# NON LOCAL MEANS IMAGE DENOISING ALGORITHM BASED ON TEXTURE FEATURES

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Submitted by

**Bibhuti Shekhar**

**2K13/SPD/03**

Under the supervision of

**Mr. Rajesh Birok**
**(Associate Professor)**

**DEPARTMENT OF ELECTRONICS & COMMUNICATION ENGINEERING**
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

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# *Certificate*

This is to certify that the dissertation title ***"Non local means image denoising algorithm based on texture features"*** submitted by **Mr Bibhuti Shekhar**, Roll. No. *2K13/SPD/03*, in partial fulfilment for the award of degree of Master of Technology in Signal Processing & Digital Design at **Delhi Technological University, Delhi**, is a bonafide record of student's own work carried out by him under my supervision and guidance in the academic session 2014-15. To the best of my belief and knowledge the matter embodied in dissertation has not been submitted for the award of any other degree or certificate in this or any other university or institute.

Rajesh Birok
Supervisor
Associate professor
Deptt. Of ECE
Delhi Technological University
New Delhi

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**Bibhuti Shekhar**

**M.Tech (SPDD)**

**2K13/SPD/03**

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# Abstract

While transmission of an image it generally happens that it gets affected by noise. Well then applying non local means denoising algorithm in order to recover the original image, structural information such as texture and edges are easily lost due to the smoothening effect which it creates.

Our work is basically centered at embedding the texture features in the filtered image so that PSNR of the filtered image is increased. Firstly, we extract the texture features using entropy and standard deviation functions and then these texture features are used in modified weight function to get the modified weights values in non local means algorithm.

In order to increase the weights of the similar structure we have not only considered the Euclidean weighted Gaussian distance but texture structure has also been contemplated and merged with the Euclidean weighted Gaussian distance function.

Experimental results have validated that our method is superior to non local means algorithm. Using standard deviation texture feature we are getting a PSNR of 36.2774 and using local entropy texture feature we are getting a PSNR of 36.34. and when these features are used simultaneously i.e local entropy as well as standard deviation then we are getting a PSNR of 34.88. Please note that above values have been calculated for a single image and for a single value of standard deviation.

# Chapter I

# Introduction

# Introduction

## 1.1 Noise

Noise can be mainly categorized in to two types :

1) Impulse noise
2) Gaussian white noise

The real noise has been approximated to the white Gaussian noise, and in my work I have mainly focused on additive white Gaussian noise. Till now many effective methods have been proposed methods for image denoising, which can be classified basically in to two categories according to their areas of implementation.

**Impulse noise** can also termed as salt and pepper noise. Other terms which are often used in place of impulse noise are spike noise, random noise or independent noise. This type is very easy to identify since it occurs in black and white dots in an image. These kind of noises appears in an image due to the sharp or sudden changes in the intensity values in an image. Image is corrupted not to a greater extent by this kind of noise.

Fig.1 Original image Image with 30% salt & pepper noise

**Gaussian noise** is also known as amplifier noise. It is additive in nature i.e. it at any pixel noise model can be expressed as sum of the pixel intensity value and a true, Gaussian distributed noise value. It is also independent of the pixel intensity value. Because of its additive nature it is often called as additive white Gaussian noise. The term white signifies that Gaussian noise has uniform power through out the frequency spectrum. It is an analogy to the white colour which has uniform emissions at all the wavelengths in the visible spectrum of light.

PDF of Gaussian noise is illustrated below:

$$P(x) = 1/\sigma\sqrt{2\pi} * exp\ (-(x-\mu)^2/2\ \sigma^2)$$

$$\text{where} \quad -\infty < x < \infty$$

Figure 2

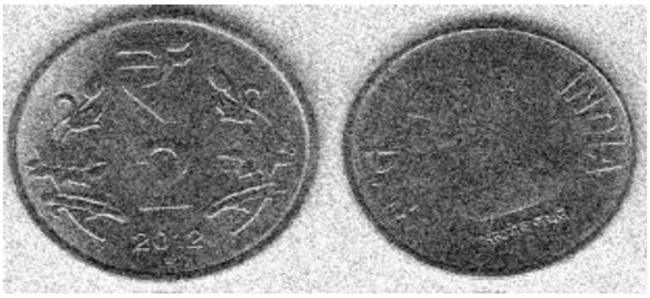



Image affected by Gaussian with zero mean

**Poisson noise**

When the number of photons sensed by the sensor is not sufficient to provide a perceivable statistical information then the kind of noise introduced in that situation is termed as poisson noise. It is also independent of the pixel values.


Fig. 3 Image corrupted by poisson noise

**Speckle Noise**

It is granular noise which is inhibited in the active radar and SAR image, reduction of which could lead good quality images.

## 1.2 Image denoising

Image denoising is considered as one of the most fundamental problem in image processing. It is the process through which we try to remove all kind of noises from an image. These are noises which gets added on to image in transmission and denoising is the process through which we try to recover a denoised image which is as close as possible to the original image.

### 1.2.1 Filters

Methods which work in spatial domain exploiting the feature smoothness which is used for the removal of noise are

1) Gaussian filter
2) Morphological filter
3) Bilateral filter
4) Total Variation Majorisation - minimization algorithm
5) Non local means algorithm, etc

Methods which work in frequency domain are as follows:

1) Wiener filter
2) Wavelet threshold shrink, etc

Among all these methods the performance of non local means filtering which was proposed by Buades in 2005 has a greater significance and it provides us with much better result when compared with the other classical approaches of denosing.

A noisy image can be represented as

$$\mathbf{I} = \mathbf{S} + \mathbf{N}$$

**I =** Observed Noisy Image

**S =** Pure Original Image

**N =** additive white Gaussian noise

**N** represents the additive white Gaussian noise which has mean = 0 and $\sigma^2$ variance

Our goal is to extract **S** from its noisy counterpart **I**.

Image denoising filters can be broadly categorized in to three types of categories:

- Averaging filter
- Order statistics filter
- Adaptive filter

**Averaging Filter**

Averaging filter is also called as mean filter. It basically finds out the mean of a pre-specified area in an image and replaces the central value of that are with the mean area in order to get a filtered output.

**Order Statistics Filter**

Order- statistic filters are those filters whose output depends on the ordering of the pixels enclosed in a given area. The filter is called as max filter if the value of a centre pixel in a given area is replaced by $100^{th}$ percentile and the same is also called as min filter if that pixel is replaced by the $0^{th}$ percentile.

**Median Filter**

Median filter is an example of order statistic filters where the central pixel value is replaced by the median of the pre-specified filtered region. The term order signifies that the result is basically dependent on the ranking of the pixels.

**Adaptive filter**

Their behaviour is dynamic in nature i.e. their behaviour according to the statistical characteristics of the image region enclosing the filtering region keeps on changing.

The denoising algorithm involved is a three step process:

*a) Analysis*

*b) Processing*

*c) Synthesis*

During analysis the image is divided in to blocks of fixed size. From these, similar blocks are kept in a group, blocks in each group can stacked together to form a 3D data arrays, which are then decorrelated .

During processing the obtained result from the analysis step is filtered using hard thresholding.

And during synthesis original image is reconstructed by sending the blocks to their original positions. The reconstructed image is said to be filtered image.

## 1.3Non local means

*Buades et al.* [1] in 2005 proposed a new algorithm, called as the non local means (NL-means). It is basically based on a non local averaging of all the pixels in the image. Finally, presented some experiments comparing the NL-means algorithm and the local smoothing filters.

