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Artificial Neural Network Based Fast Edge Detection Algorithm for MRI Medical Images

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Abstract

Currently, magnetic resonance imaging (MRI) has been utilized extensively to obtain high contrast medical image due to its safety which can be applied repetitively. To extract important information from an MRI medical images, an efficient image segmentation or edge detection is required. Edges are represented as important contour features in the medical image since they are the boundaries where distinct intensity changes or discontinuities occur. However, in practices, it is found rather difficult to design an edge detector that is capable of finding all the true edges in an image as there is always noise, and the subjectivity of sensitiveness in detecting the edges. Many traditional algorithms have been proposed to detect the edge, such as Canny, Sobel, Prewitt, Roberts, Zerocross, and Laplacian of Gaussian (LoG). Moreover, many researches have shown the potential of using Artificial Neural Network (ANN) for edge detection. Although many algorithms have been conducted on edge detection for medical images, however higher computational cost and subjective image quality could be further improved. Therefore, the objective of this paper is to develop a fast ANN based edge detection algorithm for MRI medical images. First, we developed features based on horizontal, vertical, and diagonal difference. Then, Canny edge detector will be used as the training output. Finally, optimized parameters will be obtained, including number of hidden layers and output threshold. The edge detection image will be analysed its quality subjectively and computational. Results showed that the proposed algorithm provided better image quality while it has faster processing time around three times time compared to other traditional algorithms, such as Sobel and Canny edge detector.

Keywords: *MRI images; artificial neural network; edge detection; Canny edge detector*

1. Introduction

Nowadays, magnetic resonance imaging (MRI) is one of the most important imaging technique to obtain a medical image with high contrast. In addition, MRI acquisition device could be controlled to provide different gray levels for different tissues, and it provides higher contrast compared to computerized tomography (CT). MRI scanning is relatively safe and can be used as many times as required. It is based on the hydrogen nucleus due to their abundance amount in the human body and their magnetic resonance sensitivity [1].

Artificial Neural Network (ANN) has been successfully used in many computer-aided diagnosis of medical imaging [2]. Moreover, medical image segmentation and edge detection remains an important problem for all medical imaging applications, in which any computer assisted diagnosis will require edge detection and other techniques, such as watershed, snake modelling, region growing, and contour detection [2]. Additionally, ANN has been utilized to exploit its learning capability and training mechanisms to classify medical images into content consistent regions to complete segmentation as well as edge detection [3].

There are many researches have been conducted on edge detection or edge features for medical image segmentation [4] as well as encryption [5]. In [6], spiking neural network (SNN) has been used for medical image segmentation and edge detection. SNN has lower computational requirement and add temporal dimension to the representation capacity and the processing abilities of neural networks. In other research, cellular neural network has been used

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for edge detection of noisy images [7]. Beside ANN, many other algorithms have been developed for edge detection, such as intensity gradient and texture gradient features [8], cellular automata based tumor segmentation [9], optimized Canny edge detector [10], active contour model [11], wavelet threshold [12], and graph theory [13]. Due to its high computational cost, the edge detection algorithms could be parallelized as described in [14] into a cluster computer.

Although many algorithms have been conducted on edge detection for medical images, however higher computational cost and subjective image quality could be further improved. Therefore, the objective of this paper is to develop a fast ANN based edge detection algorithm for MRI medical images. First, we developed features based on horizontal, vertical, and diagonal difference. Then, Canny edge detector will be used as the training output. Finally, optimized parameters will be obtained, including number of hidden layers and output threshold. The edge detection image will be analysed its quality subjectively and computational time compared to other traditional algorithms, such as Canny, Sobel, Prewitt, Roberts, Zerocross, and Laplacian of Gaussian (LoG). Results showed that the proposed algorithm provided better image quality while it has faster processing time around three times.

2. Proposed Features for ANN Based Edge Detection Algorithm

Previous researches used rather complex features for ANN training and testing. In this research, we propose a rather simple feature extraction using gray level values of an MRI medical images and extracted its horizontal (*dx*), vertical (*dy*), and diagonal (*dz*) differences as shown in Figure 1. This feature extraction could be further extended to include the difference in the opposite directions (3x3 neighbourhood). However, this will implied higher computational cost despite higher edge quality.

