Performance Analysis of Image Denoising using Deep Convolutional Neural Network

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Abstract. A performance analysis of conventional Convolutional Neural Network (CNN) based denoising method is proposed. In this image denoising method, the contrast of images is adaptively enhanced. Generally, it is not possible to capture the images with good quality for all situations. Because they are captured in various light conditions. So, the captured images are suffered by noise, which results in poor perceived image quality. Thus, it is necessary to improve the quality of images with edge detail preservation as much as possible. The convolutional neural network model for low light image enhancement is already developed and is named as DnCNNs. Here, the performance analysis of image denoising using the DnCNN model is presented. The DnCNN implicitly removes the noise in the image. The simulation results afford better reference for application developers.

Keywords: CNN, denoising, hidden layer, SSIM, contrast enhancement

1. Introduction

Image denoising plays vital role in performance improvement of image processing technologies in last two decades\cite{2}\cite{4}. The image processing has various applications in the field of medical, remote sensing, consumer electronics and video surveillance\cite{3}. In each application, different image processing technique is needed. For example, in medical field, image analysis, detection/classification of tumor/cancer cells and in remote sensing field, analysis/classification of resources in an earth are used as image processing techniques\cite{5}.

Consider the input image is degraded by noise and the noisy image is represented by $Y=X+N$. Here 'N' is the Additive White Gaussian Noise(AWGN) with standard deviation $\sigma$. The objective of image denoising is recover the original input image from the noisy image. In this denoising process, image prior modelling is the core process. Over the past few decades, there are number of image prior modelling have been developed. The Histogram Equalization(HE) method is used to enhance the image\cite{1}. The histogram equalization method fails to preserve the edge details. Hence, the Dynamic Histogram Equalization(DHE) technique achieves the image enhancement with edge preservation. In DHE, before quantization, the image histogram is separated with different graylevel based on local minima. By using repartitioning test, the separated greylevels are examined and ensure about the missing of any dominant regions.

In \cite{7}, both the contrast enhancement and denoising methods are proposed as a combined framework. In the first step, the super pixels are segmented from the input noisy image. The ratio of local standard deviation and local gradient is determined and it is used to predict the texture of the noise in super...
pixels. The BM3D filter is used to adaptively extract the smooth layer with respect to noise texture level. Now, the image is inverted and the differentiation of inverted image is used to extract the another detail layer and structural filter is smoothed it. The edge preserved enhanced image is obtained by combining these two smooth and detail layers \([9][10]\). Finally, the contrast enhancement is accomplished by an adaptive enhancement parameter.

The convolutional neural network (CNN) is widely used in computer vision\([6]\). It produces constructive performance in image denoising applications by learning from experience \([5][12]\). In CNN model residual learning is used to speed up training phase and regularization methods are utilized to improve the denoising performance. This DnCNN model can able to remove additive white Gaussian noise (AWGN) with various noise level. This work concentrates on performance analysis of the image denoising with Salt and Pepper noise with various noise level.

2. Image Quality Metrics

The quality of denoised image is determined by both subjective and the objective methods. The subjective measure is the perceived image visual quality and the objective method is nothing but the computational measures. The standard objective measure is Peak Signal to Noise Ratio (PSNR) which is based on Mean Square Error (MSE)\([8]\).

\[
PSNR = 10 \log_{10} \left( \frac{MAX_i}{MSE} \right) \tag{1}
\]

\[
MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [x(i,j) - y(i,j)]^2 \tag{2}
\]

Here, \(MAX_i\) is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. During denoising there is the possibility to lose some detail/edge information of the image. Structural Similarity Index Metric (SSIM) is correlated with the quality and perception of the human visual system (HVS colour model)\([11]\). Hence the SSIM is used as second objective method. It determines the structural similarity between reference and denoised images.

\[
SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{\mu_x^2 + \mu_y^2 + C_1(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{3}
\]

Where,

- \(\mu_x\) is the mean value of \(x\);
- \(\mu_y\) is the mean value of \(y\);
- \(\sigma_x^2\) is the variance of \(x\);
- \(\sigma_y^2\) is the variance of \(y\);
- \(\sigma_{xy}\) is the covariance of \(x\) and \(y\);
- \(C_1 = (K_1L)^2, C_2 = (K_2L)^2\) are used to stabilize the division with weak denominator;
- \(L\) the dynamic range of the pixel values (typically it is \(2^{\text{bits per pixel}} - 1\))
- \(K_1 = 0.01\) and \(K_2 = 0.03\) by default.

The SSIM value lies in the range \((0, 1)\). Value 1 means that the two images are totally the same.

3. Proposed Method

In this work, image denoising using convolutional neural network is proposed. The noise is separated from the input noisy image by adopting residual learning in convolutional neural network. Batch normalization is used to speed up the training phase. Also, regularization method is used in CNN to improve the performance of denoising. This DnCNN model can able to perform denoising with unknown noise level and contrast enhancement.

The block diagram of Denoising Convolutional Neural Network (DnCNN) is as shown in Figure 1. From figure 1, there are training and test phases in DnCNN model. In training phase, the model is trained with noisy images of salt and pepper. In test phase, experimental results are analysed with denoising performance of the proposed method with different level of salt and pepper noise.
3

Figure 1. Fully customized Denoising Neural Network

4. Results and Discussion
The proposed method is demonstrated using Deep learning toolbox with standard test images of size 255×255. The simulated Gaussian noise is added with the input image. The pretrained Deep Convolutional Neural Network is used to perform the denoising operation. The objective and subjective performance of the proposed method is analysed. The objective measures like PSNR(dB) and SSIM values for both the proposed method and the existing methods are determined.

