An Advance Method for Edge Detection in Image Corrupted by Salt-and- Pepper Noise

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ABSTARCT

Edge detection is a crucial preparatory stage in image processing. The current edge detection methods suffer from the problem of high frailty to noise. In the present paper, a new method for image edge detection in images damaged by salt-and-pepper noise introduced. The simple structure of the proposed method is composed of four neural networks, a neuro-fuzzy network and an adaptive median filter. The internal parameters of these networks are adaptively optimized in training through using simple synthetic images that can be generated in a computer. The proposed method is tested on many popular images such as cameraman,boat,lena and etc. Then the results have been compared with those of the previous edge detectors such as Sobel and Canny. Empirical statistics show that the newly-introduced method presents much better performance than the previous ones and can be benefited in any process of edge detection of the Salt-and-pepper noise-damaged images.

KEYWORD: Neuro-fuzzy Network, Edge Detection, Salt and Pepper Noise, Neural Network.

1. INTRODUCTION

The edge being the most important character of an image is an abrupt change in intensity of an image [1, 2]. Image edge is the points with different grey levels and is located mostly between object and object, object and background, area and area [3,4]. Edge detection is one of the most important tasks in the field of image processing and pattern recognition [5]. It plays crucial role in the multimedia and computer vision, image enhancement and image compression and so forth [6]. It is usually the first things done prior to other operations such as image segmentation, boundary detection, object recognition, classification and image registration etc [7]. Simply put, to be successful in the complicated operation of image processing, the entire attention should be invested in the field of edge detection. With the advent of new developments in the field of mathematics and artificial intelligence (AI), lots of different edge detection methods are on hand, including mathematical morphology, wavelet transformation, Roberts's method, Prewitt method, Sobel method, zero-crossing method, canny method, LOG method and so on. The most important element decreasing the quality of the edge detection is the noise in the digital image. Digital images are almost always damaged by the salt-and-pepper noise (the common image noise, mostly noticed as white or black spots) during image acquisition or transmission. Salt-and-pepper noise is experienced as a result of the environment features and conditions, quality of sensing elements, and communication channels [8, 9]. An important consideration while working with the image processing programs is the image noise removal which should be done first especially because of the noise-sensitiveness condition of later image processing tasks such as segmentation, feature extraction, and object recognition. Failure to do so may result in severely degraded images.

A new advance method for edge detection in the digitally corrupted images will be presented here using salt and pepper noise. The proposed method is quite simple and includes only four identical neural networks (nn), a neuro-fuzzy network and an adaptive median filter. The internal parameters are chosen carefully under testing conditions. Training of the above mentioned networks is simply done by using a simple computer-generated picture. The most important advantage of the proposed method over the other methods is its higher performance delivery in the edge detection process while working with noisy input images. Tests have shown so far that the introduced method is way more efficient when put into action with salt and pepper damaged images []. The rest of this paper is divided as follows:

In the next part (2) the discussion will be drawn to some of the generally known edge detectors plus their sensitivity to noise (Literature Review). Part (3) explains the proposed method and its building blocks. Part (4) discusses the experimental results of the proposed method and classical methods such as Canny and Sobel. Finally, part (5) which is concludes the paper.

2. LITERATURE REVIEW

So far all the previously introduced edge detection methods have been dependent on the lighting conditions and noise. Generally speaking edge detectors have been stiff in adapting to noisy conditions. For example, the Marr-Hildreth, which used to be a popular edge detector with many professionals, is a gradient-based operator. This edge detector which uses the Laplacian to take the second by-product of an image is sensitive to noise. The Prewitt, Sobel and kirsch detectors use the first directional derivative method. Although, these detectors are easy to carry out, they are usually inaccurate and very sensitive to noise [10, 11, 12, and 13]. The zero-crossing edge detectors, which use the second derivative with Laplacian operator, are also highly sensitive to noise. Similarly, the canny edge detectors, highly favoured by many professional users in the industry, are noise sensitive. During the recent years researchers have invested their attention in soft computing techniques, such as neural networks and fuzzy systems, to solve the problems hurdling the way of digital image processing [14, 15]. In fact, neuro-fuzzy systems provide the neural networks with the capacity to solve the problem by introducing the capability of fuzzy systems to model the seemingly unavoidable uncertainty in noisy conditions.