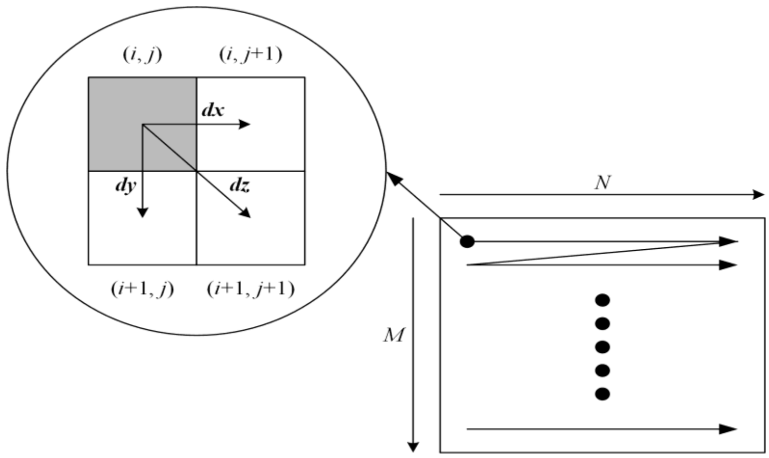


Figure 1. Proposed Difference Features for ANN based Edge Detection Algorithm

Figure 1 shows that grayscale MRI image is used to extract the difference features. Suppose that we have a grayscale MRI image *I*(*x*,*y*) with size of *M* by *N pixels*. For every pixel position ($i = 1, \ldots, M$ and $j = 1, \ldots, N$) we calculate three difference features, i.e. horizontal (*dx*), vertical (*dy*), and diagonal (*dz*), as shown in Equation (1)-(3).

$$dx(i, j) = I(i, j+1) - I(i, j), \ \forall i, j \tag{1}$$

$$dy(i, j) = I(i+1, j) - I(i, j), \ \forall i, j \tag{2}$$

$$dz(i, j) = I(i+1, j+1) - I(i, j), \ \forall i, j \tag{3}$$

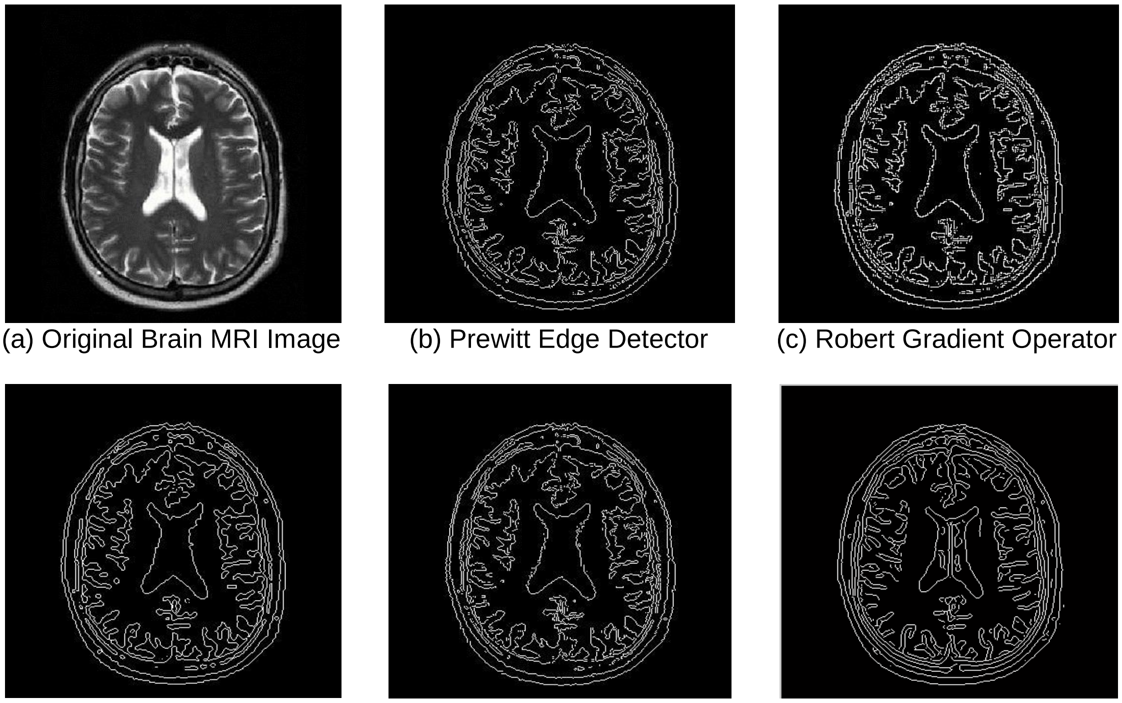
We further normalize the feature vector by dividing with the maximum of image grayscale value, i.e. 255, so that the feature value will be between -1 and 1. These three features are then combined into feature vector **m** for the training and/or testing of ANN, as shown in Equation (4).