4.1 Subjective Measure
The subjective performance of the proposed method is determined by the visual quality of the denoised/enhanced image. Figure 1 shows the perceived image quality comparison of the proposed and the existing methods.
Figure 2. Qualitative performance comparison of the proposed method with the existing methods.

From Figure 2, it is inferred that the output of the proposed Deep CNN based approach appears more naturally than other existing methods. Because, CNN learns to adaptively enhance image contrast and increase image brightness.

4.2. Objective Measures
The quantitative performance comparison of the proposed method with the existing methods is presented in Table 1.
Table 1. Objective performance comparison of the proposed method with the existing methods

| Input  | Performance Metrics | Histogram Equalization (HE) | Adaptive Histogram Equalization (AHE) | Proposed Method |
|--------|---------------------|-----------------------------|--------------------------------------|-----------------|
| Bamboo | PSNR(dB)            | 16.8769                     | 17.1505                              | 27.4683         |
|        | SSIM                | 0.7851                      | 0.7459                               | 0.8953          |
| Barbara| PSNR(dB)            | 31.2810                     | 18.4864                              | 29.6063         |
|        | SSIM                | 0.9755                      | 0.8461                               | 0.9174          |
| Cameraman| PSNR(dB)          | 18.9804                     | 19.9885                              | 43.9433         |
|        | SSIM                | 0.8476                      | 0.7831                               | 0.9955          |

The proposed deep convolutional neural network produces better PSNR and SSIM than existing method and it is evident from Table 1. The residual learning is used to improve the PSNR and SSIM measures.

Table 2. Objective performance comparison of the proposed method with the existing methods

| Input Images | Mean | Variance | Histogram Equalization | Adaptive Histogram Equalization | Proposed Method |
|--------------|------|----------|------------------------|--------------------------------|-----------------|
|              |      |          | PSNR(dB) | SSIM  | PSNR(dB) | SSIM  | PSNR(dB) | SSIM  |
| IMG 1        | 0.001| 0.005    | 16.5174 | 0.7853 | 16.4147 | 0.7255 | 38.6856   | 0.9501 |
|              | 0.010| 0.015    | 17.0493 | 0.8267 | 16.4206 | 0.7521 | 25.6406   | 0.6844 |
|              | 0.020| 0.001    | 17.2820 | 0.8466 | 16.2508 | 0.7748 | 23.7873   | 0.6306 |
|              | 0.005| 0.005    | 10.4427 | 0.6250 | 16.7393 | 0.7284 | 36.2002   | 0.8881 |
| IMG 2        | 0.010| 0.015    | 10.5379 | 0.5968 | 14.2366 | 0.6881 | 26.0947   | 0.5882 |
|              | 0.020| 0.001    | 10.5967 | 0.6138 | 13.8754 | 0.6874 | 24.3129   | 0.5234 |
|              | 0.001| 0.005    | 10.6794 | 0.6337 | 13.5291 | 0.6940 | 23.0569   | 0.4753 |
|              | 0.010| 0.015    | 11.9934 | 0.5846 | 15.0565 | 0.6905 | 36.6509   | 0.9368 |
|              | 0.020| 0.001    | 12.1303 | 0.6179 | 13.7925 | 0.6844 | 28.3246   | 0.7492 |
| IMG 3        | 0.010| 0.015    | 12.3076 | 0.6551 | 12.9301 | 0.6931 | 25.1355   | 0.6411 |
|              | 0.020| 0.001    | 12.4559 | 0.6819 | 12.5503 | 0.7072 | 23.3423   | 0.5732 |
|              | 0.001| 0.005    | 12.5834 | 0.7029 | 12.4071 | 0.7225 | 22.1956   | 0.5311 |
|              | 0.010| 0.015    | 10.7416 | 0.6862 | 12.9369 | 0.7077 | 27.0433   | 0.8647 |
|              | 0.020| 0.001    | 10.8249 | 0.6963 | 12.4373 | 0.7058 | 24.7690   | 0.7350 |
| IMG 4        | 0.010| 0.015    | 10.9261 | 0.7079 | 12.1674 | 0.7130 | 22.9189   | 0.6247 |
|              | 0.020| 0.001    | 11.0287 | 0.7173 | 12.0415 | 0.7218 | 21.8375   | 0.5625 |
|              | 0.005| 0.015    | 11.1524 | 0.7279 | 11.9915 | 0.7313 | 20.9977   | 0.5192 |
From Table 2, it is inferred that the Histogram Equalization (HE) and Adaptive Histogram Equalization (AHE) methods are not produce any significant change in PSNR and SSIM value while increasing noise variance. But the proposed method decreases both PSNR and SSIM value.

5. Conclusion and Future Scope
The imagedenoisingConvolutional Neural Network with residual learning is presented. Both the existing and the proposed methods are implemented using standard test images. Also, comparison of the denoisingability of the proposed method with the existing method is performed using subjective and objective methods. The objective performance metrics of the proposed and the existing methods for the input images with Standard Mean value as 0.2 and different variances are analysed.

From the simulation results, it is observed that the visual quality of the proposed method is better than the existing two methods. The average PSNR value of the proposed method is improved by $\sim11\text{dB}$ than the existing methods. Also the average SSIM value of the proposed method is improved by $\sim0.2$ than the existing methods.

However, for increasing value of noise variance the proposed method does not show improvement than the existing methods. The decrease in SSIM value shows there is loss in detail information. This work may be extended to preserve the detail information of the denoisedoutput image by optimizing convolutional neural network. Also, may extend to enhance the color images through our pretrained network model.

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