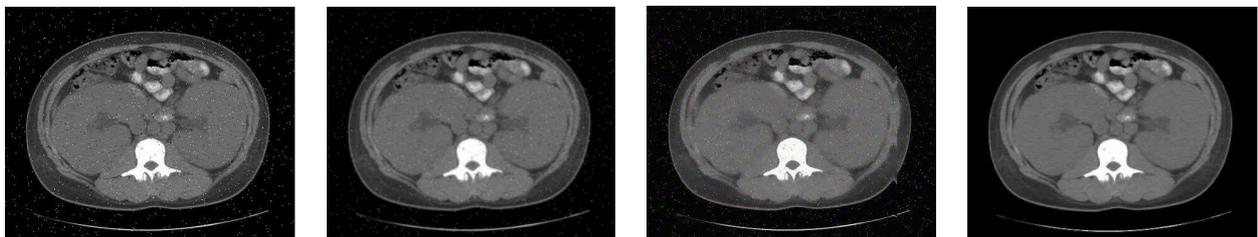


Figure.2 (a) Original Kidney image (0.01 noise) (b) TCA filtering results (0.01 noise) (c) ADTCA filtering results (0.01 noise) (d) IMACA filtering results (0.01 noise)

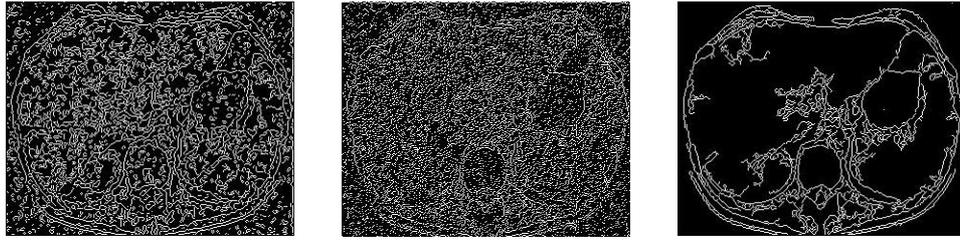


Figure.3 (a) Liver TCA segmentation results (0.1 noise) (b) ADTCA segmentation results (0.1 noise) (c) IMACA segmentation results (0.1 noise)

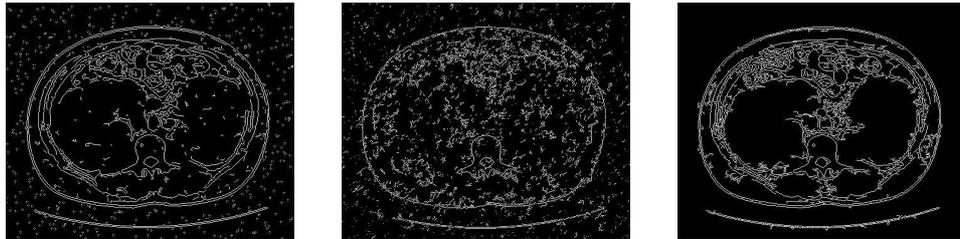


Figure.4 (a) Kidney TCA segmentation results (0.01 noise) (b) ADTCA segmentation results (0.01 noise) (c) IMACA segmentation results (0.01 noise)

The optimal high threshold value can be obtained through Otsu self-adapting algorithm. According to different value of k , the low threshold value can be calculated, as shown in Table 1

Table 1 The different high and low threshold value through the improved Otsu self-adapting algorithm

		$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	$k=9$
Liver (0.1 noise)	High threshold	0.1422	0.1422	0.1422	0.1422	0.1422	0.1422	0.1422	0.1422	0.1422
	Low threshold	0.1422	0.0711	0.0474	0.0355	0.0284	0.0237	0.0203	0.0178	0.0158
Kidney (0.01noise)	High threshold	0.1483	0.1483	0.1483	0.1483	0.1483	0.1483	0.1483	0.1483	0.1483
	Low threshold	0.1483	0.0745	0.0503	0.0395	0.0312	0.0293	0.0241	0.0216	0.0191

The operating time and signal-to-noise ratio of three algorithms under non-noise condition is further calculated. Through comparing with the data in table, the improved algorithm IMACA of this paper has faster operating speed and better signal-noise ratio than TCA and ADTCA under non-noise or noise environment, as shown in Table 2.

Table 2 Comparison of running time and signal-noise ratio of three different algorithms

	Liver		Kidney	
	Time (s)	Signal-noise ratio	Time (s)	Signal-noise ratio
TCA (0.01 noise)	0.332	7.9543	0.325	7.7627
TCA (0.1 noise)	0.433	3.4561	0.475	3.5087
ADTCA [4] (0.01 noise)	0.711	8.2254	0.757	7.1234
ADTCA[4] (0.1 noise)	0.682	3.5853	0.677	3.8827
IMACA (0.01 noise)	0.072	8.3547	0.074	7.7417
IMACA (0.1 noise)	0.089	3.6361	0.059	3.9665

Finally, we get the liver image out of the CT scans through IMACA method. Then inputting segmented liver image into 3DMax software, the liver virtual 3D model had been established with

viscoelasticity mathematical formula and modeling approach. Fig.6 is the platform of robot virtual training system. Fig.7 is the liver virtual model in robot training system.



Figure.5 The platform of robot virtual training system

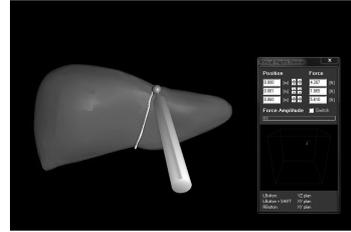


Figure.6 The liver virtual model based on IMACA

Conclusion

This paper studied on edge detection of traditional canny operator and previous literatures, applied median filter with improved Gaussian weighting and modified adaptive threshold selection algorithm into edge detection of medical image, and obtained clear edge detection image by simulation. Especially in environments with salt-and-pepper noise of different scales, this algorithm reveals significant advantage, by avoiding information gap caused by insufficient edge information and information redundancy resulted from too much information, and locating detailed information of medial image edge more accurately. For generating effective medial organ model in following virtual operation training system, this is an important groundwork.

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