Abstract

According to recent advances in Digital devices, the problem of image noise reduction becomes more significant than ago. Median filter (MF), as an efficient solution for this problem, has been widely applied in practice. In this paper, to improve the quality of filtered image, using a Neural Network (NN) is proposed. A NN, which is trained in a real time manner, can be estimated the noise density of moving window/mask in MF and changes its size adaptively. By using the NN as a supervisor for MF, better performance can be achieved. Simulation results are obtained to show the ability of the proposed combination in image noise reduction.

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1. Introduction

One of the major research fields in image processing is noise reduction [1]. The acquisition or transmission of digital images through sensors or communication channels is often interfered by impulse noise. Impulse noise randomly and sparsely corrupts pixels to two intensity levels, high or low, when compared with its neighboring pixels. Typically, salt-and-pepper noise, which is a special case of impulse noise, is considered in this situation [2-5]. In many applications such as military, medical and media, noise reduction plays a significant role. So, many filters/techniques have been proposed by different authors for image noise reduction. In addition, noise reduction in image processing not only is used to improve image
quality/enhancement but also is used as a preprocessing stage in many applications such as image encoding, pattern recognition, image compression and etc. [2]

One of the most effective filter for image noise reduction is Median filter (MF) [2-3]. It exploits the rank-order information (i.e., order statistics) of the input data to effectively reduction salt-and-pepper noise by substituting the considered pixel with the middle-position element (i.e., median) of the re-ordered input data. Simplicity and good performance of MF make it a well-known practical filter [2].

Now, Neural Networks which are an interesting alternative to classical solution of problems in image processing are found to be very efficient tool for image enhancement [6].

In this paper, image noise reduction by MF is improved using NN. Noise reduction in MF is done based on using a moving window/mask which its size is fixed/constant. The MF performance depends on the size of moving window. Using a small moving window when the image corrupted with high density of noise, causes the low MF performance and using large moving window produces vague images. Therefore, choosing the optimal size of moving window is important. Hence, to achieve better performance an adaptive size for moving window is proposed. The size of moving window at each pixel is determined according to the estimation/prediction of noise density in it. The estimation of noise density is obtained by a NN. For this purpose, a NN is used similar to the application of NN in noise reduction /system identification) [7-9]. The simplicity of the proposed structure with the acceptable results is a significant property for using the scheme in practice.

The remainder of this paper is organized as follows; in Section 2, the MF and application of NN in noise reduction /system identification) are briefly discussed. In Section 3, combination of NN and MF is introduced. In Section 4, the simulation results are reported. Finally, in Section 5, the conclusion of this work is given.

2. Image noise reduction

The need to remove salt-and-pepper noise is imperative before subsequent image processing tasks such as edge detection or segmentation is carried out [2]. This is because the occurrence of salt-and-pepper noise can severely damage the information or data embedded in original image. One of the simplest ways to remove salt-and-pepper noise is by windowing the noisy image with a MF [2].

Also, NN as an adaptive filter is used in many practical applications [10]. One of the NN applications is separating a signal from additive noise (i.e., noise cancellation) which is a common problem in signal processing [7]. It is noticeable that although many filters for this object are proposed, the noise cancellation cannot be done perfectly. Therefore, it would be better that noise reduction is used instead of noise cancellation. Due to the real-time learning capability of NN, it can be used as an adaptive noise reduction filter which its performance can be much better than the classical filter [7-9].

In the following, MF as an efficient filter for image noise reduction and the principle of using the NN for noise reduction are reviewed.

2.1. The Median Filter

MF is a non-linear filter which is useful for the reduction of salt-and-pepper noise in an image. It is implemented to an image using a $W_h \times W_v$ window/mask which it is moved across the input image, where $W_h$ denotes the horizontal and $W_v$ denotes the vertical size of the window in pixels. The center sample of the window is replaced by the median of the samples within the window (Fig. 1). The current window is marked with white dashed square, the next window is marked with black dashed square; the new samples (which have
to be processed to generate a new output) are dark grey. One of the most advantages of using MF is the property of preserving the edges of the input image [2-3].