$$\mathbf{m} = \begin{bmatrix} \mathbf{dx} \\ \mathbf{dy} \\ \mathbf{dz} \end{bmatrix} \tag{4}$$

3. Proposed ANN Based Edge Detection Algorithm

3.1. Output of Canny Edge Detector for ANN Training

Of the various traditional edge detection algorithm, Canny edge detector is a derivative of the Gaussian function and is one the best edge detectors for its low error rate and strong denoising capability [5, 10] as shown in Figure 2. An MRI image is firstly smoothed by Gaussian filter. Then, intensity gradients of the image is obtained using convolution masks of other edge detectors, i.e. Sobel or Prewitt detectors. Next, it calculates the gradient approximations and the directions by non-maxima suppression, and uses the double-thresholding algorithm to detect and link edges. The performance of Canny algorithm depends heavily on the selected threshold values as well as on parameter of Gaussian filter σ. Parameter σ controls the size of the Gaussian filter, the larger the value, the larger the size of Gaussian filter and the more blur the image, vice versa. In this research, we utilize the output of Canny edge detector as the output training for our proposed ANN in which feature vector **m** is used as the input of ANN.



(a) Original Brain MRI Image (b) Prewitt Edge Detector (c) Robert Gradient Operator

(d) Laplacian of Gaussian (e) Sobel Operator (f) Canny Edge Detector

Figure 2. Comparison of Various Edge Detection Algorithms for MRI Brain Image

3.2. Implementation of ANN

Figure 3 shows the proposed feed-forward neural network with 1 input layer with 3 neurons (the same size with feature vector **m**), 1 hidden layer (number of neurons can be varied and it will be part of experimentations), and 1 output layer with 1 neuron with one threshold variable, *T*. The output layer is using *satlins* transfer function which limits the output value *y* to be between -1 and 1. To determine the final value, we then threshold the output of neural network, so that it will be 0 (no edge) or 1 (edge), as follows:

$$f(y)=\begin{cases}1 & if\ y>=T\\ 0 & if\ y<T\end{cases} \tag{4}$$

As the training output, we used the output from canny edge detector (0 indicates no edge while 1 indicates edge). The neural network structure is shown in Figure 3. The threshold value, type of training function, and number of hidden layer is varied and simulated to obtain the best parameter for the most efficient results.

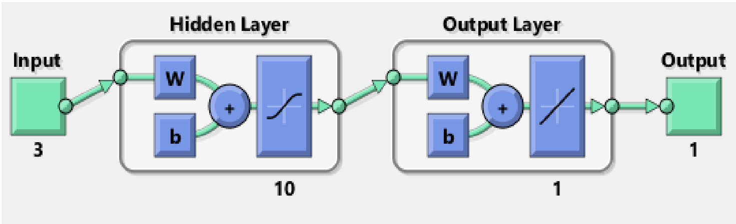


Figure 3. Proposed Feed-forward Neural Network Structure for Edge Detection

To find the optimum parameters, we trained the network using three different training functions which are Levenberg-Marquardt Backpropagation (trainlm), Resilient Backpropagation (trainrp), and Gradient Descent Backpropagation (traingd). For every training function, the threshold *T* also are varied heuristically to find the optimum threshold. Additionally, the number of neurons contained in the hidden layer is varied with using the optimum threshold obtain earlier.

