Image Denoising

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Abstract

It is said that some of the most basic things of the real world are the hardest things to explain, and even harder to put in terms of machine language. With this in mind, we chose one of the most fundamental part of image processing as our practical research topic - Image Denoising, since there isn't ever a perfect picture. Image Denoising or noise reduction is now a fundamental part of a larger image processing operation. Most computer vision techniques that have images as their inputs need a certain standard for quality. For example, size of the image, contrast level, exposure, noise level, resolution or aspect ratio, alignment or angle, etc. For this reason, almost every image processing chain has some sort of noise reduction as one of its steps. In this paper, we will look at some of the most common Image Denoising techniques used today, implement these techniques, try them on some images, and list their advantages and disadvantages, and see in which scenarios we can use these techniques. We will also take a deeper look into Wavelet Shrinkage method of image denoising since it's a relatively newer approach.

1 Introduction

Image Denoising is a very fundamental topic, so much so that this topic often gets considered as trivial. But, it's not! With a rise in Automation and Robotics, pictures have transformed from being just the things we look at for pleasure or leisure, to the things we look at for data or information. Scientists and Technicians are analyzing pictures at an ever-increasing rate. However, when sensors capture the scene, the picture that gets taken often comes out noisy. This noise must be removed from the image data before it is analyzed. Without proper noise removal, we may not be able to achieve our goal.

We looked at a few different previously done work that had the newest and some of the most effective denoising methods. Almost all of the methods in these papers were new to us, even though we had come across the concepts they were wrapped around before. We have a high level understanding of what sub methods were used overall in these algorithms/techniques. However, we still have to figure out a way to put them all together in a way that they give an appreciable result, and this will only be possible by going through papers that had implemented similar algorithms. Out of all the algorithms we looked at, wavelet shrinkage seemed to be the most capable and efficient. Nevertheless, before jumping straight to a conclusion, let us look at a few other image denoising approaches and results obtained from these approaches.

2 Previous Work

Imola K. Fodor and Chandrika Kamath, in their "Denoising through wavelet shrinkage: An empirical study" [1], converted image into wavelets, where signals are represented as coefficients. Important data gets converted to larger coefficients, and trivial data to smaller coefficients; noise. They modified the coefficients to differentiate between the pixels are are crucial to the image from the pixels that are considered to be noise, and removed the noise after detection.

Hari Om and Mantosh Biswas [4] have attempted to enhance the visual quality of noisy images by performing wavelet transformation and modifying the coefficients using soft thresholding. For each subband level obtained by the 2D orthogonal wavelet transform a new threshold is created which uses soft thresholding to get the noiseless wavelet coefficients. The inverse wavelet transform of the resultant image will give the denoised image.

Yongjian Yu and Scott T. Acton [5] developed a nonlinear anisotropic diffusion technique, speckle reducing anisotropic diffusion, for removing multiplicative noise in images. Unlike other existing diffusion techniques that process log-compressed data, their technique processes the data directly in order to preserve useful information in the image. Raghuram Rangarajan, Ramji Venkataramanan and Siddharth Shah [7] used a Gaussian based model to perform combined denoising and compression for natural images and compare its performance with methods like SUREShrink, VisuShrink and BayesShrink.

3 Noise Reduction Techniques

There are a handful of techniques that can be used to reduce noise in images. Some work in certain conditions, and some work in some other conditions. Some perform quite well, and some not so much. Keeping that aside, most methodologies are invented to target some specific form of noise in the images. There are many types of noise that appear in images. For example, motion blur, salt and pepper noise, gaussian noise, periodic noise, etc. and some methodologies work well to counter some of these specific forms of noise.

We, in this experiment, are going to target the most common one that is the Gaussian noise. This type of noise is induced in the images during the acquisition of the scene, i.e. when the camera sensor snaps the real-world scene. There can be thousands of factors, known and unknown both, that causes introduction of noise in images. Trying to exhaustively prevent them is practically impossible. The best we can do is use the best hardware in the best environmental condition to click a picture, and then do some processing on our part to reduce the gaussian noise, if any, in the image. So, we looked at some of these techniques [1][5][6][7] from several literatures to learn them and understand when they can be useful.

