# Efficient Neural Network Based Edge Detection On Medical Images

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***Abstract: -*** Edge detection is an important but rather difficult task in image processing and analysis. In this research, artificial neural networks are employed for edge detection based on its adaptive learning and nonlinear mapping properties. Fuzzy sets are introduced during the training phase to improve the generalization ability of neural networks. The application of the proposed neural network approach to the edge detection of medical image for automated lung cancer. So simulation results are obtained .

Index Terms: ANN, fuzzy, filter.

## I. INTRODUCTION

Edges in images are the curves that characterize the boundaries (or borders) of objects. Edges contain important information of objects such as shapes and locations and are often used to distinguish different objects and or separate them from the background in a scene. In image processing, edge detection can be employed to filter out less relevant information while preserving the basic structural properties of an image. It can significantly reduce the amount of data to be processed in the subsequent stops such as feature extraction, image segmentation, registration, and interpretation. Edge detection has found many applications in pattern recognition, image analysis, and computer vision.

Since edges are associated with abrupt intensity changes, edge detection is the process to identify and locate such sharp intensity contrasts, in an image. It is well known that slow changes correspond to small values of derivatives while fast changes correspond to large values of derivatives. Based on this principle, a two dimensional spatial filter (also called "the gradient operator") is often employed in conventional edge detection algorithms. This filter is designed to be sensitive to detect the gradient of image intensity while yields no response to non-edge (uniform) regions (i.e., the areas with constant intensity) in the image. A variety of filters (or "masks") have been developed to detect various types of edges. For example, different masks can be composed and optimized to detect edges in horizontal, vertical, or diagonal directions respectively. Once the mask is constructed, it convolves with the entire image pixel by pixel, to detect edges. Typical conventional edge detection algorithms include the Sobel detector, the Prewitt of detector as well as Canny detector, etc [I]. The limitation of the above traditional algorithms is that multiple threshold values need to be set through a trial-and-error process; and the values can dramatically affect the performance of each algorithm.

Recently, artificial neural networks (ANN) have been **ap**plied to edge detection. Based on the adaptive learning ability and nonlinear mapping ability, neural networks can be trained to detect edges and can serve as nonlinear filters once they are fully trained. In [2], Terry and Vu investigated the application of multi-layer feed forward neural networks for the edge detection of the LADAR (laser radar) image of a bridge. Multiple neural networks are trained by synthetic edge patterns; each one of them can detect a specific edge pattern (e.g., horizontal, vertical, diagonal). If desired, one can also combine the outputs from the "group" of neural networks to detect multiple types of edges in images. Li and Wang applied neural networks to detect tile defect in an image. They divided gray-scale image (with 256 levels) into 8 sub gray-scale bit planes, and designed 8 input neurons in neural networks to process the image in a parallel form. The output of each neural network is then combined based on the weight of each bit to generate the final result. Testing results indicate that the middle to high bit planes contain more edge information than the low bit planes (e.g., bit plane 6 has more influence on the accuracy of edge detection than bit plane 1).

In gray-scale images, intensity levels may range from 0 to 2. To reduce the number of training patterns required to train a neural network. He [4] and Mehrara [5] suggested a shortcut. They converted gray-scale images to binary images first, and then trained neural networks to detect edges in binary images instead of gray-scale images. Since the intensity levels in binary images only have two discrete values (0 and 1), all the possible edge patterns can be included in the training set and the output of neural network converges very fast. However, choosing the appropriate threshold to binarize gray-scale images requires additional works and may also introduce some efforts that give the accuracy of edge detection.

In this research, a multi-layer feed forward neural network is employed for edge detection of gray-scale images. Unlike the multiple neural work approaches proposed in [2] and [3] only a single neural network is used for edge detection. No pre-processing on gray-scale images is needed. The methods presented in [4] and [5] proposed new concepts. **F**uzzy concepts introduced during the neural network training phase to improve its generalization ability. The proposed neural network approach is applied to some typical test images (e.g Lung image) and satisfactory computer simulation results are obtained.

With the recent developments on computational intelligence, the design of computerized medical diagnosis system has received more and more attention. An automated Diagnosis system not only saves man power and reduces cost, but also minimizes human bias in the diagnosis process. One of the most challenging tasks in machine learning to interpret medical Images obtained from clinical tests. In this research we investigate the application of artificial neural networks for lung cancer image detection. Computer simulation results show that the performance of the proposed neural network detector is very promising.

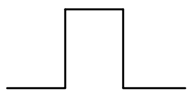
The rest of the paper is organized as follows. In section 2, two of the typical conventional algorithms for edge detection, i.e., the Sobel detector and the Prewitt detector are summarized. The neural network model employed for this research is discussed in section 3. In section 4 computer simulation results are presented. In section 5 concludes the paper and also gives the direction for future works.

