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Edge Detection in Magnetic Resonance Images using Global Canny Algorithm

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ABSTRACT

Magnetic resonance imaging is an important modality in the diagnosis and pathology detection. Edge detection is used for image segmentation and feature extraction as part of the medical image analysis. There is no ideal and universal algorithm which performs perfectly under all conditions. Conventional Canny edge detector is not suitable to be used in Magnetic resonance images that contaminated by Rician noise. In this paper, we propose the use of customized non-local means into the Canny edge detector instead of Gaussian smoothing in the conventional Canny edge detector to effectively remove Rician noise while preserving edges in Magnetic resonance image of an internal organ. The result shows that our method can yield better edge detection than conventional method, with minimal false edge detection. The proposed method undergoes several attempts of parameter adjustment to detect true edges successfully using optimal parameter setting.

INTRODUCTION

Edge detection is one of the most important features in the application of image processing, computer vision and machine vision. The purpose is to extract information of boundaries of the object within image by detecting discontinuities in brightness level. The ideal edge detection algorithm will produce a set of connected curves that indicate boundaries of objects. Since edge detection have been used widely in many applications, it is important to design an effective and efficient edge detector as it will directly influence the image analysis.

The existing edge detectors are mostly designed on the basis of spatial domain detection that utilize gradient and Laplacian information to execute high pass filtering (Savant, 2014). Examples of gradient-based algorithms are Sobel, Prewitt, Roberts and the Laplacian of Gaussian (LoG) algorithms (Huertas & Medioni, 1986). These methods are known to be straightforward and fast where a simple convolution operation involved between small convolution mask and the input, in order to detect gradient in the image. On top of that, it is simple to be implemented. This simplicity raised from the “single focus” approach properties of edge enhancement, but lack of smoothing operation. Hence, the gradient-based edge detectors are very sensitive to noise, inaccurate and imperfect in engineering applications (Wang & Fan, 2009).

Canny edge detection is the most well-known Laplacian-based edge detector. This method is the most favorable to detect edges corrupted by noise. John F. Canny (Canny, 1986) uses a multistage algorithm to detect a wide range of edges in images. Through this technique, he define three optimal criteria as a guidelines for an effective result. First, the detector must minimize the probability of false edges caused by noise, as well as missing real edges. Second, the edges detected must be as close as possible to the true edges. Third, the detector must return one point only for each true edge point. In summary, the criteria presented by Canny filter are good detection, good localization and single response (Canny, 1986).

The performance of Canny edge detection is outstanding among other common filters in most cases, yet there is always room for improvement. In the past, some researchers offered many improved version of Canny filter. (Li *et al*., 2009) proposed optimization on the gradient level calculation operator and automatization of edge detection method using Otsu thresholding. The results showed good edge detection achieved to some extent. Agaian *et al.* (Agaian et al., 2009) introduced optimization of gradient kernel by employing Nercessian’s generalized kernels of derivative approximation (Agaian *et al*., 2009; Nercessian *et al.*, 2009). The results is effective in detecting branch edges in the application of asphalt concrete detection as compared to traditional Canny algorithm. Hou *et al.* (Hou et al., 2009) proposed the histogram-based fuzzy *c*-means clustering algorithm to modify the original Canny method. The results showed good detection on the application of road surface distress image.

The traditional Canny algorithm is widely used in removing the Gaussian noise corrupted of CT (Bandyopadhyay, 2012; Punarselvam & Suresh, 2011) and X-ray images (D.C *et al.*, 2012; Lakhani *et al.*, 2016) to detect edge line of the organ, but its purpose is limited. Recently, there are numerous literature that proposing different technique to detect and extract edges in other noisy medical images. This includes the edge detection in the speckle-noise corrupted of ultrasound phantom images (Chai *et al.*, 2012; Nikolic *et al.*, 2016). (Chai *et al*., 2012) introduced the speckle-reducing anisotropic diffusion (SRAD) technique in the image denoising part of Canny algorithm framework. The proposed method is capable in removing speckle noise while pertaining image details. Similar approach had been demonstrated by (Nikolic *et al*., 2016) but using different technique and different phantom image. The study propose a modificaton in Canny operator, by replacing the Gaussian filter with adjusted median filter and weighted dynamic smoothing filter. The results show a more precise edge detection as compared with the traditional Canny algorithm. Plus, the proposed method is assuringly more simpler than that in (Chai *et al.*, 2012).