## 1.4 Algorithm of Non local means filtering:

Given a discrete noisy image $v = \{v(i) \mid i \in I\}$, the estimated value $NL[v](i)$ , for a pixel $i$, is computed as a weighted average of all the pixels in the image,

$$NL[v](i) = \sum_{j \in I} w(i,j)v(j) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

where the family of weights $\{w(i, j)\}_j$ depends on the similarity between the pixels *'$i$'* and *'$j$'*, and it should satisfy the conditions $0 \leq w(i, j) \leq 1$ and $\sum_j w(i,j) = 1$.

The similarity between two pixels $i$ and $j$ depends on the similarity of the intensity gray level vectors $v(N_i)$ and $v(N_j)$, where $N_k$ denotes a square neighborhood of fixed size and centered at a pixel $k$. This similarity is measured as a decreasing function of the weighted Euclidean distance,

$$\|v(N_i) - v(N_j)\|_{2,a}^2$$

where $a > 0$ is the standard deviation of the Gaussian kernel.

The application of the Euclidean distance to the noisy neighborhoods raises the following equality

$$E\|v(N_i) - v(N_j)\|_{2,a}^{\mathbf{2}} = \|u(N_i) - u(N_j)\|_{2,a}^{\mathbf{2}} + 2\sigma^{\mathbf{2}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

This equality shows the robustness of the algorithm since in expectation the Euclidean distance conserves the order of similarity between pixels.The pixels with a similar grey level neighborhood to $v(Ni)$ have larger weights in the average, see Figure 4.

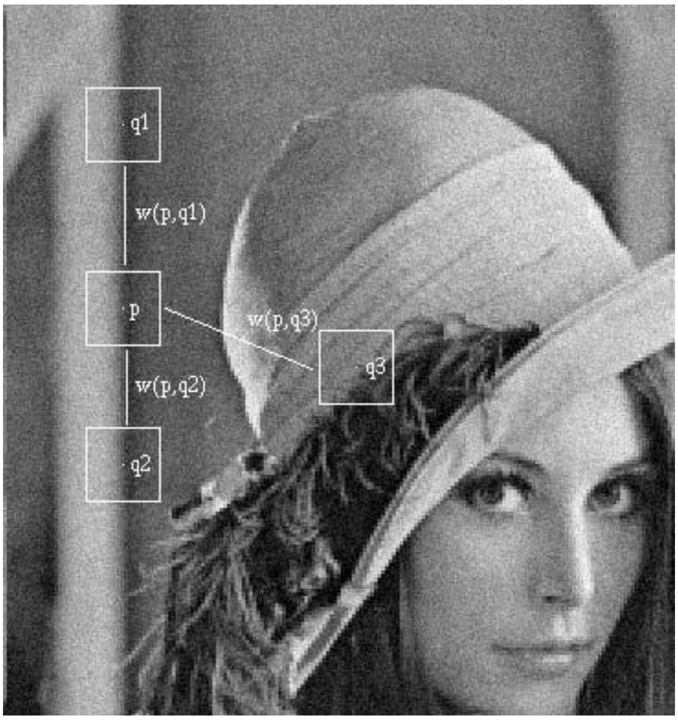



Figure 4:
Scheme of NL mean strategy. Similar pixel neighbourhoods give a large weight, *w(p,q1)* and *w(p,q2)*, while much different neighbourhoods give a small weight *w(p,q3)*.

Here $\|v(N_i)-v(N_j)\|_{2,a}^2$ is termed as *d(i,j)* which is called as Gaussian weighted Euclidean distance.

If *d(i,j)* is shorter then it means that we have higher similar regions and if its longer than usual then it means that we have lesser similar regions.

*d(i,j)* is calculated by using a Gaussian kernel.

$$d(i,j) = \|G_a * v(N_i)-v(N_j)\|_{2,a}^2 \quad \text{..................................................(3)}$$

where $G_a$ is termed as gaussian kernel and * denotes the multiplation of the corresponding elements in the Gaussian kernel and the difference matrix i.e $v(N_i)-v(N_j)$ .

Weight $w(i, j)$ can be defined as

$$w(i, j) = \frac{1}{Z(i)} \exp(-\|v(N_i)-v(N_j)\|_{2,a}^2/h^2) \text{……………………….………….(4)}$$

where *Z(i)* is termed as normalizing constant which is defined as:

$$Z(i) = \sum_j \exp(-\|v(N_i)-v(N_j)\|_{2,a}^2/h^2) \text{……………………..………………..(5)}$$

And the parameter ‘h’ is termed as degree of filtering which is proportional to standard deviation of the noise.

**1.5 Scope and Objectives :**

Our work is basically centered at embedding the texture features in the filtered image so that PSNR of the filtered image is increased. Firstly, we extract the texture features using entropy and standard deviation functions and then these texture features are used in modified weight function to get the modified weights values in non local means algorithm.

In order to increase the weights of the similar structure we have not only considered the Euclidean weighted Gaussian distance but texture structure has also been contemplated and merged with the Euclidean weighted Gaussian distance function.

### 1.6 Achievements:

It was found experimentally that our method provides better results when compared to the classical non local means algorithm in terms of PSNR. Greater values of PSNR have been achieved as compared to that what had been achieved using non local means algorithm.

### 1.7 Overview

Basically our method is a modification in the classical non local means algorithm i.e. non local means has been integrated with the texture features aspiring to provide us with better results than that we had got using classical non local means.

# Chapter - II

# Literature Review

## Literature Review :

*Buades et al.* [1] proposed a new measure, to evaluate and compare the performance of digital image denoising methods. They first computed and analysed the methods of denoising for a wide class of denoising algorithms, namely the local smoothing filters. Secondly they proposed a new algorithm, the non local means (NL-means), based on a non local averaging of all pixels in the image. Finally, they presented some experiments which gave comparison between the non local means algorithm and other smoothening algorithms.

*Yanli lieu et al.* [2] propose a robust and fast image denoising method. Their approach integrates both 'Non-Local means algorithm and Laplacian Pyramid. Given an image to be denoised, they first decomposed it into Laplacian pyramid. Exploiting the redundancy property of Laplacian pyramid, they then performed non-local means on every level image of Laplacian pyramid. Essentially, they used the similarity of image features in Laplacian pyramid to act as weight to denoise image. Since the features extracted in Laplacian pyramid are localized in spatial position and scale, they are much more able to describe image, and computing the similarity between them is more reasonable and more robust. Also, based on the efficient Summed Square Image (SSI) scheme and Fast Fourier Transform (FFT), they presented an accelerating algorithm to break the bottleneck of non-local means algorithm - similarity computation of compare windows.

*Li lin et al.* [3] proposed a method, they combined the extensive self-similarity of images in non-local means algorithm with the minimum mean square error of Wiener filetring in wavelet domain, and then proposed an image denoising algorithm based on the non local means with Wiener filtering in wavelet domain. The experimental results demonstrate that one can get denoised image with higher subjective visual quality and peak signal to noise ratio based on the proposed algorithm.

*Junez Ferreira et al.* [4] proposed a fast algorithm that uses a preliminary segmentation combined with NL-means for image denoising. Firstly, the algorithm performs a subsampling, called Preliminary Segmentation-Based Subsampling (PSB Subsampling) while reducing the data quantity to be processed, based in the preliminary segmentation information given by the noisy image. This preliminary segmentation finds out an image partition where regions are labeled as significant or non-significant. In a second step, the denoising procedure is done, but NL-means is applied only on some pixels, reducing the data quantity again. The selection of these pixels is done based on information contributed by a segmentation of the subsampled image. Experimental results show that the implementation of this proposal is quite faster than existing bibliography and it could be used in other image processing tasks like segmentation.

