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A Comparative Study of Image Denoising in the Internet of Things (IoT)

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Abstract

While capturing and transmitting images in IoT devices, recorder media have some physical constraints that make them noise-prone. Noise shows itself in the form of signal disturbances that result in the inhibition of observation, analysis, and evaluation of images. Various image-denoising algorithms have been proposed to remove noise from the degraded image. In particular, the application of soft computing methods such as utilizing deep neural networks on digital images as an approach with better results has recently been considered. Concerning the importance of accurate and noise-free storage of images taken from surveillance cameras in spatial systems of the water and wastewater industry, this paper describes some key concepts. After that, an additive noise is utilized on the original image captured by surveillance cameras. Then, two approaches, the Wiener filter and a deep neural network method called DnCNN are being compared for the denoising purpose. Results showed that the deep neural network led to better performance than the Wiener filter in terms of PSNR measure.

Keywords: Noise, Image denoising, Internet of Things (IoT), Wiener filter, Deep Neural Network(DNN)

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1. Introduction

Nowadays, digital images are used in miscellaneous domains such as intelligent health monitoring, medical areas, aerology, traffic surveillance, etc. Due to some limitations, the images taken from sensors or cameras are prone to noise. Noise can arise from the device itself, or data collection, transmission, compression processes and also environmental conditions, etc. Therefore, analysis of noisy images can cause imprecise results.

Denoising has gained importance due to the growing need for digital images. In fact, image denoising can improve the accuracy of low-level operations such as segmentation and facilitate understanding of basic image statistics and processing (Lebrun et al., 2012).

Various media equipped with different types of wireless technologies over the years have led to a concept called the Internet of Things or IoT; the ability to communicate through various heterogeneous devices on the Internet, which are essentially not designed to communicate with one another. IoT can be described as connecting entities such as smartphones, Internet TVs, sensors, and other actuators to the World Wide Web, where devices are smartly interconnected and capable of establishing new forms of communication between people-people, people-things, and things-things (Piyare et al., 2013). If accurate, the massive amounts of data collected by these media represent some important parameters. IoT has seen remarkable progress in recent years as it introduces a new field to the world of ICT.

By 2020, there will be 50 billion connected devices, which is about seven times of world population (Swan, 2012). Now, anyone can connect to anything, anytime, anywhere, and these connections are expected to expand and create a dynamic fully-connected web of objects.

The Internet of Things enables organizations to collect, process, and analyze their huge and valuable data. This data can show real intelligence. For example, in the water and wastewater industry whose data is part of the smart city infrastructure, we can use machine vision capabilities as one of the applications of artificial intelligence to receive sensor data, images, and videos received from spatial parcels and then an immediate response is made to the system as if human beings are monitoring and responding the information.

According to the aforementioned, the use of artificial neural networks is widespread today and is becoming increasingly diverse. Artificial neural networks are the simulation of activity and the learning process of the human brain on the computer. These networks are also one of the ways to make computers intelligent, in other words, machine learning and vision. In the artificial neural networks used so far, the input of the network was vector, that is, changes to the training (and test) data had to be made first, and after these changes, feature or specific features were extracted, and finally, the extracted features were given to the neural network as a vector. This process was slightly different from the learning process of the human brain since it captures data without modification and completes the learning or testing process. Therefore, an alternative to existing artificial neural networks has been studied and the result has been deep neural networks or networks that benefit from the deep learning process. Although the original idea of deep learning was introduced many years ago, it was not possible to implement these algorithms because of hardware weakness in the past. With the advances in hardware, these algorithms are now being implemented. Recently, many deep learning algorithms have been proposed to solve traditional artificial intelligence problems.

In this paper, the Wiener filter and one type of deep neural network were used and compared to embed an image processing system in imaging media of spatial parcels in water and wastewater installations for noise-free image storage in spatial databases. Finally, a comparison of the experiments is also presented in terms of the PSNR measure.

2. Methodology

In the noise removal process, filtering techniques are used. In this paper, we focus on two filtering techniques to find the most efficient one in the process of noise-free image storage in spatial databases.