4. Results and Discussion
4.1. Experimental Setup

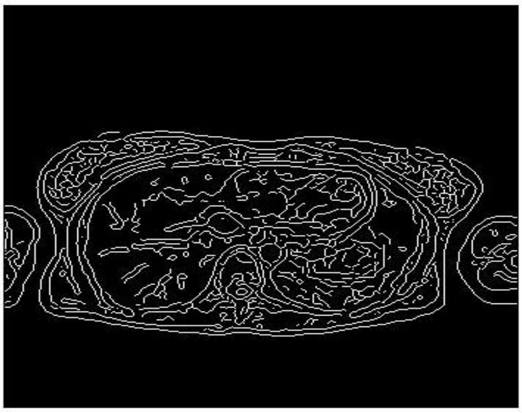
Table 1. MRI Image Database

Image #	Image Details	Size (pixels)	Image #	Image Details	Size (pixels)
Image1	Horse Brain	300 x 300	Image21	Human Knee (Side)	350 x 350
Image2	Horse Foot	300 x 300	Image22	Human Brain (Back)	386 x 386
Image3	Human Knee (Side)	500 x 500	Image23	Human Brain (Top)	536 x 538
Image4	Human Brain (Top)	512 x 512	Image24	Human Brain (Side)	717 x 717
Image5	Human Spine	1024 x 1024	Image25	Human Brain (Side)	400 x 400
Image6	Human Brain (Back)	512 x 512	Image26	Corn	600 x 600
Image7	Human Brain (Top)	512 x 512	Image27	Human Spine	512 x 512
Image8	Human Ankle	500 x 498	Image28	Human Brain (Top)	512 x 512
Image9	Baby In Womb	756 x 756	Image29	Human Brain (Side)	512 x 512
Image10	Human Brain (Top)	586 x 586	Image30	Human Knee	512 x 512
Image11	Cucumber	500 x 500	Image31	Rodent Brain (Top)	560 x 560
Image12	Human Brain (Back)	512 x 512	Image32	Human Neck (Side)	336 x 337
Image13	Human Foot	512 x 512	Image33	Human Neck (Front)	512 x 512
Image14	Human Foot	512 x 512	Image34	Human Spine (Front)	605 x 605
Image15	Human Brain (Side)	3543 x 3543	Image35	Human Shoulder	300 x 300
Image16	Human Knee (Side)	600 x 600	Image36	Human Ankle	575 x 575
Image17	Human Brain (Side)	600 x 600	Image37	Human Brain (Side)	626 x 626
Image18	Human Brain (Top)	225 x 225	Image38	Human Brain (Top)	300 x 300
Image19	Human Spine	300 x 300	Image39	Human Brain (Side)	512 x 512
Image20	Human Knee (Top)	350 x 350	Image40	Human Brain (Back)	400 x 400

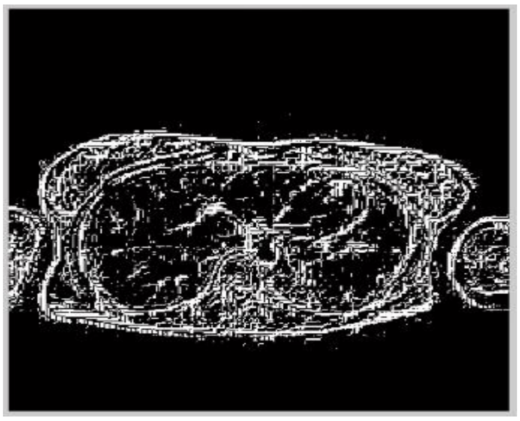
Table 1 shows the MRI image database consists of 40 MRI images with various size, in which the first 24 images (60%) will be used for training, and the last 16 images (40%) will be used for testing. During the training stage, three parameters are varied, including training functions, number of hidden layers, and output threshold. The image output as well as the performance are then recorded. By observation, the set of parameters that provides the best result and performance are selected and utilized in the testing stage. The proposed algorithm was implemented using Matlab R2017a on Microsoft Windows 10 64bits. The hardware used was a computer with i7 Core, 16 GB RAM, and 1 TB hard disk.