*Yi zhan et al*. [5] proposed a improved non-local means (NLM) filter for image denoising. Due to the drawback that the similarity is computed based on the noisy image, the traditional NLM method easily generates the artifacts in case of high-level noise. The proposed method first preprocesses the noisy image by Gaussian filter. Then, a moving window at each pixel of the noisy image is chosen as the search window, and meanwhile, a improved calculation method of spatial distance based on the preprocessed image is used for computing the similarity. Finally, combining the improved distance with search window based on the noisy image, the intensity of each pixel is restored as the traditional NLM method. The standard images had been used to evaluate restoration performance of the proposed method.

*Kaihua Gan et al.* [6] proposed a Non local Means image denoising algorithm based on edge detection. Initially they extracted edge features using improved sobel operator and these features were used to improve the weight function of non local means algorithm. To make the neighbourhood with similar structure obtain more weights, not only the weighted Euclidean distance but also the edge structure are considered when the similarity of neighbourhoods are measured. Experimental results also demonstrated that their algorithm performance is superior to the non local means algorithm.

*M.Ertas et al.* [7] have proposed that when total variation (TV) minimization is combined with Non-local means algorithm it reduces noises in a more effective manner. Visual and numerical results have shown an important improvement in image denoising has been achieved in the sense of structure similarity (SSIM) and RMSE. The optimum NLM filtering parameters selection has also been studied to increase the performance of the method proposed.

*Mingju chen et al.* [8] have proposed a method which classifies the image into several region types, according to the region character, an adaptive decay parameter and local window is adaptively adjusted to match the local property of a region. The results of experiments has shown that the adaptive NLM model denoise the image and retain the details more effectively than traditional NLM diffusion.

*Jing tiang et al.* [25] proposed that Nonlocal filtering has been proved to yield attractive performance for removing additive Gaussian noise from the image by replacing the intensity value of each pixel via a weighted average of that of the full image. The key challenge of the nonlocal filtering is to establish the kernel function for computing the above-mentioned weighting factors, which control the quality of the denoised image result. In contrast to that the exponential function is used in the conventional nonlocal filtering, they have proposed several new kernel functions to be further incorporated in to conventional non local filtering framework to develop new filters. Extensive experiments are conducted to demonstrate not only that the kernel function is essential to control the performance of the algorithm, but also that the new kernel functions proposed in this paper yield superior performance to that of the conventional nonlocal filtering.

# Chapter – III

# Non local means denoising based on texture features

## 3.1Non local means denoising algorithm using texture features:

### 3.1.1 Texture Analysis :

Texture analysis basically deals with the characterization of an image by their texture content. It analyses any images due to its inhibited qualities such as rough, smooth, silky, or bumpy as a function of the spatial variation in pixel intensities. These inhibited qualities can also be referred as variation in the intensity values or gray levels.

It is used in a variety of applications such as remote sensing, automated inspection, and medical image processing. Texture analysis is helpful in finding the texture boundaries, and also known as texture segmentation. It is helpful when objects in an image are more characterized by their texture rather than by intensity.

### 3.1.2 Texture features :

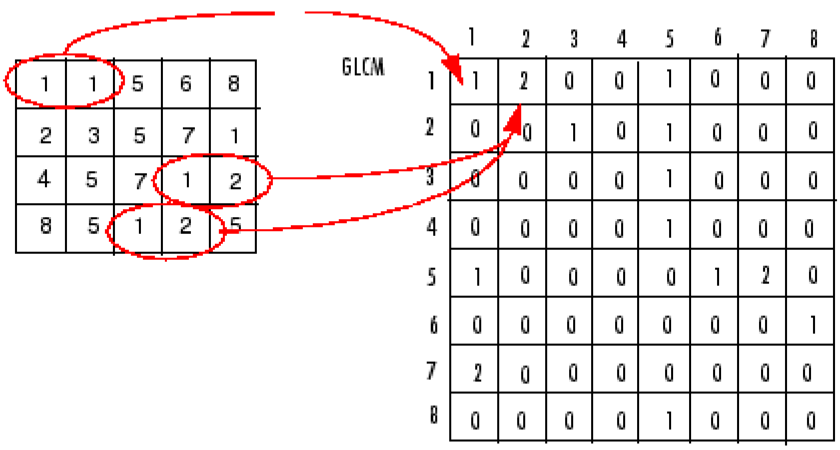
Texture features is nothing but texture feature itself. Different types of texture features which are helpful in analysis of an image are as follows:

1) GLCM

   It stands for Gray Level Co-occurrence Matrix. It is a statistical method which considers the spatial relationship of pixels. It works on the principle of co-occurrence of values of pairs of pixels with specific values in a predefined spatial relationship in an image.

   Process used to create GLCM :

Figure 5



To demonstrate what is actually happening we can see that the output GLCM contains 1 as it very first element since there is only one instance where (1,1) is occurring rather the second element i.e. glcm(1,2) contains the value 2 which signifies that there are two instances of co-occurrence of (1,2). Similarly, it calculates rest of all the values.

2) ENTROPY

Entropy gives us the measure of complexity of an image. If the entropy is large then the image is said to have a non-uniform texture and vice versa.

In our work we have considered local entropy rather than considering the whole entropy at once.

In general formula used in the evaluation of entropy is :

Entropy =

### 3.1.3 Non local means denoising and texture features

Non local means algorithm can give better results in the smooth regions of an image because the intensity of the neighbourhood possess high similarity with its structure.

However in the areas of rich texture regions, there is actually a large difference between the intensity values of the neighbourhood matrices. This is in turn provides us with a large Gaussian weighted Euclidean distance and which leads to smaller weight of the neighbourhood with similar structure. Thus reducing the effectiveness of non local means algorithm.

In order to overcome this side effect we have come with the idea of integrating the texture features with the non local algorithm.

the weight function will look like :

$$w(i,j) = \frac{1}{Z(i)} \exp(-\|v(N_i)-v(N_j)\|_{2,a}^2/h^2 - \|tf(N_i)-tf(N_j)\|_{2,b}^2/h_1^2) \quad \text{.................(6)}$$

$$\textit{where } d(i,j) = exp(-\|v(N_i)-v(N_j)\|_{2,a}^2/h^2 - \|tf(N_i)-tf(N_j)\|_{2,b}^2/h_1^2 \quad \text{........................(7)}$$

*and*

$$Z(i) = \sum_j exp(d(i,j)) \quad \text{..................................................(8)}$$

where $tf(N_k)$ is the neighbourhood centered in the texture image. And $||tf(N_i)-tf(N_j)||_{2,b}$ is the texture distance between the $i^{th}$ and $j^{th}$ pixel which is calculated by evaluating the Gaussian kernel first with the standard deviation b, where $b = a$ , and multiplying elements in the gaussian kernel with that of difference of texture matices. And when the texture distance in the smooth regions is close to zero, the gaussian weighted distance is not affected and non local means retains its efficiency in those areas as well.

## 3.2 Methodology

The steps involved in our algorithm are as follows:

1) Initially we have a noisy image which is smoothened by Gaussian filtering, then the smoothened image is further processed to get texture features from it using entropy and standard deviations.
2) Then we constructed two neighbourhood matrices centered at ith and jth pixels. Then the Gaussian weighted Euclidean distance was calculated using formula (7).
3) Then the weight function was evaluated using formula (6).
4) Then the normalized constant was evaluated using formula (8).
5) Then the new value of the ith pixel is calculated by using formula (1).