2.1. Weiner Filter

This filter is a standard image denoising approach that incorporates both the degradation function and the statistical characteristic of noise into the restoration function. This filter works with overpass filters to perform de-convolution and also with low-pass filters to eliminate noise with compression operations.

The output image is obtained by the following equation where the additive noise and frequency characteristics are known.

$$\hat{f} = g * (f + n) \qquad (1)$$

The image is compared to a noise-free estimate of an image that is correct or desired. The input to a Wiener filter is a degraded image that is damaged by the additive noise (Maurya et al., 2014; Singh, 2014).

2.2. Neural Network

The most widely used neural network model is known as multilayer perceptron. This type of neural network is known as a direct/supervised network because it requires an optimal output for learning/training. The purpose of this type of network is to design a model that correctly maps the input to the output utilizing historical data so that the model can generate the output when the desired output is unknown. Multilayer perceptron and many other neural network models use a back-propagation algorithm by which the input data is continuously fed to the neural network model. With any data, the output of the neural network is compared with the desired output, and the error is calculated. This error is then sent to the neural network and used to balance the weights so that the error rate is minimized uniformly and the neural network model gets closer and closer to the desired output. The following figure shows a multilayer perceptron.

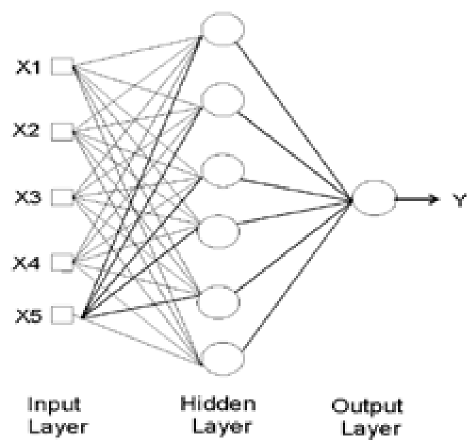


Figure 1. Multilayer perceptron

2.3. Deep Neural Network

As described in the above section, neural networks receive an input in the form of a vector and then pass it through several hidden layers, and eventually an output that results from the processing of the hidden layers appears in the output layer of the network. Each hidden layer is made up of some neurons that connect to all the neurons in the preceding layer. The neurons of each layer act independently and have no relation to each other. The last layer is known as the fully-connected layer and usually plays the role of representing each category. The following figure shows a deep neural network.

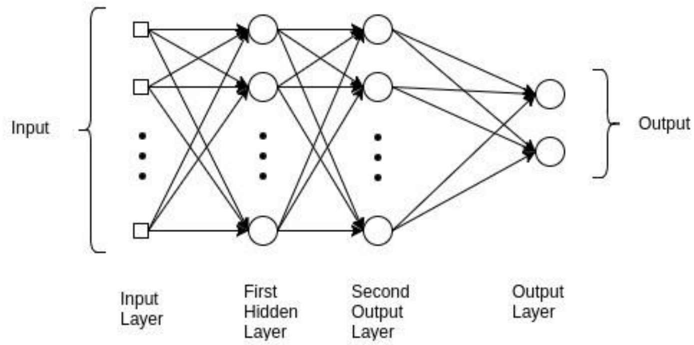


Figure 2. Deep Neural Network

One type of deep neural network is the convolutional neural network. These types of neural networks are one of the most important deep learning methods in which multiple layers are trained robustly. This method is very efficient and is one of the most common methods in different applications of computer vision. In general, a convolutional neural network consists of three main layers: the convolutional layer, the pooling layer, and the fully-connected layer. Different layers perform different tasks. There are two stages of training in each neural network: Feed-Forward and Back-Propagation. In the first step, the input image is fed into the network. This operation is nothing more than an internal multiplication between the input and the parameters of each neuron, and then applying the convolution operation in each layer. Finally, the network output is calculated. Here, to adjust the network parameters or, in other words, network training, the output result is used to calculate the network error rate. In the next step, based on the calculated error rate, the back-propagation step is started. At this point, the derivative of each parameter is calculated according to the chain rule, and all the parameters are updated according to their effect on the error in the network. After updating the parameters, the next step of Feed-Forward starts. After repeating an optimal number of these steps, the network training will end.