However, the traditional Canny edge detection method is not suitable to remove Rician noise in Magnetic Resonance (MR) images because Gaussian filter cannot remove Rician noise effectively. Hence, noise will be perceived as the detected edges. SRAD filter maybe useful, but this filter is not designed to remove the Rician noise appeared in MR images.

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In this paper, an algorithm for edge detection in MR images is proposed. The proposed algorithm is based on the Canny edge detection algorithm. Non-local means (NLM) filter is proposed instead of Gaussian filter. The proposed algorithm was designed in a way that can remove Rician noise significantly while preserving edge information in the MR image.

MATERIALS AND METHOD

Noise modelling

MR images are contaminated by Rician noise. This kind of noise arises from complex Gaussian noise in the original frequency domain measurements which obtain from the raw data. Mathematically, the Rician probability density function for the contaminated image intensity x is given by

$$p(m) = \frac{m}{\sigma_n^2} exp\left(-\frac{m^2+A^2}{2\sigma_n^2}\right) I_0\left(\frac{Am}{\sigma_n^2}\right) \quad (1)$$

where A is the underlying true intensity, σ is the standard deviation of the noise, and I_0 is the modified zeroth order Bessel function of the first kind.

Proposed Global Canny algorithm

The term global is also known as the non-local component. Global Canny is referred to the hybrid NLM filter and Canny edge detection based algorithm. The NLM algorithm was pioneered by Buades and his colleagues in 2005. They introduced a novel approach by evaluating the similarity between two pixels x and y, not only done by the intensity, but also by the difference of intensity in whole spatial neighborhood (Buades *et al*., 2005).

A. Image smoothing

In our proposed method, the first step is to remove Rician noise with NL-means filter. NLM's algorithm is designed in a way that a discrete noisy image $= \{v(i) \mid i \in I\}$, the estimated $NL[v](i)$, for a pixel i, is computed as a weighted average of all the pixels in the image,

$$NL[v](i) = \sum_{j \in 1} w(i,j) v(j) \quad (2)$$

where $w(i,j)$ is the weight assigned to value $v(j)$ for restoring the pixel i. The weight $w(i,j)$ depends on the similarity between pixels i and j, and satisfy the general conditions $0 \leq (i,j) \leq 1$ and $\sum_{j \in 1} w(i,j) = 1$. Under this condition, the weight $w(i,j)$ evaluates the similarity between the intensities of the local neighborhoods (patches) $v(N_i)$ and $v(N_j)$ centered on pixels i and j. Mathematically, the weight can be defined by:

$$w(i,j) = (1/Z(i)) exp\left(-\left\|v(N_i) - v(N_j)\right\|_{2,\sigma}^2 / h^2\right) \quad (3)$$

with normalization;

$$Z(i) = \sum_j \exp\left(-\left\|v(N_i) - v(N_j)\right\|_{2,\sigma}^2 / h^2\right) \quad (4)$$

In the weight and normalization equation, there is a parameter h. This parameter control the decay of the weights and is usually related to the level of noise in the image. Thus, a natural selection of h will be of the form $h = c.\sigma$ where c is a scalar and σ is the level of noise in the image (Buades *et al.*, 2005).