3.1 Local Averaging

One of the simplest, commonly used, and easy to implement noise reduction is Local Averaging. The idea behind this is the assumption that a pixel is always influenced by the pixels around it. We can do some form of averaging, weighted or not weighted, in an area that surrounds a pixel and assign it this average value. The fact that pixels do not differ much from each other in an area sounds true and logical, but has some wrong assumptions in it. This could have been true if there were only one thing in the image. However, how often does that happen to us?

An average indoor image may contain up to a hundred different objects in it and in an outdoor image, it may have even thousands at once scattered all over the place! This puts the whole idea of neighboring pixels being like one another into question when there are several objects around one another and in high frequency in the image. Averaging will smear the details of objects with each other and lose the edge information in the image. For this reason, this method has never become a core denoising technique in imaging world. We will see in figures shown at the end of the document how inefficient this method is for removing noise.

3.2 Median/Rank-Selection filtering

Median filtering comes from a more generic form of filtering algorithm called Rank Selection. It is a nonlinear filter and it basically has the same premise as that of local averaging. A pixel is more likely to have a value that is in majority in an area. Where local averaging used mean of block of pixels to get a new pixel value, median filtering uses median of pixels to get the new pixel value. This filtering technique is one of the best performing and favorite in the vision industry. It is capable of eliminating most of the grain-type noise while retaining the sharpness in the edges of the objects.

However, even this method isn't foolproof. Well, none of them are, but this one has some big disadvantages to it. This method can introduce sampling and can cause blocking effect in the image. This affects the smoothness of the image and introduces unnecessary faint edges in it. Considering tradeoff that comes with this technique, it has reduced to being just a small trivial part of larger imaging chain.

3.3 Quantization

Quantization is a lossy compression technique achieved by compressing a range of values to a single quantum value. The range of pixel color values is reduced to the number of values that it is then mapped to. It is mostly used to convert images with gradients of colors to clusters of similar colors. Quantization has the same problem that median filtering has along with more loss of information. This technique has reduced to a simple lossy compression method.

The fewer the number of quantization levels used gets, there is a progressive loss of spatial detail. Furthermore, certain artifacts such as contouring or false contouring begin to appear. These refer to artificial boundaries which become visible due to the large and abrupt intensity changes between consecutive color (usually gray) levels. Quantization can be applied manually as well and that way each level need not have an equal range of values.

3.4 Bi-Lateral Transform

The bilateral filter [16] is a non-linear technique to smooth images and reduce the noise in them while preserving edges. It acts just like a normal filter by scanning the window through the entire image while replacing the intensity of each pixel with a weighted average based on a Gaussian distribution of intensity values from the pixels around it. Except for the Euclidean distance of pixels, these weights also depend on the differences in color intensity, depth distance, range, etc. The fact that the weights allotted depends on these minute aspects preserves sharp edges in the image. In simple computer vision computation, each pixel is replaced by an average of the pixels surrounding it and the number of pixels to be considered will be decided by the window size of the bilateral filter. It depends only on two parameters that indicate the size and contrast of the features to preserve. The parameters are easy to set since it can be used in a non-iterative manner and their effect is not cumulative over several iterations. It is possible to be run even on large images at a great speed.

3.5 Anisotropic/Perona–Malik diffusion

Anisotropic diffusion [5] (also called as Perona–Malik diffusion) is a noise reduction technique that aims at removing noise while keeping important features of the image data like edges, lines, colors, exposure etc. It operates in multiple scale spaces i.e. a geometric pyramidal decomposition of images over its spatial resolution that iteratively compresses the image by reducing the resolution of it. Each of it is a two dimensional Gaussian filtered image whose filters depend on the data of the original image. This process of gradual diffusion is a linear and space-invariant transformation of the original image. It produces a family of images which are the resulting images of combination of original image with a filter that depends on the local data of the original image.