# Chapter IV

# Results and Discussions

Figure 6

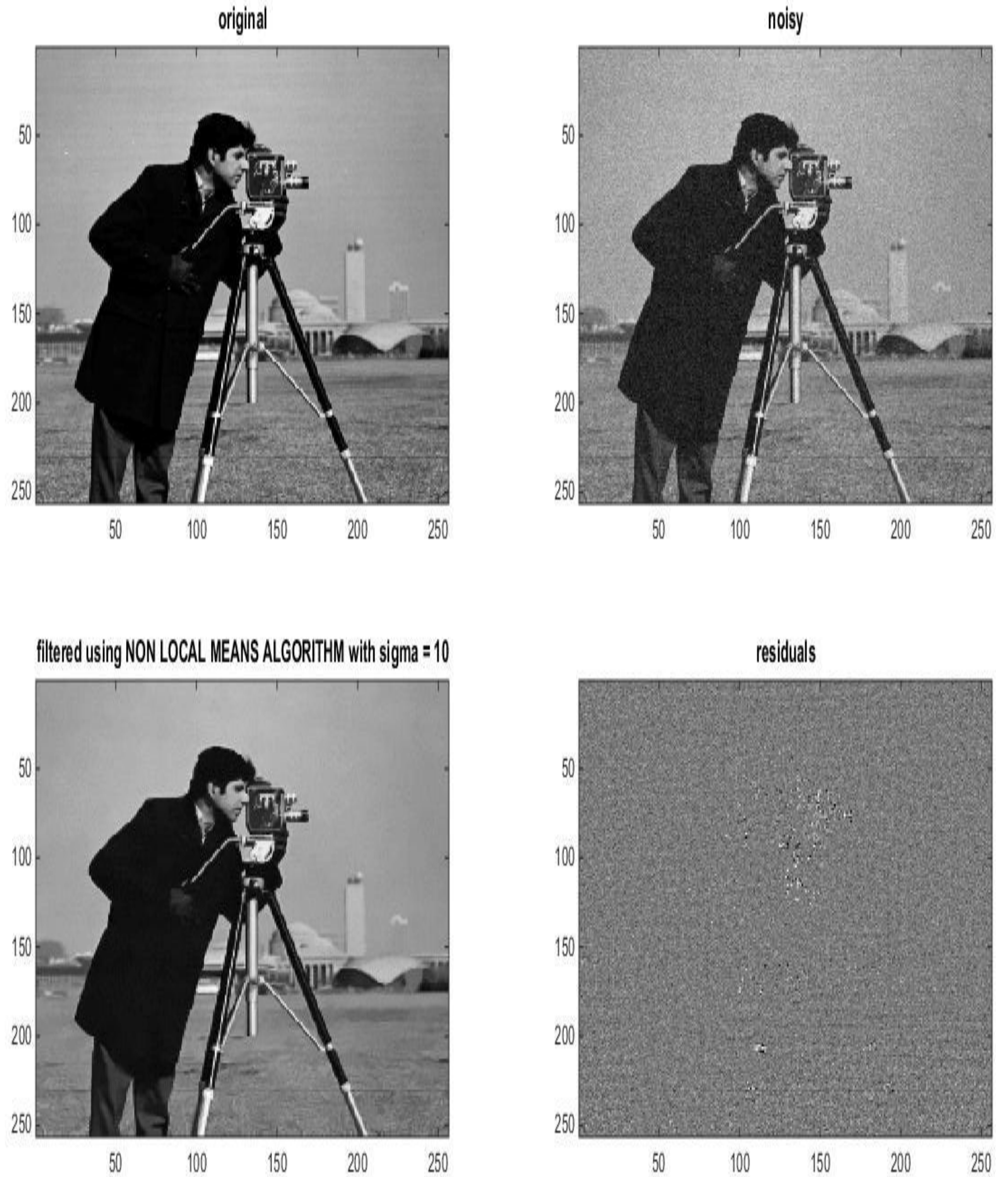



Figure 6 shows the original, noisy, filtered and the residual images. The noisy image is affected by additive random noise with standard deviation 10 and it has been filtered using Non Local Means algorithm, , shown in the figure super scribing *"filtered using non local means algorithm"*.

And the table below illustrates the PSNR comparison between original and noisy image, and between filtered and original image using Non Local Means Algorithm.

**Table 4.1**

| **Standard Deviation** | **Filtering using NON LOCAL MEANS Algorithm** | |
|---|---|---|
| | **PSNR in decibels (db)** | |
| | **Between Original and Noisy** | **Between Filtered and Original** |
| $\sigma = 10$ | 28.16 | 31.99 |

Figure 7

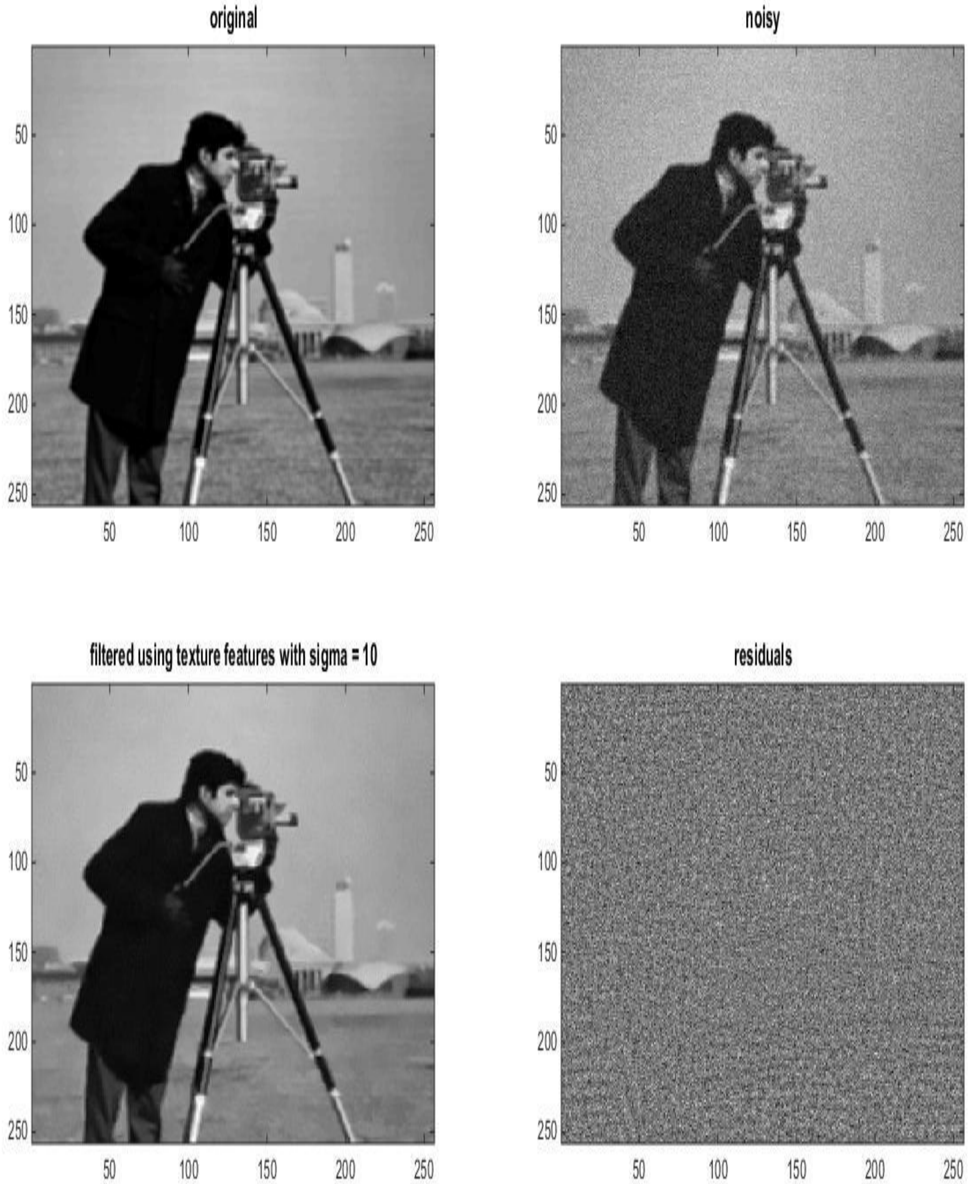



Figure 7 shows the original, noisy, filtered and the residual images. The noisy image is affected by additive random noise with standard deviation 10 and it has been filtered using Non Local Means algorithm integrated with texture features.