4.2. Experiments on Various Training Functions, Number of Neurons in the Hidden Layer, and Output Threshold.

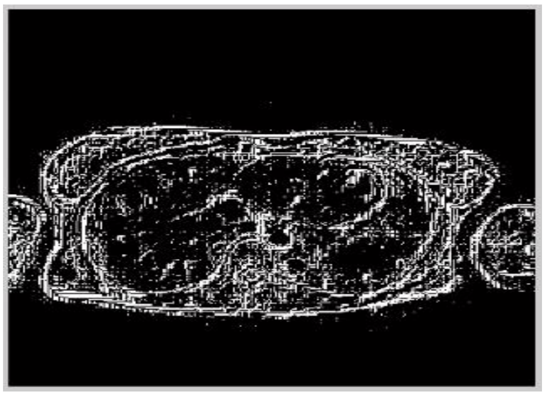
These functions, i.e. trainlm, trainrp, and traingd, were used to train the neural network. The number of neurons in the hidden layer were varied from 3 to 180, while the threshold value was varied between 0.05 to 0.35. By observation, we selected the optimum parameters for each training function as shown in Figure 4. Based on the mean squared error (*mse*), training time ($t_{training}$), and subjective image quality, trainlm function with T=0.1 and N_{hidden}=180 were selected as the optimum.



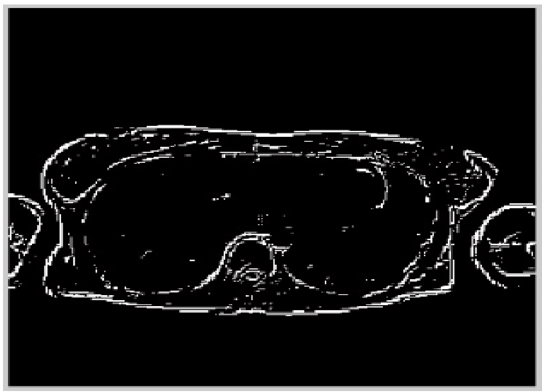
(a) Canny edge detector



(b) trainlm, with T=0.1, N_{hidden}=180, *mse*=0.0525, $t_{training}$=343 seconds



(b) trainrp with T=0.1, N_{hidden}=180, *mse*=0.0527, $t_{training}$=755 seconds



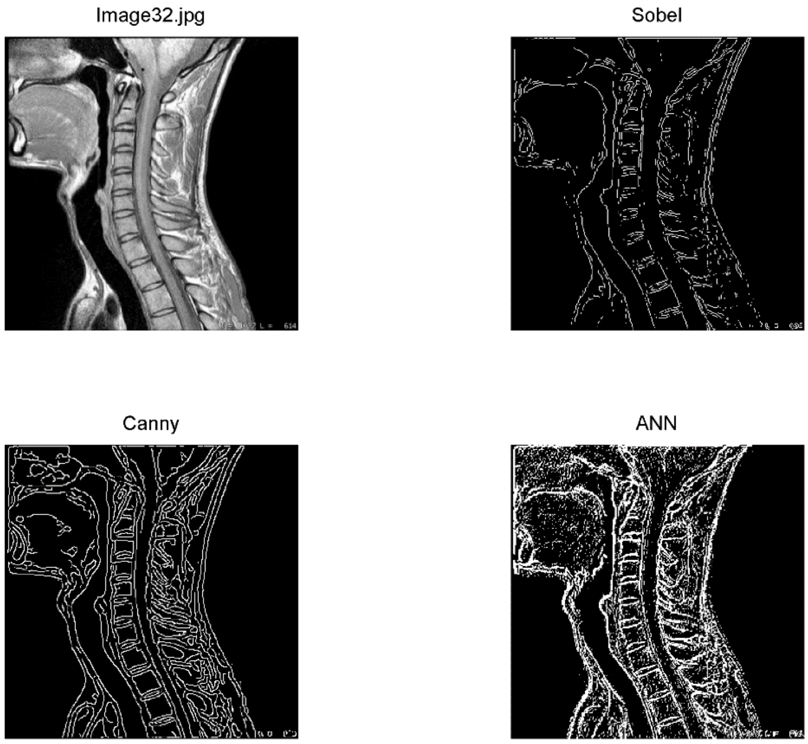
(c) traingd with T=0.1, N_{hidden}=10, *mse*=0.341, $t_{training}$=2752 seconds