3. PROPOSED METHOD

Fig. 1 shows the structure of the proposed method in this paper. As previously mentioned, this hybrid method consists of properly integrating four similar neural networks (vertical, horizontal, left diagonal and right diagonal) with a single function, a neuro-fuzzy network and an adaptive filter. The NF network utilizes the information from neural networks to compute the result of the system, which is equal to the edge points. When a noisy image enters into the system, the adaptive median filter is first applied to it. This will partially remove the noise. Then a 3×3 window is shown in fig. 2 that is Moore neighbourhood moves on the image. For every pixel (p) of image obtained by the adaptive median filter, four types of neighbours namely, vertical (p2, p, and p6), horizontal (p8, p, and p4), left diagonal (p, p, p5) and right diagonal (p3, p, and p7) enter into four similar neural networks. Then the networks decide which points are near the edge. Afterwards, four obtained pixels from neural networks are fed into the NF network. Finally, the NF network using fuzzy technique in the frame of neural network, extracts the edge points. Sections A, B, C, and D describe the adaptive median filter, NF network, neural network and training method respectively.

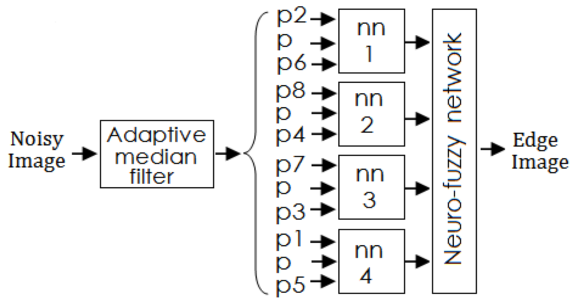

Fig. 1: Proposed Method

p1	p2	p3
p8	p	p4
p7	p6	p5

Fig. 2: Moore neighbourhood

3.1 Adaptive Median Filter

Adaptive median filter can handle salt-and-pepper noise while preserving the details [16]. This filter works in a rectangular window area S_{xy}. Depending on certain conditions, adaptive median filter changes the size of S_{xy} during filtering operation. Consider the following notations:

$z_{\min}$ = Minimum intensity value in S_{xy}
$z_{\max}$ = Maximum intensity value in S_{xy}
z_{med} = Median of intensity values in S_{xy}
z_{xy} = intensity value at coordinates (x,y)
$S_{\max}$= Maximum allowed size of S_{xy}

The adaptive median filter algorithm works in two stages, denoted stage A and B, as follows:

Stage A: $A1= z_{\text{med}} - z_{\min}$
$A2= z_{\text{med}} - z_{\max}$
If A1 > 0 and A2 < 0, go to stage B
Else increase window size
If window size <= $S_{\max}$ repeat stage A
Else return z_{xy}

Stage B: B1= $z_{xy} - z_{min}$
B2= $z_{xy} - z_{max}$
If B1 > 0 and B2 < 0, return z_{xy}
Else return z_{median}

3.2 Neuro-fuzzy Network

The NF network which is utilized in the process mentioned earlier attempts to build an edge as output using the pixels obtained from the four neural networks. The settings for the fusion are represented by the settings in the rule base of the NF network. The NF network is a first order Sugeno type fuzzy system with four inputs and one output. Each of these inputs has three Generalized Bell type membership function and the output has a linear membership function. Sugeno-type systems are generally popular for non-linear modelling tools as they are suitable for tuning by customization. They also use polynomial type output membership functions, which greatly simplifies defusing process. The input-output connection of the NF network is as follows: Let x_1, x_2, x_3 and x_4 denote the inputs of the NF network and denote Y as its output. Therefore, in the structure of the proposed method x_1, x_2, x_3 and x4 represent the output of the nn1, nn2, nn3, and nn4 respectively that are pixels. Each possible merging of inputs and their associated membership functions is represented by a rule in the rule base of the NF network. Because the NF network has four inputs each with three membership functions, the rule base includes a sum of 81(3^4) rules, which are as follows [17]:

1) If (x_1 is M_{11}) and (x_2 is M_{21}) and (x_3 is M_{31}) and (x_4 is M_{41}) , then $R_1=F_1(x_1, x_2, x_3, x_4)$.
2) If (x_1 is M_{11}) and (x_2 is M_{21}) and (x_3 is M_{31}) and (x_4 is M_{42}) , then $R_2=F_2(x_1, x_2, x_3, x_4)$.
3) If (x_1 is M_{11}) and (x_2 is M_{21}) and (x_3 is M_{31}) and (x_4 is M_{43}) , then $R_3=F_3(x_1, x_2, x_3, x_4)$.
4) If (x_1 is M_{11}) and (x_2 is M_{21}) and (x_3 is M_{32}) and (x_4 is M_{41}) , then $R_4=F_4(x_1, x_2, x_3, x_4)$.
5) If (x_1 is M_{11}) and (x_2 is M_{21}) and (x_3 is M_{32}) and (x_4 is M_{42}) , then $R_5=F_5(x_1, x_2, x_3, x_4)$.
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81) If (x_1 is M_{13}) and (x_2 is M_{23}) and (x_3 is M_{33}) and (x_4 is M_{43}), then $R_{81}=F_{81}(x_1, x_2, x_3, x_4)$

Where M_{ij} denotes the jth membership function of the ith input , R_k denotes the output of the kth rule and F_k denotes the kth output membership function with i=1,2,3,4 and j=1,2,3 and k=1,2,4,…,81. The input membership functions are Generalized Bell type

$$Mij(u) = \frac{1}{1+\left|\frac{u-a_{ij}}{b_{ij}}\right|^{2C_{ij}}} \quad (1)$$

And the output membership functions are linear:

$$F_k(u_1 , u_2 , u_3 , u_4) = d_{k1}u_1 + d_{k2}u_2 + d_{k3}u_3 + d_{k4}u_4 + d_{k5} \quad (2)$$

Where u1, u2, u3 and u4 are formal parameters and the parameters a, b, c, and d are the constants that characterize the shape of the membership functions. The optimal values of these parameters are obtained through training. The latter will be discussed in upcoming sections. As noticed in Fig. 3 the Sugeno-type NF network includes five layers. This network contains input layer, input membership function layer, rule layer, output membership function layer and output layer.

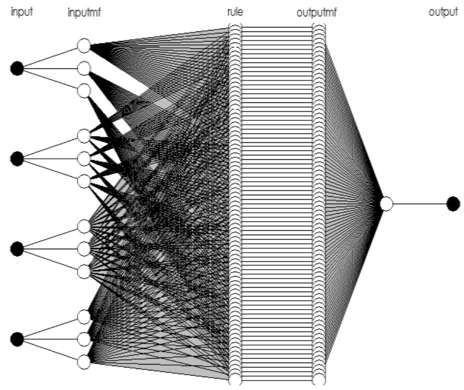

Fig. 3: The structure of Sugeno-type neuro-fuzzy network

The optimal number of the membership functions is mostly pointed out heuristically and verified by testing. It has been experimentally determined that three membership functions offer an outstanding cost balance. The output of the networks is overall average of the individual rule outputs. The measuring factor W_k of each of rule is calculated by evaluating the membership expressions in the previous of the rule. This is performed by first converting the input values to fuzzy membership values by utilizing the input membership functions and then applying the AND operator to these values. So that the measuring factors of the rules are calculated as follows:

$W_1 = M_{11}(x_1)* M_{21}(x_2)* M_{31}(x_3)* M_{41}(x_4)$
$W_2 = M_{11}(x_1)* M_{21}(x_2)* M_{31}(x_3)* M_{42}(x_4)$
$W_3 = M_{11}(x_1)*M_{21}(x_2)* M_{31}(x_3)* M_{43}(x_4)$
$W_4 = M_{11}(x_1)* M_{21}(x_2)* M_{32}(x_3)* M_{41}(x_4)$
$W_5 = M_{11}(x_1)* M_{21}(x_2)* M_{32}(x_3)* M_{42}(x_4)$

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$$W_{81} = M_{13}(x_1)* M_{23}(x_2)* M_{33}(x_3)* M_{43}(x_4) \quad (3)$$