3.6 Wavelet Transform

The above-mentioned techniques are not the only ones that do noise reduction in images. Those are some of the most common ones. And the one we'll be looking at in depth in this experiment is Wavelet Shrinkage, with both, hard and soft thresholding. Wavelet Shrinkage is a technique in which the image data is converted to wavelets and are decomposed spatially by retaining the important aspects of the data and throwing away the trivial ones. It attempts to reject noise by damping or thresholding in the wavelet domain. Analysis of multi-resolution images can be done in a generic way by bringing them in the wavelet domain.

The reason for doing Wavelet transform rather than Fourier transform on our image is that wavelet transform lets us map our data to a function that is dependent on both time and frequency. On the other hand, Fourier transform requires past and future information of the signal and it loses the connection between time and frequency thereby reducing it to a function of just frequency. They have become crucial in compression of the image since wavelets allow simultaneous analysis of both, the time, and the frequency. It is a more suitable technique for image compression as compared to Fourier transform. However, in recent times, Wavelet transform has become a huge deal in the industry by coming up with an answer for reduction of noise in noisy images. It applies the same basis as that of image compression and then builds on it by doing a thresholding over the decomposed original image. We will see how this happens in detail soon below.

We used Mathworks' MATLAB programming environment [20] that provides an exhaustive set of toolboxes/libraries for programming mathematically complex algorithms for implementing our own Image Denoising program. MATLAB has a toolbox called Wavelet Toolbox specifically for analyzing and synthesizing signals, images, and data in wavelet domain. It provides us with an overwhelming number of flexibly implemented algorithms and visualizations for discrete wavelet analysis, and wavelet transforms.

A brief overview of the general steps while using wavelet shrinkage method is given below. If Y denotes the observed data, X denotes the noiseless data and ϵ denotes the error matrices, the three steps of denoising using wavelet coefficient shrinkage technique are as follows:

1. Calculate the wavelet coefficient matrix w by applying a wavelet transform W to the data:

   w = WY = WX + Wϵ

2. Modify (threshold or shrink) the detail coefficients of w to obtain the estimate w' of the wavelet coefficients of X:

   w $\Rightarrow$ w'

3. Inverse transform the modified coefficients to obtain the denoised estimates:

   X' = W^{-1}*w'

3.6.1 Wavelet Transform

Traditional means of removing noise from images and signals have been using spatial filters to smooth the data to reduce the noise but end up blurring the data in the process as well. Several new techniques have been recently developed that improvise on the spatial filters such that they help to remove noise while maintaining the edges to a great extent. These techniques use various concepts like computational fluid dynamics, non-oscillatory schemes and isotropic and anisotropic diffusion. The class of methods we plan to approach exploits the decomposition of the data into the wavelet basis and shrinks the wavelet coefficients to denoise the data.

The first step in denoising is to select a wavelet for the forward and inverse transformations W and W^{-1} in 1. and 3., respectively. We use orthogonal and biorthogonal wavelets, including the B-spline and V-spline families. We ended up using biorthogonal wavelet with 3 reconstruction filters and 5 decomposition filter since it gave us visually better looking outputs. See our results at the end of this paper. 2. depicts the shrinkage (or thresholding) step. The shrinkage or thresholding function determines how the thresholds are applied to the data. In cases where the noise distribution is known, it can be used to calculate σ (noise scale), otherwise it must be estimated from the observed data.

For image denoising, it is important that the total number of input samples should be equal to the total number of wavelet coefficients at any point during the decomposition process. The methods that follow these rules are known as non expansive methods. To make sure this is maintained, discrete wavelet transform (DWT) can be employed. DWT methods that are non expansive require symmetric filters to implement symmetric extension. Symmetric extension can be implemented with orthogonal wavelets using DWT implementation methods that make use of matrices. The DWT performs a subband decomposition of the frequencies included in the image. After the subbands have been created, the image appears to be more compact since almost all of its energy is concentrated in relatively fewer decomposed DWT coefficients. Any wavelet transform for which the wavelets are discretely sampled is called a discrete wavelet transform (DWT) [13].