And the table below illustrates the PSNR comparison between original and noisy image, and between filtered and original image using Non Local Means Algorithm integrated with texture features.

**Table 4.2**

| **Standard Deviation** | **Filtered using NON LOCAL MEANS algorithm integrated with texture features** | |
|---|---|---|
| | **PSNR in decibels (db)** | |
| | **Between Original and Noisy** | **Between Filetered and Original** |
| $\sigma = 10$ | 28.14 | 36.36 |

Figure 8

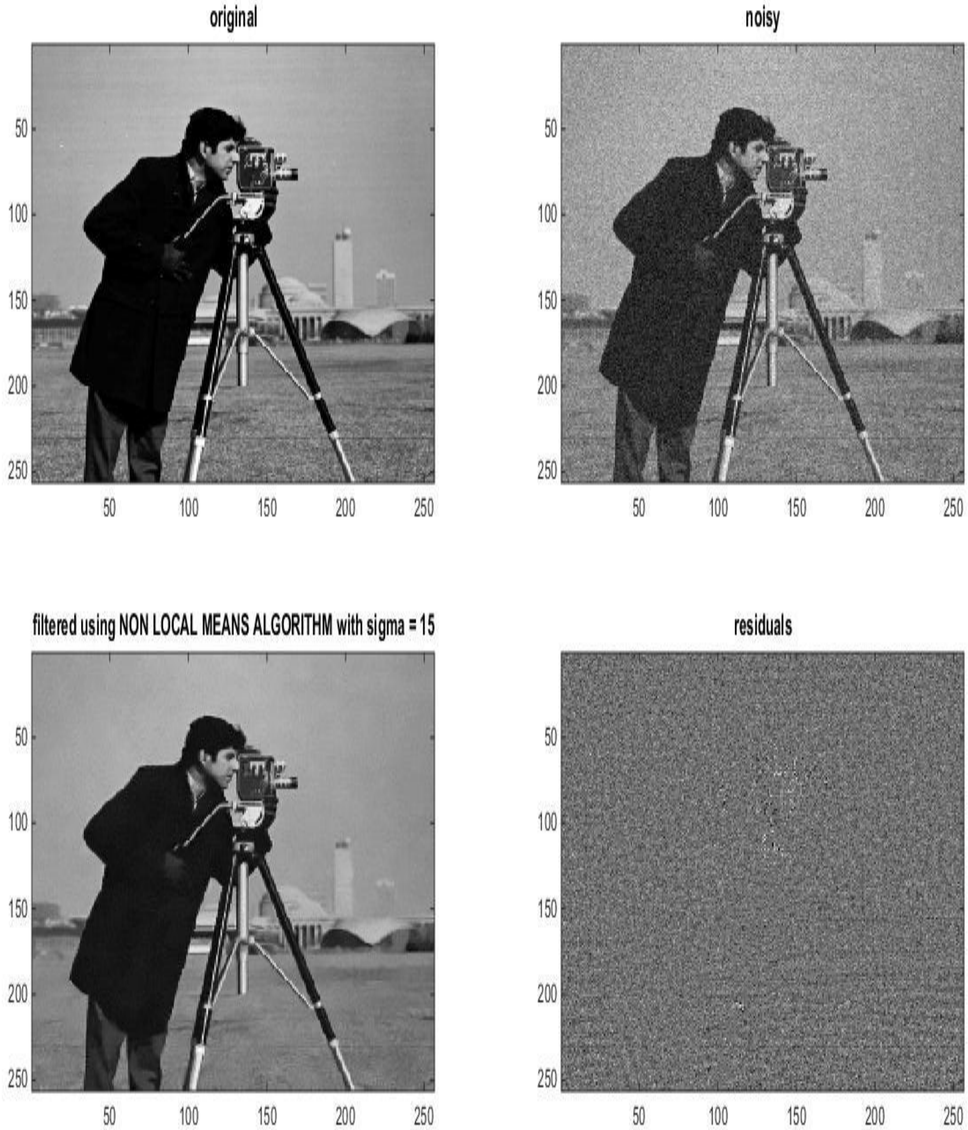



Figure 8 shows the original, noisy, filtered and the residual images. The noisy image is affected by additive random noise with standard deviation 15 and it has been filtered using Non Local Means algorithm, shown in the figure super scribing *"filtered using non local means algorithm"*.

And the table below illustrates the PSNR comparison between original and noisy image, and between filtered and original image using Non Local Means Algorithm.

**Table 4.3**

| Standard Deviation | Filtered using NON LOCAL MEANS algorithm | |
|---|---|---|
| | PSNR in decibels (db) | |
| | Between Original and Noisy | Between Filtered and Original |
| $\sigma = 15$ | 24.57 | 30.55 |