## II. THE CONVENTIONAL EDGE DETECTION ALGORITHMS

Most of the conventional edge detection algorithms can be classified into two categories. i.e., the gradient based method and the Prewitt based- method. The former uses the value of the first order gradient while the latter searches the zero crossings in the second order derivative. The two distinct approaches are illustrated in Fig.1.

**(a) Convex roof edge** **(b) Concave roof edge**

**(c) Concave ramp edge** **(d) Step edge**



**(e) Bar edge**

**Fig.1. Types of Edges**

Sobel operator (developed in early **70s')** is a commonly used discrete first-order gradient detector . The gradient at each pixel. In the image a vector which as two components, one tor horizontal direction and the other one for vertical direction:

$$\nabla f = \begin{bmatrix} grad_x \\ grad_y \end{bmatrix} = \begin{bmatrix} \dfrac{\partial f(x,y)}{\partial x} \\ \dfrac{\partial f(x,y)}{\partial y} \end{bmatrix} \qquad \textbf{(1)}$$

Where$\nabla f$ represents the gradient at location $(x, y)$ of an image *f*. The direction **if** the gradient vector points to the direction of the largest possible intensity change (from low intensity to high intensity) and its magnitude denoted by Mag ($\nabla f$) represents the rate of change in that direction:

$$Mag(\nabla f) = \sqrt{(grad_x)^2 + (grad_y)^2} \qquad (2)$$

The **3x3.** two dimensional Sobel masks for edge detection are shown in Fig.2 (one for horizontal direction and one for vertical direction). Note that using "2"s in center locations provides image smoothing. In fact, the edges detected by a Sobel detector are usually several pixels wide due to the smoothing effect.

| | | |
|---|---|---|
| -1 | -2 | -1 |
| 0 | 0 | 0 |
| 1 | 2 | 1 |

| | | |
|---|---|---|
| -1 | 0 | -1 |
| -2 | 0 | 2 |
| -1 | 0 | 1 |

**Fig. 2. The Sobel operator (1)**

Another type of edge detectors finds edges by searching the zero crossings in the second order derivative of the image 1. The Prewitt operator is a typical example. It employs the second order differentiation and searches the points where the Prewitt operator of Gaussian function changes its sign (is., crosses zero). The Prewitt operator is defined as:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \qquad (3)$$

The 2-D Gaussian function is defined as:

$$G(x,y) = \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \qquad (4)$$

It can be shown that the expression of the Prewitt and Gaussian (LOG) can be written as

$$\nabla^2 G(x,y) = \left[\frac{x^2+y^2-2\sigma^2}{\sigma^4}\right] \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \qquad (5)$$

One of the major advantages of the Prewitt operator is isotropic i.e., it is invariant to rotation. This important property indicates the similar to the characteristics of the human visual system is filter responds equally changes in intensity in different directions [1]. Therefore, unlike the Sobel operator

or other similar first order derivative operators The output of the Prewitt detector is usually a binary image with single pixel thickness lines showing the positions of the zero crossing points. Note the performance of the detector is mainly governed by the standard deviation of the Gaussian function the higher this value is set, the fewer zero crossings can be detected.

## III. THE NEURAL NETWORK MODEL

In this section a multi-layer feed forward artificial neural network (A*) model for edge detection is discussed. It is well known that ANN can learn the input-output mapping of a system through an iterative training and learning process [6]. Thus ANN is an ideal candidate for pattern recognition and data analysis.

The ANN model employed in this research has one input layer, one output layer, and one hidden layer. There are 9 neurons in the input layer. In other words, the input of this network is a 7x1 vector which is converted from a 2x2 mask. There are 6 hidden neurons in the hidden layer; and one neuron in the output layer which indicates where an edge is detected. That is, the neural network model is a multi-input, single-output system. The output neuron is linear: the activation function for each hidden neuron is chosen as the hyperbolic function

$$f(x) = \frac{1-e^{-x}}{1+e^{-x}} \qquad (6)$$

The weights of the neural network are updated using the equations (8) and (9) to minimize following objective function.

$$J(k)=\frac{1}{2}e^2(k)=\frac{1}{2}\left[d(k)-y(k)\right]^2 \qquad (7)$$

where $d$ is the desired output and $y$ is the output of neural network; e is the output error (i.e., the difference between the neural network output and the desired output); $\boldsymbol{k}$ is the index of a training pair. Let W be the weight matrix of the neural network. Then

$$W(k+1)=W(k)+\nabla W \qquad (8)$$

$$\nabla W=\left(J_a^T J+\mu I\right)^{-1} J_a^T e \qquad (9)$$

where $J$, is the first order derivative of the error function with respect to the neural network weight (also called the Jacobian matrix); $\boldsymbol{r}$ is the output error. The difference between the neural network output and the desired output is used for weight adjustment. The learning parameter is considered for neural network training adjustment.