![Fig. 1. The window of MF](image)

### 2.2. NN in Noise Reduction

In this paper, the estimation of noise density is done by the focus on the using NN in signal noise reduction problem. The usual structure of noise reduction by NN is described briefly. The basic problem of noise reduction is illustrated in detail in Fig. 2 [10]. The model of a corrupted signal \( d(k) \) is

\[
  d(k) = s(k) + v(k)  \tag{1}
\]

where \( s(k) \) is an unknown primary signal and \( v(k) \) is the undesired interference or noise signal and \( k = 1, 2, \ldots, n \) is discrete time. The reference noise \( v_R(k) \) is assumed to be available. Reference noise is related to the interference signal \( v(k) \) via an unknown nonlinear operator \( H \) (i.e., unknown nonlinear feed forward filter). Signals \( s(k) \), \( v(k) \), and \( v_R(k) \) are all assumed to be stationary random processes with zero mean. The solution consists of identifying the unknown nonlinear operator \( H \) by a nonlinear filter (e.g., a neural network) \( W \). The output \( \hat{s}(k) \), which is an estimation of the desired signal \( s(k) \), is then given by

\[
  \hat{s}(k) = d(k) - \hat{v}(k)  \tag{2}
\]

There is no explicit training set of input–output examples for learning of the NN in reference to the noise reduction problem. Hence, the objective becomes the minimization of the cancellation system output power, which is equivalent to the minimization of mean squared error between \( v(k) \) and \( \hat{v}(k) \) under assumption that \( s(k) \) is uncorrelated with both \( v(k) \) and \( \hat{v}(k) \) [6]. Thus, we can use \( d(k) = s(k) + v(k) \) as the “desired output” and \( \hat{v}(k) \) as the actual output for learning of the NN. The “error” \( e(k) \), whose power is to be minimized, is \( s(k) + v(k) - \hat{v}(k) \), (i.e., output of the filter). A multi-layer perceptron (MLP) with backpropagation training algorithm can be used as adaptive noise canceller \( W \) [10].

![Fig. 2. Noise cancellation/reduction structure](image)
3. NN with MF

Clearly, the performance of MF depends on the size of moving window. While the size of moving window is small, the chance of selection of noisy pixel as a median of window increases. This situation becomes critical when the density of noise is high. Therefore, the filtered image has a low quality. On the other hand, while the size of moving window is large, the median value of window, which is replaced as a value of center pixel of window, is obtained between the large numbers of pixels. It causes that filtered image becomes vague and details of original image are disappeared. Therefore, using fixed size for moving window can decrease MF performance especially when image corrupted with high density noise. To overcome this shortcoming, using a NN is proposed. By NN, the density of noise at each pixel can be estimated. Then, based on the estimation of density of noise, the size of moving window is adjusted. NN can estimate the density of noise according to its application in noise reduction which was described in previous section. Fig. 2 shows that the \( \hat{v}(k) \) becomes the estimation of \( v(k) \) through the training algorithm. Therefore, in Fig. 2, noisy pixel, noiseless pixel and the reference noise can be considered as \( d(k), \hat{s}(k) \) and \( v_R(k) \), respectively. NN attempts to make \( \hat{d}(k) \) as close as possible to \( s(k) \) (i.e., \( \hat{v}(k) \) becomes \( v(k) \)). Also, the neighborhood pixels for each pixel are considered as inputs of NN. The NN can be a multi-layer perceptron (MLP) with backpropagation training algorithm. The output of NN at each pixel shows the estimation of its noise density. By using a threshold for output of NN, a proper size for moving window can be assigned in MF. When the estimation of noise density is high (i.e., output of NN is high), the size of window in MF can be considered large and a small size can be used when the output of NN is low.

The simulation results show that using a NN with MF without heavy burden of computation can increase the enhancement and restoration of filtered image.