The architecture of the deep neural network utilized in this article is a CNN with depth D called DnCNN (Zhang et al., 2017), comprising three types of layers, for the first layer, 64 filters of size $3 \times 3 \times c$ are used to generate 64 feature maps, and rectified linear units are then utilized for nonlinearity; c represents the number of image channels, i.e., $c = 1$ for gray image and $c = 3$ for color image. For layers $2 \sim (D - 1)$, 64 filters of size $3 \times 3 \times 64$ are used. For the last layer, c filters of size $3 \times 3 \times 64$ are used to reconstruct the output.

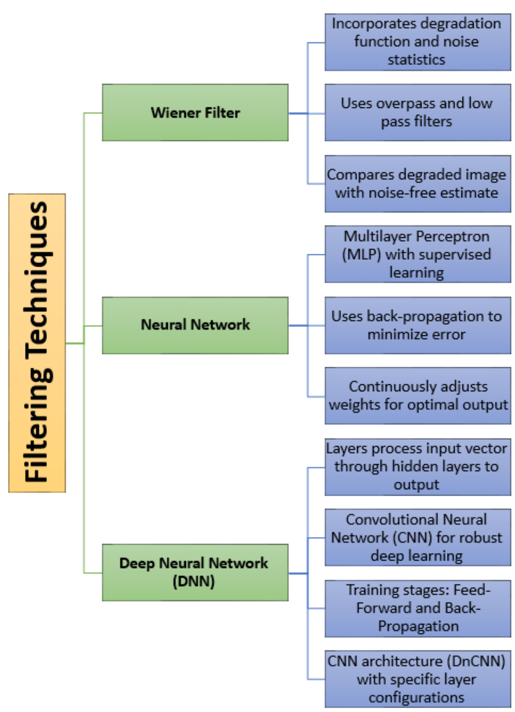


Figure 3. Flow chart of methodology

3. Experiments and Results

At first, the DnCNN was trained by a dataset called ImageNet. After training the model and approaching the network to the optimum weights and biases, a sample image was used for testing. the gray spectrum was obtained from the sample image. Afterward, the Wiener filter and then DnCNN were utilized to eliminate the Gaussian noise that was added to the sample image with different variances. For this purpose, MATLAB environment was used. Figure 4 shows the original image and Figure 5 shows the effect of applying two filters on the original image. The results of the experiments, which were measured based on the Peak Signal-to-Noise Ratio (PSNR) measure, showed that using the deep neural network, the noise level was reduced more than the Wiener filter and therefore, we get a clearer output.

$$PSNR = -20 \log_{10} \frac{MAX_f}{\sqrt{MSE}} \quad (2)$$

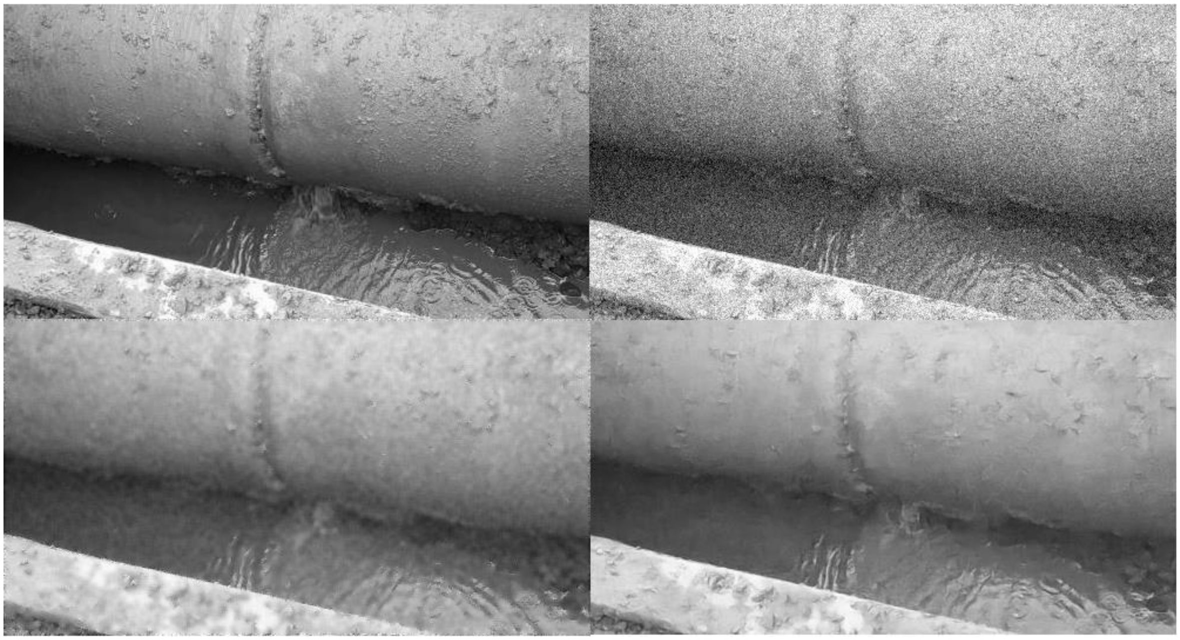
MAX_f = Maximum Power of Signal in Original Image