A 1-D discrete wavelet transform can be obtained from row and column vectors individually. The decomposition of a 2D image in the wavelet domain is performed by applying those 1-D discrete wavelet transform (DWT) obtained from vector, along the rows of the image first, and then the results obtained from applying the DWT to rows of the image are decomposed along the columns. The figure above shows the structure of a 1-level 2-D wavelet decomposition of an image. For multiple levels of decomposition, the band containing the approximation coefficients (LL band) is decomposed on an iterative basis. This helps obtain a pyramid structure for the subbands wherein the coarsest subband is placed at the top and the finest subband is placed at the bottom. See figure 1. This figure illustrates the pyramid structure obtained after two-level decomposition of the primary image we have used. Notice that the band containing the approximation coefficients is at the top right corner and it has been transformed into 4 subbands.

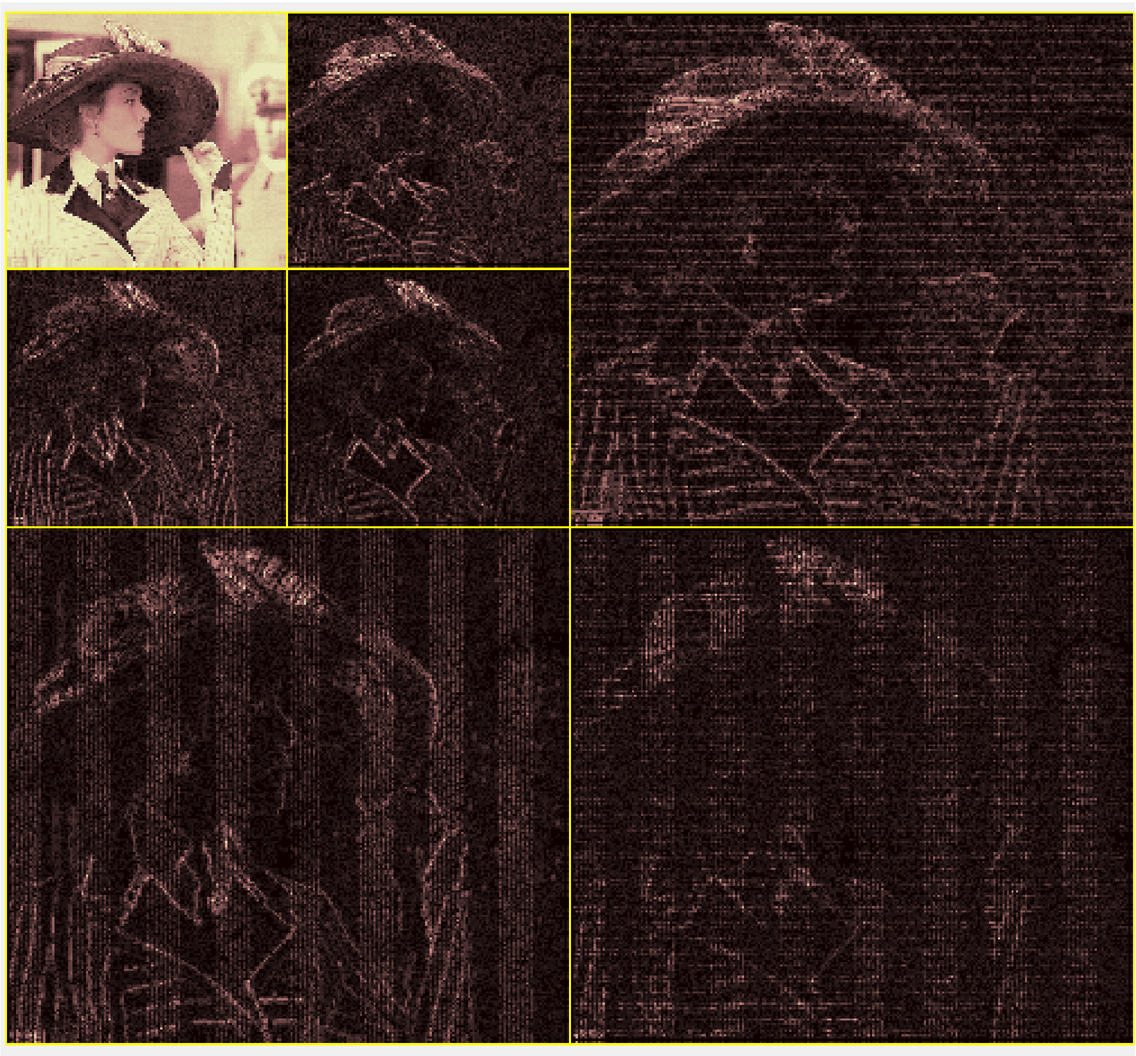


Figure 1: Level 2 Decomposition.