When the measuring factors are gained, the output of the NF network can be found by estimating the measured average of the individual rule outputs:

$$Y = \frac{\sum_{k=1}^{81} w_k R_k}{\sum_{k=1}^{81} w_k} \quad (4)$$

3.3 Neural Network

The neural network used in the proposed method includes 4-input and 1-output. It also contains 2-hidden layers and 1-output layer. Its hidden layers have 15 and 10 neurons respectively and the output layer has just one neuron. The internal parameters are determined by training. The training ends when the output of neural network converges to an ideal output. Activation functions in the whole neurons of the network are defined as following [17] :

$$F(x) = \frac{1}{1+e^{-x}} \quad (5)$$

3.4 Training of the Network

The internal parameters of the neural networks and NF network are optimized by training. As shown in Fig. 4, this image is used as a setup for the training. The parameters of the networks are optimized continually so that the gained outputs will stay close to the ideal edge detectors' output which delivers the true edge image for the input image. The parameters of the neural networks and NF network are then tuned in a way that the learning errors will be minimized. In the latter, the Levenberg-Marquardt and Back propagation optimization algorithm will be used [17].

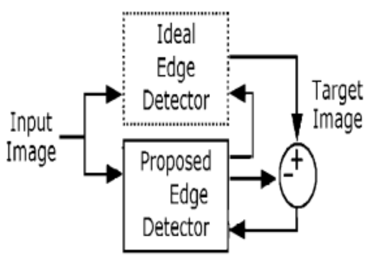

Fig. 4: Training the networks

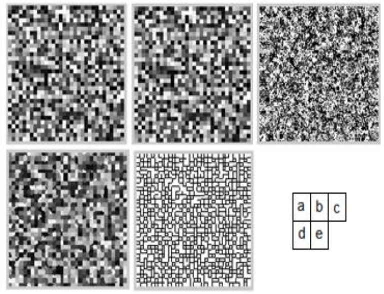

Fig. 5: Training images (128*128 pixel) , (a) (b) Base training image (c) (d) Input training image, (e) Target training image.

The images above are artificial and can be easily created by any computer. Fig. 5a is the base training picture. All the square boxes above are 4×4 in size (16 Pixels), each with the same brightness value. The picture in Fig. 5(b) is gained by 4-bits upper order of the picture. In Fig. 5(a) to fulfil this purpose, 4-bits of lower order is considered equal to the zero in value, application of this function to any fundamental variations on the image is not possible. For instance, he total navigate of image is preserved. The image in Fig. 5(c) would be the input training image obtained from the image in Fig. 5(b) which is saturated by the salt-and-pepper noise. The image in Fig. 5(d) is the other input training picture and is the result of applying the adaptive median filter to the picture in Fig. 5(c). The image in Fig. 5(e) is the target training picture. It's a black and white picture (binary) where the black pixels represent the edges of the input picture and the white pixels tell us that there are no edges in those points (edge exists when the difference between the intensity of two neigh boring pixels is lower than 32; otherwise, there is no edge at all).The images in Figs. 5(c) and 5(d) are applied as inputs for the neural network and the image in Fig. 5(e) is considered as the target picture of the neural and NF networks in the training period.

4. RESULTS

The proposed method discussed in the paper, was implemented in the computer. As shown in Fig. 6, the performance of this method is tested under noise condition (salt and pepper noise) and with six famous test images collected from the literature, i.e., flower, boats, cameraman, stone, Lena and Pentagon. The sample images used in this experiment were under the same conditions regarding size and noise. The images were 256×256 pixels and damaged by salt and pepper noise with 40% noise density before applying the proposed method. Many tests were carried out to compare the images processed by the proposed method with the same images processed by Sobel and Canny. Fig. 5 shows the output pictures of the experiment, according to performance reports of the proposed method the numbers are at high levels while the numbers obtained from Sobel are very poor and unsatisfactory. The final images are severely damaged and in poor quality because of noise but the Canny numbers are in a relatively better condition than of those of Sobel. There is proper noise pulse detection. But the distortions caused by the salt-and-pepper noise are still visible at the edges gray levels. In the images where the brightness variation is not very sharp the edges are almost lost. The flower image can be a good example. Finally it can be said that the newly-proposed method shows excellent detection performance and detects almost all the edges in all the experimental images. Not to mention the fact that the effect of noise has become to its lowest amount after the application of the proposed method. In other words the proposed method outperforms all the previously used methods as the differences are obviously visible especially for the Pentagon picture.

5. CONCLUSION

An extraordinary edge detection method for digital images corrupted by salt and pepper noise was proposed. The advantages of this method are listed at following:

1. The images that can easily be generated by computer are used in the training process.
2. Due to its simplicity, it can be easily implemented.
3. The proposed method makes edge detection in highly salt-and-pepper noise damaged images possible.
4. Using a hybrid method to make enhanced images that are damaged through careless use of salt-and-pepper noise is possible.