Buades' filter utilizes the similarity concept of local patches to determine the pixel weights. As the reduction in patch size equal to one pixel, NLM filter becomes equivalent to the bilateral filter. Under stationarity assumptions, as the size of the image grow, there will be many similar patches to be found in all image details (Buades *et al*., 2005; Kumar, 2013). In summary, the NLM filter is effective at removing noise and smoothing the edges without losing too many details. This pre-processing step is taken to reduce the high frequency components before the differentiation step.

B. Image gradient calculation

The second step is to find the image gradient magnitude and direction. The edges should be marked in the location that have large magnitude gradient. Canny edge detection algorithm adopts limited difference of 2x2 neighboring area to compute the magnitude and the direction of image gradient, vertically and horizontally (Jia, 2009). The approximation for the first order partial derivative on the horizontal and vertical direction can be obtained from these following formulas:

$$E_x[i,j] = I(i+1,j) - I(i,j) + I(i+1,j+1) - I(i,j+1)/2 \quad (5)$$

$$E_y[i,j] = I(i,j+1) - I(i,j) + I(i+1,j+1) - I(i+1,j)/2 \quad (6)$$

Therefore, the template operator that can be used to calculate image gradient can be written as follows:

$$G_x = \begin{pmatrix} -1 & 1 \\ -1 & 1 \end{pmatrix} \quad (7)$$

$$G_y = \begin{pmatrix} 1 & 1 \\ -1 & -1 \end{pmatrix} \quad (8)$$

Then, the magnitude and direction of image gradient can be computed using following equation. The image gradient magnitude is:

$$\|M(i,j)\| = \sqrt{E_x[i,j]^2 + E_y[i,j]^2} \quad (9)$$

The direction of image gradient is:

$$\theta(i,j) = \arctan\left[E_y[i,j] / E_x[i,j]\right] \quad (10)$$

C. Non-maximum supression

The next step is to execute non-maximum suppression. It should be only local maxima need to be marked as edges, so that we can accurately position edges. The process will ensure that each edge is one pixel width. Canny algorithm uses 3x3 neighboring area which consists of eight directions to execute interpolation to the gradient magnitude along gradient's direction. If the magnitude M[i,j] is bigger than the two interpolation results on the gradient direction, it will be marked as candidate-edge point, otherwise it will be marked as non-edge point. Therefore, the candidate edge image is acquired through the process.

D. Checking and connecting edges

The Canny algorithm adopts double-threshold method to select edge points after carrying on non-maximum suppression. The pixels whose gradient magnitude is above the high-threshold will be marked as edge points, and those whose gradient magnitude is under the low-threshold will be marked as non-edge points, and the rest will be marked as candidate edge points. Those candidate edge points who are connect with edge points will be marked as edge points. This process of selecting true edges from weak edges is named as hysteresis. This method reduces the influence of noise on the edge of the final edge image.

RESULTS AND DISCUSSION

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Experimental results

The proposed method for edge detection in MR images of brain was implemented in Matlab R2012a. Experiments were performed on the platform Intel(R) Core(TM) i3-2310M CPU at 2.10GHz, 6GB RAM, Windows 7 Ultimate OS.

In order to test our proposed method, phantom MR image of kidney was used. The experimental results were organized in similar way as in (Chai *et al.*, 2012), but the mentioned paper used phantom ultrasound image. The image used in this paper is shown in Fig. 1(a) and is publicly available at YEZITRONIX Group Automation & Control Industries Inc. website. Phantom MR image acquired was first being read into MATLAB workspace.

Fig. 2 shows edge detection in test image shown in Fig. 1(a) by our proposed method. It was tested at different threshold values in order to determine the optimal one. In Fig. 2, Canny operator are tested at threshold T=0.05, 0.10, 0.15, and T=0.20 with standard deviation at σ= 0.2, 0.4, 0.6 and σ=0.8 respectively, for both original and new proposed method. In the first attempt, the threshold and standard deviation is set at 0.05 and 0.2 respectively, as shown in Figure 2 (a). Many of noisy parts were recognized as edges with this parameter values especially in original Canny algorithm. However, less noise is accepted as edges when using our proposed method.