Figure 9

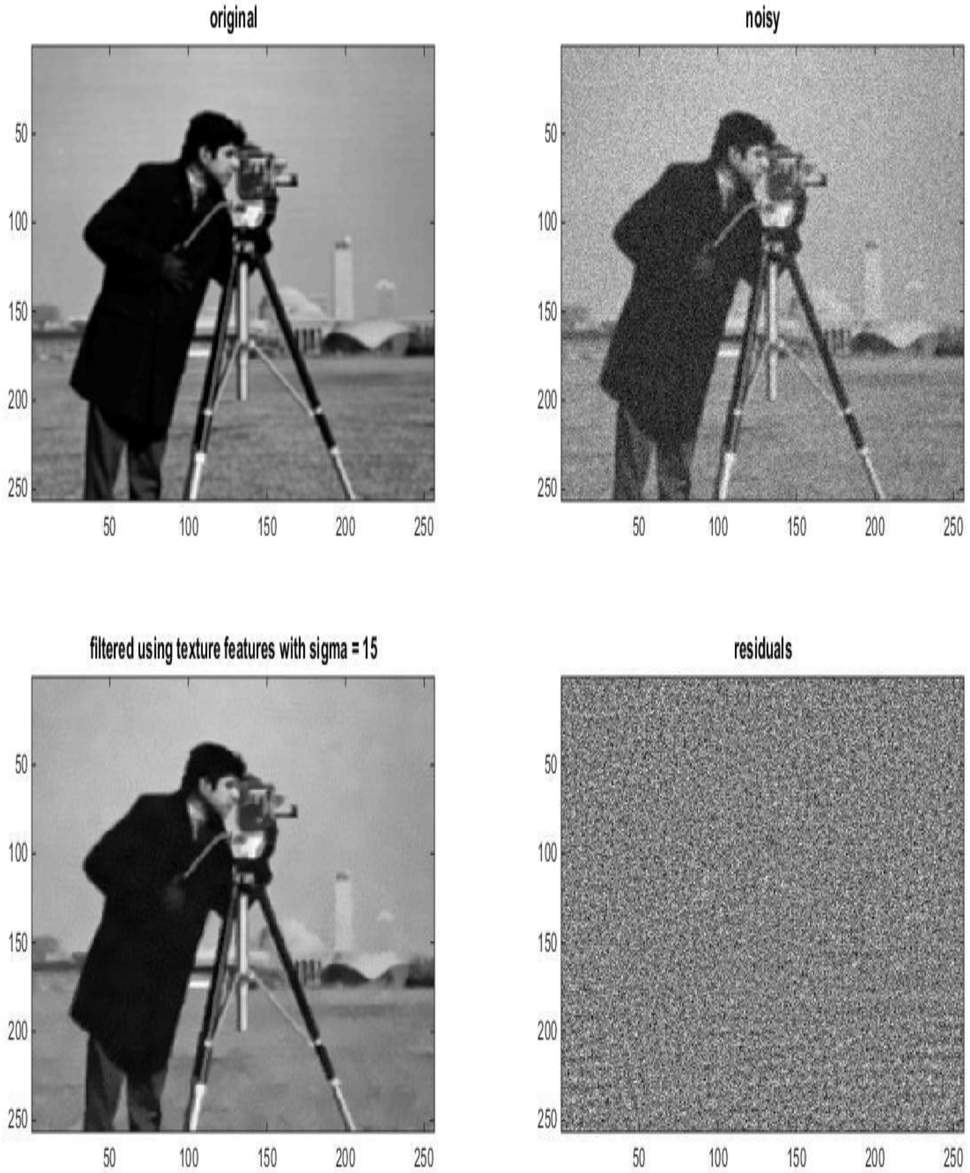



Figure 9 shows the original, noisy, filtered and the residual images. The noisy image is affected by additive random noise with standard deviation 15 and it has been filtered using Non Local Means algorithm integrated with texture features.

And the table below illustrates the PSNR comparison between original and noisy image, and between filtered and original image using Non Local Means Algorithm integrated with texture features.

**Table 4.4**

| **Standard Deviation** | **Filtered using NON LOCAL MEANS algorithm integrated with texture features** | |
|---|---|---|
| | **PSNR in decibels (db)** | |
| | **Between Original and Noisy** | **Between Filtered and Original** |
| $\sigma = 15$ | 24.6 | 34.01 |

Figure 10

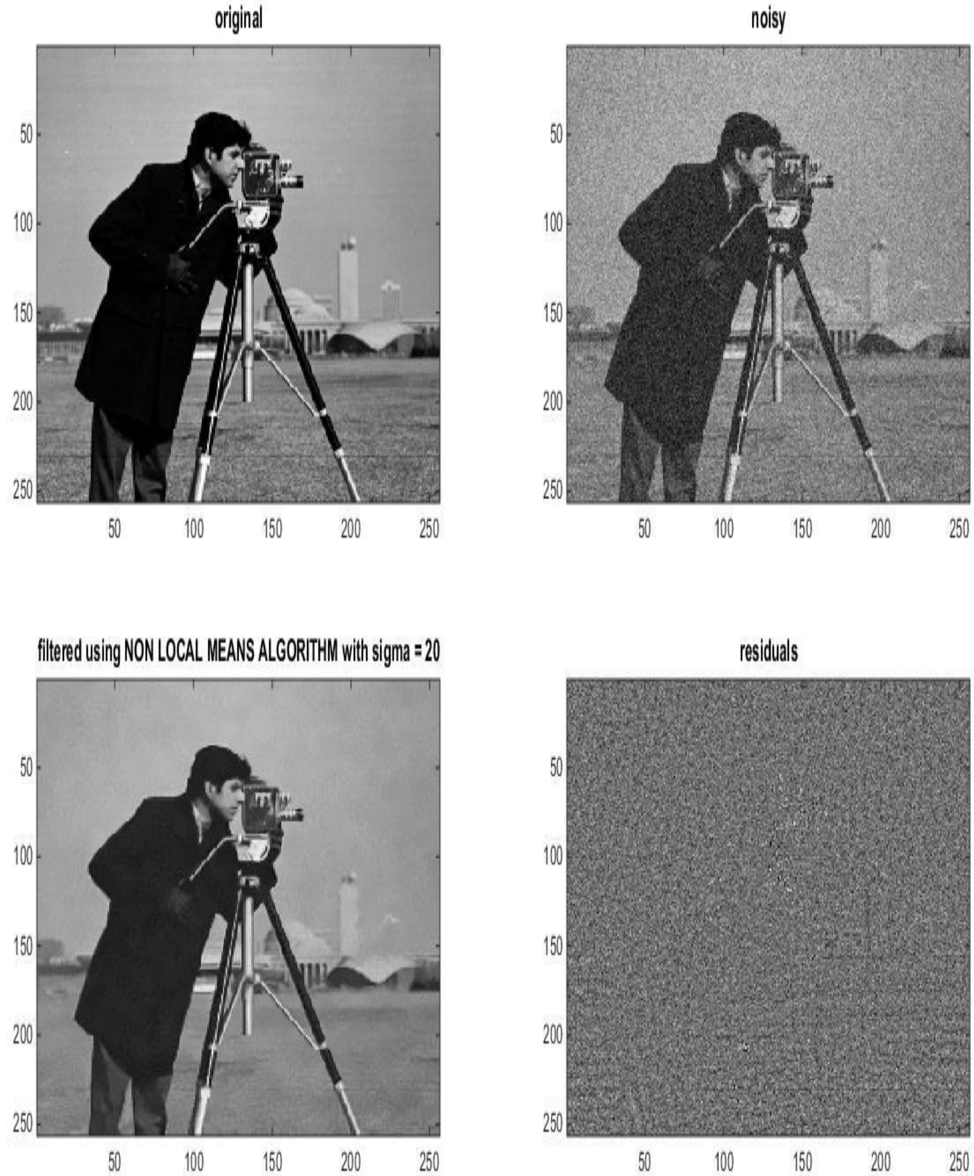



Figure 10 shows the original, noisy, filtered and the residual images. The noisy image is affected by additive random noise with standard deviation 20 and it has been filtered using Non Local Means algorithm, shown in the figure super scribing *"filtered using non local means algorithm"*.

And the table below illustrates the PSNR comparison between original and noisy image, and between filtered and original image using Non Local Means Algorithm.

**Table 4.5**

| **Standard Deviation** | **Filtered using NON LOCAL MEANS algorithm** | |
|---|---|---|
| | **PSNR in decibels (db)** | |
| | **Between Original and Noisy** | **Between Filtered and Original** |
| $\sigma = 20$ | 22.13 | 29.37 |