The training patterns for the neural network are shown in Fig. 3. Totally 17 patterns are considered including 8 patterns for "edge" and remaining patterns for "non-edge". During training, all 17 patterns are randomly selected. For simplicity all training patterns are binary images.

Initial test results show that, though the neural network is fully trained by the above 17 binary patterns, the performance of the neural network detector is poor when it is applied to test images. The reason is that all the test images are gray-scale (i.e., the intensities of images ranging from 0 to *255).* Thus, we normalize the gray-scale intensities so they are within the range between 0 and 1. Furthermore to improve the generalization ability of neural network, fuzzy concepts are introduced during the training phase so that more training patterns can be employed by the neural network. The membership functions are shown in Fig. 4. The grade of Membership function can be defined as:

$$\mu(x)=\exp\left(-\frac{(x-\xi)^2}{2\sigma^2}\right) \qquad (10)$$

| | | |
|---|---|---|
| 0 | 0 | 1 |
| 0 | 0 | 1 |
| 0 | 0 | 1 |

| | | |
|---|---|---|
| Low | Low | High |
| Low | Low | High |
| Low | Low | High |

Fig3 & Fig4: Training patterns

Similar to the above example, more training patterns can then be generated using fuzzy concepts to improve. Now the training patterns in Fig. 3 are represented using fuzzy membership functions. Fig. 4 shows an example of a fuzzy training pattern. The original pattern obtained by conventional edge detection algorithms, including the Sobel operator and the Prewitt operator are also shown as comparisons. The proposed neural network detector is also applied to Lung CT Scan images detection. Lung Cancer in United States is the fourth most common type of cancer in men and the ninth in women [8]. Early diagnosis is crucial for cancer prevention, treatment and patient survival. The current diagnosis is based on a CT scan images of Lungs. To automatic this process, edge detection should be performed as the first step for image interpretation.

The simulation results of lung images are shown in figures. These results demonstrate that the neural network detector successfully detects edges in the original image and outperforms the conventional Sobel and Prewitt detectors.

## IV. SIMULATION RESULTS

In this section, the proposed neural network approach is first tested on Lung CT Scan images. The results obtained by conventional edge detection algorithms, including the Sobel operator and the Prewitt operator are also shown as comparisons.

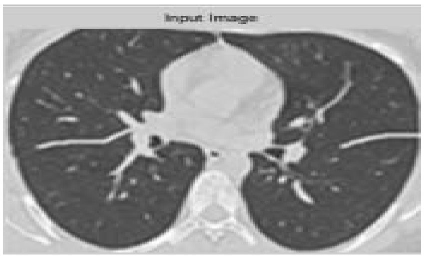



**Fig.5. Original image**

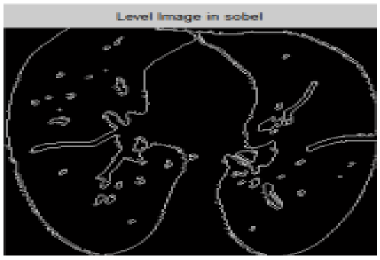



**Fig6. Sobel detector**

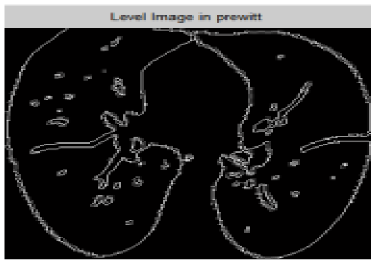



**Fig. 7. Prewitt detector**

**Fig. 8. Neural network detector**

The simulation results on "Lung CT Scan images" by Sobel, Prewitt, and the neural network detector are shown in Fig. 6 and Fig. 7 and Fig 8 respectively. The neural network is trained by the values from lung CT images. Similar to the Sobel and Prewitt detector the trained neural network detector "scans" the entire image, pixel by pixel in the size of the 2-D spatial kernel (training pattern). The resulting edge detection images show that the neural network detector not only can detect edges but also enhances the edges.

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The simulation results of lung images are shown in figures. These results demonstrate that the neural network detector successfully detects edges in the original image and outperforms the conventional Sobel and Prewitt detectors.

## V. CONCLUSION

Edge detection plays an important role in image processing and analysis. In this research, artificial neural networks are successfully applied to detect edges in gray-scale images. Fuzzy sets are introduced during the training phase to improve the generalization ability of neural networks. The real-world application of the proposed approach for Lung CT Scan images is also investigated. More tests will be performed in the future to further improve the neural network edge detector. Similar to the above example, more training patterns can then be generated using fuzzy concepts to improve the generalization ability of neural network edge detectors.

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