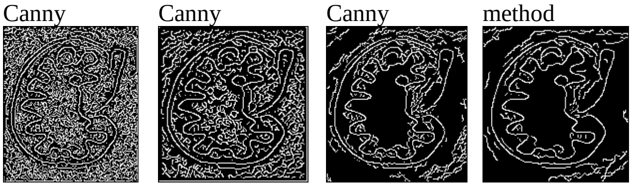
In the next following trials, we increased both threshold and sigma values. When we set T=0.10 and σ=0.4, the image (Figure 2(b)) exhibits a little less false edges but it is still not good enough to get the desired result. The presence of noise once again cause edge misdetection in most of area in the image, especially using traditional Canny and SRAD-Canny method. The image shows better edge detection in bilateral-Canny our proposed method, but some noise was regarded as edges and some parts of phantom image lines eroded.

Another trial had been done to improve the result by increasing the parameter values to T=0.15 and σ=0.6. Using this setting, better edge detection were performed as shown in Figure 2(c). Our proposed method convey better edge detection as compared to the other method. There was some noise was still recognized as edges but this occurrence was significantly lower than that in the previous attempt.

In the final attempt, Figure 2(d) shows much better edge detection. The parameter values were set at T=0.20 and σ=0.8. Obviously, our proposed method shows excellent detection as compared to the other algorithm with precise and connected edge lines. In summary, the Global Canny had minimized the probability of false edges caused by noise, as well as missing real edges. Second, the proposed method show edges detected is as close as possible to the true edges. Third, the detector return one point only for each true edge point.

(a) Original MR phantom image (b) Simulated noisy image (c) Ground truth of MR phantom image

Fig. 1 Input image for edge detection assessment



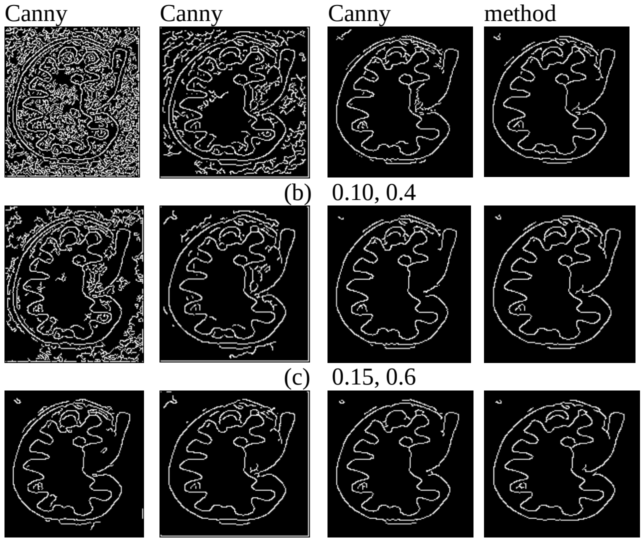


Fig. 2 Comparison between traditional Canny with other Canny-based methods with double thresholding parameter setting

Performance evaluation

The experimental results are further evaluated based on quantitative analysis. The performance of algorithm are evaluated similarly in (Deng et al., 2013) and (Wu et al., 2005). Since noise reduction and edge preservation are conflicting objectives, thus the performance assessment require simultaneous comparison. In this part, quantitative parameter such the Peak Signal to Noise Ratio (PSNR), image entropy, average gradient, the correlation coefficient and the similarity percentage are being quantified (Deng et al., 2013). However, only output image using optimum parameter are being taken into consideration.