4. Simulation Results

In this section, the performance of the NN with MF is tested on two noisy images corrupted with salt-and-pepper noise, and the obtained results are compared with the MF results. For evaluation, the mean square error (MSE), the mean absolute error (MAE), and peak signal to noise ratio (PSNR) are used. The MSE, MAE and PSNR are obtained as follows:

\[
MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (x_{ij} - \hat{x}_{ij})^2 \\
MAE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} |x_{ij} - \hat{x}_{ij}| \\
PSNR = 10 \log_{10} \frac{R^2}{MSE}
\]

where \( M \) and \( N \) are defined as dimensions of image, and \( x_{ij}, \hat{x}_{ij} \) indicates the pixel value in place \( i, j \) for the original image and the filtered image respectively. Also, \( |.| \) denotes the absolute value function. \( R \) is the maximum fluctuation in the input image data type. For example, if the input image has a double-precision floating-point data type, then \( R \) is 1. If it has an 8-bit unsigned integer data type, \( R \) is 255.

The used NN is one neuron which is trained by Delta rule, and has nine inputs (one random normal signal with covariance 0.04 and values of eight neighborhood of a pixel). While the output of NN is higher than 0.5, the size of moving window in MF is considered 5*5 else, it is 3*3. In Fig. 3, two images which are used in simulation are shown. Each image is corrupted with different percentages of salt-and-pepper noise, and the filtered images by MF and NN with MF, can be observed in Fig.4 and Fig. 5. Also, MSE, MAE and PSNR of the MF and NN with MF are shown in Table 1.
From the Table 1, it can be seen that the NN with MF performs relatively well compared with the MF. Simulation results (Fig. 4, Fig. 5 and Table 1) show that using NN with MF, has acceptable and appropriate performance statistically and visually than MF.
Table 1. Comparison of the MF and NN with MF.

<table>
<thead>
<tr>
<th>Image</th>
<th>Noise Percentage (%)</th>
<th>MSE</th>
<th>MAE</th>
<th>PSNR</th>
<th>MSE</th>
<th>MAE</th>
<th>PSNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fig. 3 (a)</td>
<td>50%</td>
<td>MAE 5.9042</td>
<td>1.2557</td>
<td>14.5577</td>
<td>MSE 0.0350</td>
<td>0.0055</td>
<td>22.5602</td>
</tr>
<tr>
<td></td>
<td>30%</td>
<td>MAE 0.2145</td>
<td>1.2933</td>
<td>22.0372</td>
<td>MSE 0.0063</td>
<td>0.0030</td>
<td>25.2632</td>
</tr>
<tr>
<td>Fig. 3 (b)</td>
<td>50%</td>
<td>MAE 0.5452</td>
<td>2.6096</td>
<td>14.1775</td>
<td>MSE 0.0382</td>
<td>0.0109</td>
<td>19.6246</td>
</tr>
<tr>
<td></td>
<td>30%</td>
<td>MAE 0.6193</td>
<td>1.5563</td>
<td>20.4753</td>
<td>MSE 0.0090</td>
<td>0.0059</td>
<td>22.2829</td>
</tr>
</tbody>
</table>

**Conclusion**

In order to deal with the problem of noise reduction in digital image, the Median Filter (MF) is considered. The MF with fixed size of moving window loses its performance when the noise density of image increases. Also, using the large window causes the filtered image become vague. In this paper, to enhance the quality of filtered image, a NN is used. Noise reduction in the proposed combination of NN and MF, performs in two stages. In the primary stage, the noise density at each pixel is estimated by NN. In the next stage; according to the estimated noise density, the proper size for moving window is assigned. While the estimated noise density in a pixel is low a MF with small moving window produces the filtered image and a large moving window is used when the estimated noise density is high. Using adjustable window increases the ability of MF in image noise reduction. The simulation results show that the proposed combination of NN and MF has a better performance than MF.

**References**