Figure 4. Comparison of Various Training Functions

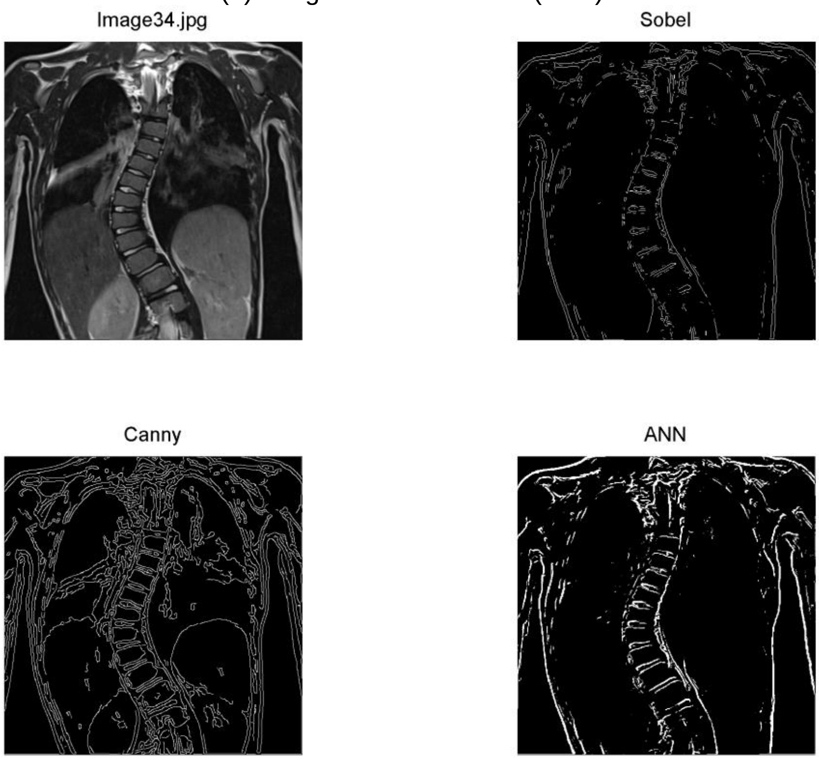
4.3. Experiments on The Testing Images

After the proposed neural network has been trained using the optimum parameters, it will be tested with the last 40% of the MRI image database. Figure 5 shows an example of edge detection results using Sobel, Canny, and the proposed ANN based algorithms for Image32 and

Image34. The results showed that the proposed algorithm produces clearer image compared to Sobel, not too sensitive as Canny without missing out the important edges.



(a) Image32 Human Neck (Side)



(b) Image34 Human Spine (Front)

Figure 5. Comparison of Sobel, Canny, and proposed ANN based edge detection algorithm

For comparison, we measured the time taken for three edge detection algorithms to complete its processing, i.e. Sobel, Canny, and the proposed ANN algorithm. Table 2 shows the comparison of processing time required for each algorithm. It can be concluded that the proposed ANN based edge detection algorithm is faster by almost three times compared to Sobel and Canny edge detectors.

Table 2. Processing Time Comparison for Various Edge Detection Algorithms

Method	Time taken (ms)
Canny Edge Detector	0.0222
Sobel Edge Detector	0.0216
The Proposed ANN based Algorithm	0.0078

5. Conclusions and Future Works

This paper has presented the design and development of ANN based edge detection algorithm for MRI medical images. First, we carefully designed the features that will be used as the input to the ANN. Three features were selected which can capture the required edge information, i.e. horizontal, vertical, and diagonal differences. Next, Canny edge detector was selected as the output training for the proposed ANN. The structure of ANN was also analysed by varying the training functions, number of neuron in the hidden layer, and the output threshold. It was found that the Levenberg-Marquardt Backpropagation was the best training function with number of neuron is 180 and the output threshold is 0.1. The trained ANN was then tested using other images, in which the results showed that the output image produces subjectively better and richer information compared to Sobel and Canny edge detectors. Furthermore, the computational cost for the proposed algorithm was smaller by almost three times compared to the traditional algorithms. Further research could be conducted on the use of deep neural network based edge detection algorithm with other modalities of medical images.

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