The PSNR is the empirical measurement of the image quality. This parameter evaluates the performance of image enhancement algorithm by comparing the enhanced image with the original input image. High quality image is defined by higher value of $PSNR$. The PSNR value is computed through the formula ratio between the maximum possible value of a signal and the power of the noise signal, which is given as follows:

$$PSNR = 10\log_{10}(\,255^2/MSE) \tag{11}$$

The image entropy defines the uncertainty in the image values by taking average of the information content in an image to encode the image values. Higher value image entropy indicates higher amount of information existed in an image. Technically, the calculation of image entropy yields the value of histogram dispersion. Mathematically, the image entropy, *H* is given by:

$$H = -\sum_{i=0}^{L-1} P_i.\log_2(P_i) \tag{12}$$

where P_i is the probability of two adjacent pixels difference (grey values) is equal to i, and i is the pixel intensity of an image.

The Pearson Correlation coefficient measure the likeliness of the original and the processed image. Higher value of correlation indicates that the output image is much closer to input image which has the maximum value of 1. Correlation of two images can be computed by using the following formula:

$$Corr_1 = \frac{\sum_i[(x_i - x_m)(y_i - y_m)]}{\sqrt{\sum_i(x_i - x_m)^2}\sqrt{\sum_i(y_i - y_m)^2}} \tag{13}$$

with magnitude of x_m and y_m is defined as:

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$$x_m = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} x_i \quad (14)$$

$$y_m = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1} y_i \quad (15)$$

In the above equation x_i is denoted as the intensity of the i^{th} pixel in image 1, y_i is the intensity of the i^{th} pixel in image 2, x_m is the mean intensity of image 1, and y_m is the mean intensity of image 2.

Image clarity measure the structural quality that reflect the change in image texture and details. Better image quality has higher value of the image clarity and can be expressed using this following equation:

$$\nabla\bar{G} = \frac{1}{mn}\sum_{i=1}^{M}\sum_{j=1}^{N}\sqrt{\left[\left(\frac{\partial f(i,j)}{\partial x}\right)^2 + \left(\frac{\partial f(i,j)}{\partial y}\right)^2\right]} \quad (16)$$

where $\partial f(i,j)/\partial x$ and $\partial f(i,j)/\partial y$ are one-order differential of pixel (i,j) in x and y direction respectively.

Table 1 shows the performance comparison between Global Canny with other Canny based algorithm. In term of noise reduction, SRAD-Canny perform the best with the highest PSNR value. The SRAD-Canny method outstands traditional Canny and other method as well. However, the filter downfall is that it also remove image detail which cause blurry image representation. The image quality is not preserved and complicate the correct edge detection process.

Image texture and fine details is the most prominent using traditional Canny method. This can be seen in the high image entropy and image clarity value. However, it is possible that the method was influenced by the existence of the noise. This cause edge misdetection to be occurred. This problem happens when the noisy edges dominate the process and causes the miss for valid edges while creating noise-induced false edges.

Table 1 Performance evaluation of traditional Canny, SRAD-Canny, Bilateral-Canny and Global-Canny-based method

Evaluation parameter	Ground truth image	Traditio-nal Canny	SRAD-Canny	Bi-lateral Canny	Global Canny
PSNR	-	25.669	25.742	25.671	25.667
Entropy	6.95	6.98	6.91	6.85	6.89
Image clarity	47.30	54.36	44.79	33.09	33.35
Correlation	1.00	0.989	0.965	0.991	0.993
Similarity percentage	100	73.67	74.02	82.47	87.22

Image correlation is important in finding the degree of similarity between the input and the processed image. The proposed method exhibits the highest correlation as compared to others. It shows that the proposed method successfully remove noise while preserving image properties, as the processed image is very close to the input phantom image. This statement is supported by the highest percentage difference shown using the proposed method, by comparing the final edge detection with the synthesized ground truth.

CONCLUSION

In this paper, we proposed an algorithm based on Canny operator for edge detection in Magnetic Resonance phantom image of internal organ. The new method was incorporated NLM filter instead of using Gaussian filter in Canny operator. Experimental results have shown that with the modified Canny operator, edges in noisy Magnetic Resonance phantom image can be recognized very successfully. Future works may involve modification of the original algorithm for different application of internal organs, different type of medical images and different type of noise.

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