Figure 11

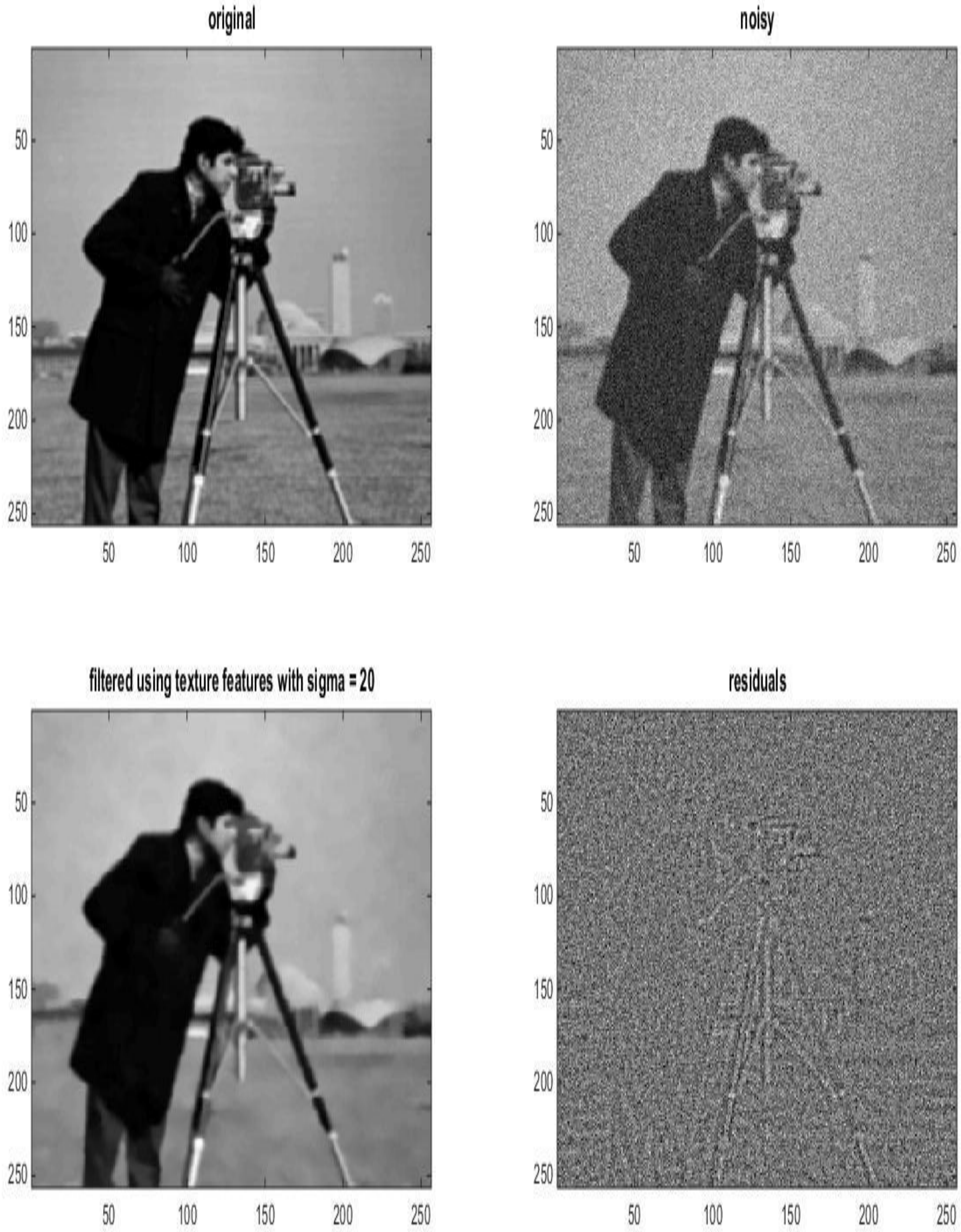



Figure 9 shows the original, noisy, filtered and the residual images. The noisy image is affected by additive random noise with standard deviation 20 and it has been filtered using Non Local Means algorithm integrated with texture features.

And the table below illustrates the PSNR comparison between original and noisy image, and between filtered and original image using Non Local Means Algorithm integrated with texture features.

**Table 4.6**

| **Standard Deviation** | **Filtered using NON LOCAL MEANS algorithm integrated with texture features** | |
|---|---|---|
| | **PSNR in decibels (db)** | |
| | **Between Original and Noisy** | **Between Filtered and Original** |
| $\sigma = 20$ | 22.08 | 32.38 |

Figure 12

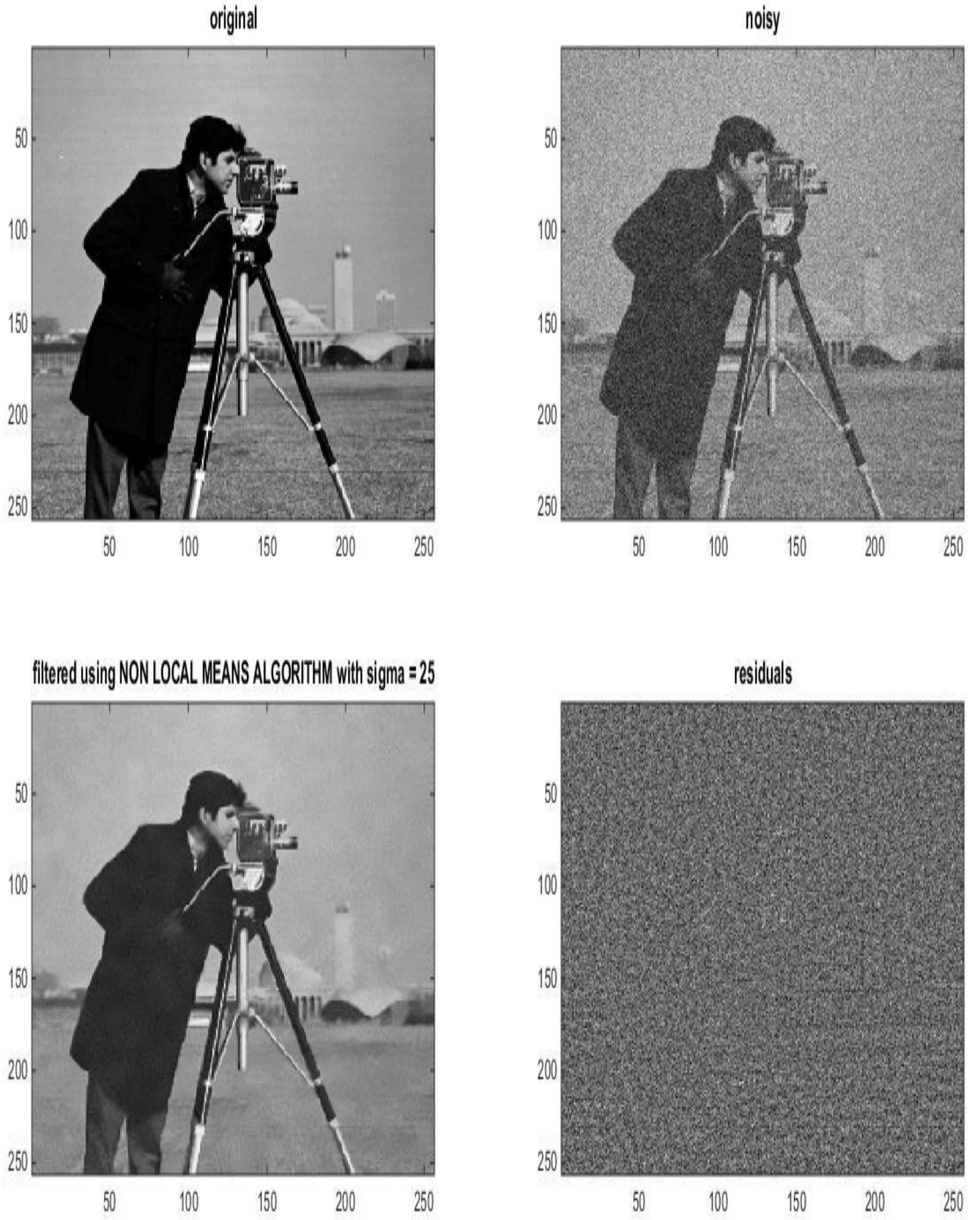



Figure 12 shows the original, noisy, filtered and the residual images. The noisy image is affected by additive random noise with standard deviation 25 and it has been filtered using Non Local Means algorithm, shown in the figure super scribing *"filtered using non local means algorithm"*.

And the table below illustrates the PSNR comparison between original and noisy image, and between filtered and original image using Non Local Means Algorithm.