MSE = Mean Square Error

Figure 4. Sample Image (leakage at an incident location in water distribution network)

Table 1. Calculation of PSNR measure for two methods

Deep Neural Network	Wiener Filter	Noise Level
37.6615	35.2205	**0.0008**
37.3735	35.0454	**0.0009**
37.1454	34.8945	**0.001**
35.7537	33.8116	**0.002**
34.8351	32.8693	**0.003**
34.2575	32.2738	**0.004**
33.6435	31.6492	**0.005**
33.2250	31.2238	**0.006**
32.9480	30.7198	**0.007**



a	b
c	d

Figure 5. Results of applying two filters

a) Grayscale image
b) Grayscale image after applying Noise
c) Noisy image after applying Weiner Filter
d) Noisy image after applying Deep Neural Network

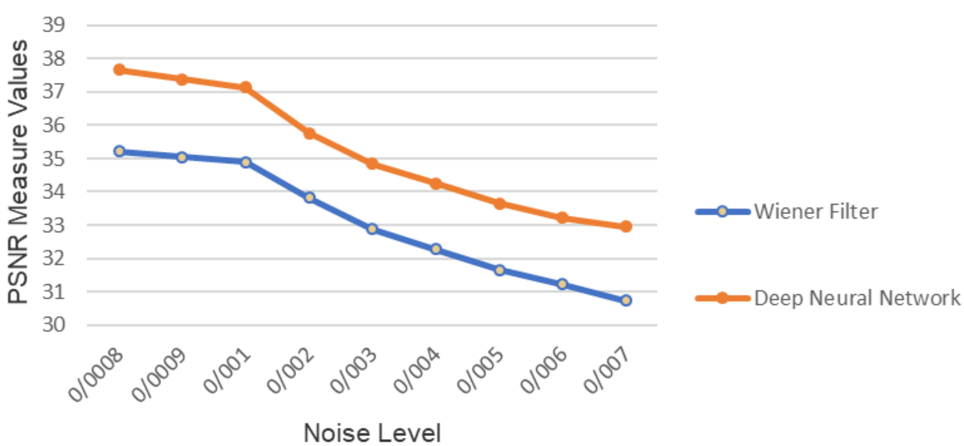


Chart 1. Comparison of PSNR measure for two filters

4. Conclusion

In this paper, two methods for restoring degraded images by noise are investigated in an IoT environment. These two methods improved the quality of the degraded image. In the remainder of the paper, a quantitative analysis of the two methods was performed, and the results showed that the deep neural network filter obtained better results than the Wiener filter for image denoising. An important advantage of using a deep neural network is that it can be much less expensive than the Wiener filter when exposed to very large image datasets. Finally, utilizing a deep neural network for pre-processing image data in an image-denoising subsystem before storing them in spatial databases can improve the accuracy of the data for future analysis and decision-making.

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