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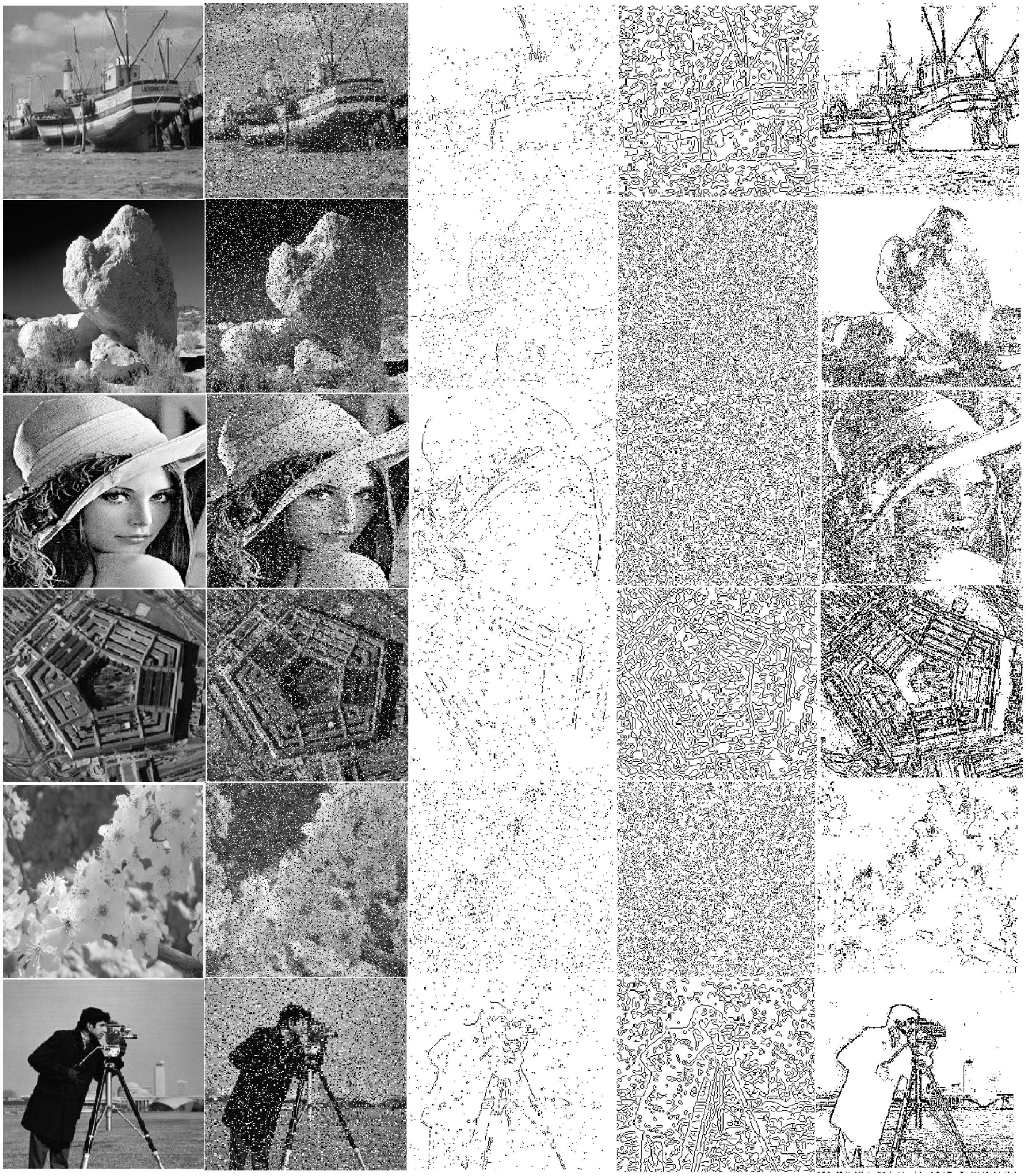

Fig. 6: Comparison of the proposed edge detector with the Sobel and the Canny edge detectors. From left to right: Original, Noisy, Sobel, Canny Proposed method.