**Table 4.7**

| **Standard Deviation** | **Filtered using NON LOCAL MEANS algorithm** | |
|---|---|---|
| | **PSNR in decibels (db)** | |
| | **Between Original and Noisy** | **Between Filtered and Original** |
| $\sigma = 25$ | 20.17 | 28.36 |

Figure 13

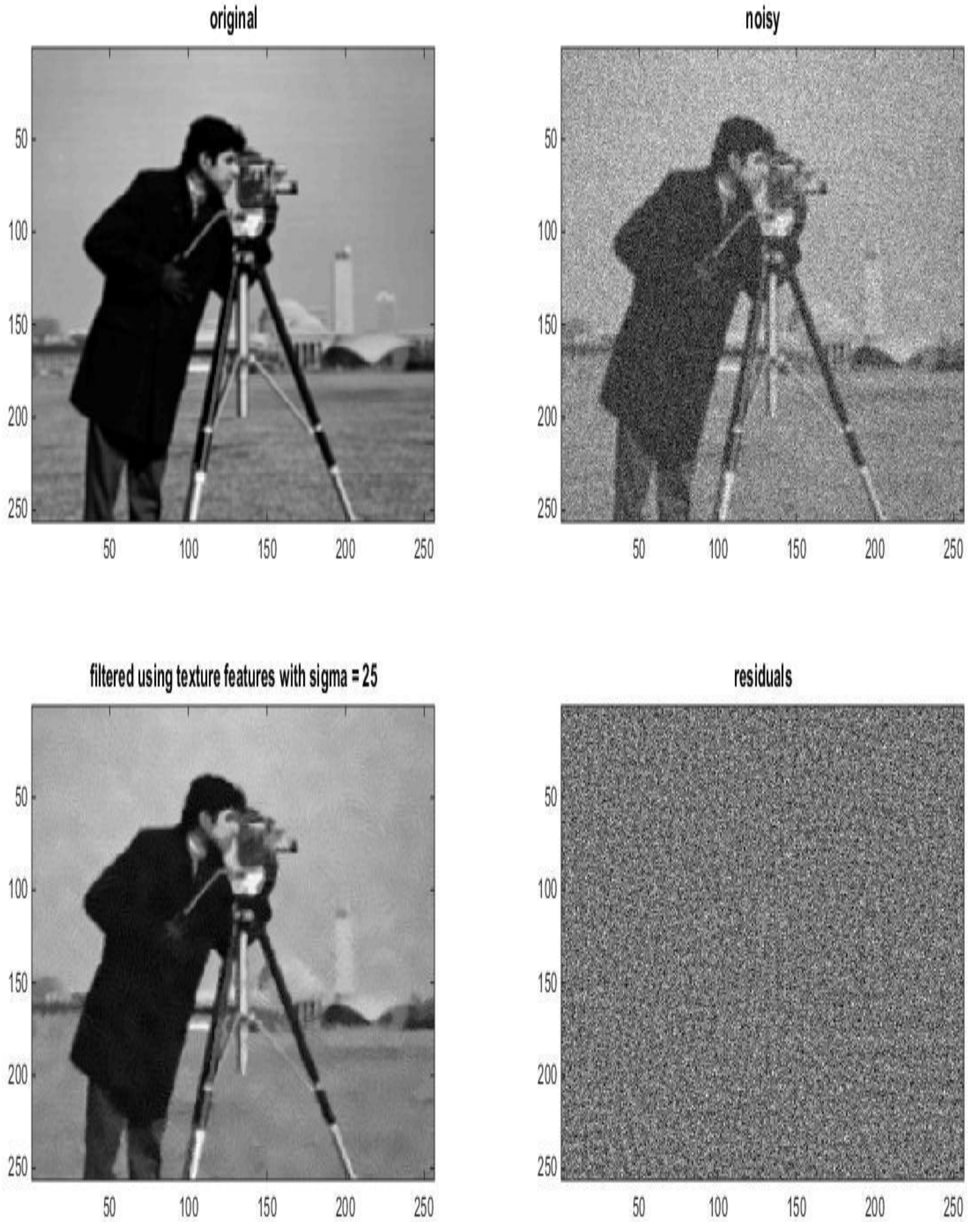



Figure 9 shows the original, noisy, filtered and the residual images. The noisy image is affected by additive random noise with standard deviation 20 and it has been filtered using Non Local Means algorithm integrated with texture features.

And the table below illustrates the PSNR comparison between original and noisy image, and between filtered and original image using Non Local Means Algorithm integrated with texture features.

**Table 4.8**

| Standard Deviation | Filtered using NON LOCAL MEANS algorithm integrated with texture features | |
|---|---|---|
| | PSNR in decibels (db) | |
| | Between Original and Noisy | Between Filetered and Original |
| $\sigma = 25$ | 20.14 | 31.03 |

## Final comparison table 4.10

| Standard Deviation | Filtered using NON LOCAL MEANS | | Filtered using NON LOCAL MEANS algorithm integrated with TEXTURE features | |
|---|---|---|---|---|
| | PSNR (db) | | PSNR (db) | |
| | **Between Original and Noisy** A1 | **Between Filtered and Original** A2 | **Between Original and Noisy** B1 | **Between Filtered and Original** B2 |
| $\sigma = 10$ | 28.16 | 31.99 | 28.14 | 36.36 |
| $\sigma = 15$ | 24.57 | 30.55 | 24.59 | 34.01 |
| $\sigma = 20$ | 22.13 | 29.37 | 22.08 | 32.38 |
| $\sigma = 25$ | 20.17 | 28.36 | 20.14 | 31.03 |

## Final difference comparison Table 4.11

| Standard Deviation | Filtered using NON LOCAL MEANS | Filtered using NON LOCAL MEANS algorithm integrated with TEXTURE features | |
|---|---|---|---|
| | **PSNR Difference in decibels (db)** (A1-A2) | **PSNR Difference in decibels (db)** (B1-B2) | **Increase in PSNR in decibels (db)** |
| $\sigma = 10$ | 3.83 | 8.22 | 4.39 |
| $\sigma = 15$ | 5.98 | 9.42 | 3.44 |
| $\sigma = 20$ | 7.24 | 10.3 | 3.06 |
| $\sigma = 25$ | 8.19 | 10.89 | 2.7 |

## 4.1 Discussions :

We have carried our experiment on the grayscale image (photographer.tif) whose size is 256 x 256. Degree of filtering h has been which is proportional to sigma has been assumed to be equal to $\sigma$.

Initially the image has been denoised using  non local means algorithm and its efficiency is evaluated in terms of PSNR. Then the same image has been denoised using non local means denoising algorithm based on texture features then its efficiency is evaluated in terms of PSNR. The typical values of PSNR has been depicted in a table below every image.

Finally we have illustrated all the values in the final table. It can be observed from the table titled 'final comparison table' that with increasing $\sigma$ PSNR with respect to the original as well as filtered image is decreasing as it is obvious that by increasing $\sigma$ we are increasing noise power where as signal power i.e. original image is same as it was.

We can also observe that PSNR is varying with respect to original image this is so because we have considered additive random noise in the experiment. As the variation in PSNR is quite negligible as the image on which it is being added is same but since the noise being added is random in nature leads to variations in PSNR value as many a times as it is calculated. Therefore for the comparison sake we have opted difference in the PSNR values.

# Chapter – V

# Conclusions and Future work

# Conclusion :

We can observe that with increasing standard deviation, PSNR with respect to the original image is decreasing and PSNR with respect to filtered image is decreasing as well.

With increasing standard deviation, increase in PSNR is also decreasing as it is obvious because of the increasing noisy input.

It can also be observed that our method is efficient than the non local means algorithm as we are getting a higher PSNR value for a given $\sigma$ . when the non local means denoising algorithm based on texture features is used, for $\sigma = 10$ increase of 4.39 db in PSNR value with respect to the filtered image has been observed. Thus this proves the efficiency of our algorithm.

## Future scope:

Other features such as edge, optical flow etc can be integrated with the non local means algorithm and can be worked upon to increase the efficiency of the classical non local means algorithm. Other methods which have come up in recent years like fast non local means which has been used to denoise noisy MRI image.

These features can be integrated in those algorithms also and we can expect to get a better output.

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