3.6.2 Thresholding

After obtaining the wavelet transform we have applied soft and hard thresholding over the image in the wavelet domain. Many wavelet based thresholding techniques like VisuShrink, SureShrink, Oracle Shrink, Normal shrink have proved better efficiency in image denoising. Wavelet Thresholding is very simple non-linear technique, which operates on one wavelet coefficient at a time, unlike filtering that takes place on regions in the image. Thresholding estimates signals of wavelet transform by considering the individual properties of the signals. Thresholding is dependent on certain parameters of the wavelet coefficients and those parameters are very crucial to determine and it gets rid of the noise by eliminating those coefficients that are not important with respect to some threshold. Just like one would perform manual quantization in the spatial domain, each coefficient is compared against the set threshold, if the coefficient is smaller than threshold, it is set to zero; otherwise it is kept to be the same or modified according to some decided and calculated function. After replacing all the small noisy coefficients by zero, inverse wavelet transform can be performed on the result, which may lead to reconstruction with the essentially expected signal characteristics and with less noise. The threshold can be varied and the corresponding changes in the results can be noted in order to reach the best possible solution. Wavelet thresholding involves three steps – A linear discrete wavelet transform, nonlinear or pixel wise thresholding step and a linear inverse wavelet transform to transform the image back into spatial domain.

For a given threshold λ (that can be dependent on resolution level), and value of wavelet coefficient d, hard thresholding is defined as:

D^H (d$|\lambda$) $=$ 0, for $|$d$| \leq \lambda$
D^H (d$|\lambda$) $=$ d, for $|$d$| > \lambda$

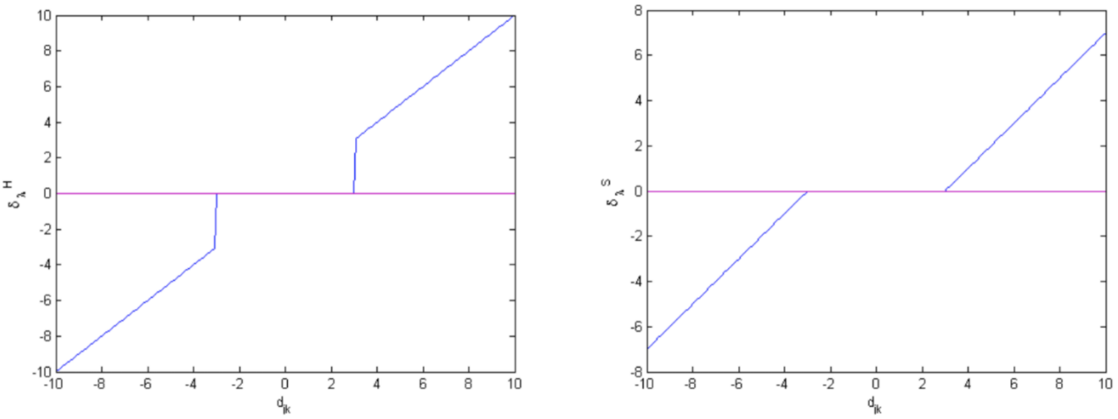
whereas soft thresholding is governed by following equation:

D^S (d$|\lambda$) $=$ 0, for $|$d$|\leq\lambda$
D^S (d$|\lambda$) $=$ d $- \lambda$, for d$>\lambda$
D^S (d$|\lambda$) $=$ d $+ \lambda$, for d$<-\lambda$

Figure 2 [15] depicts both cases:

Soft thresholding is also called wavelet shrinkage since values for both positive and negative coefficients between some threshold level are being shrunk eventually towards zero, in contrary to hard thresholding which either keeps or removes values of coefficients but does not change the values of the coefficients. It is a “shrink or kill” method and gives better visual results as compared to hard thresholding.

Hard threshold is a “keep or kill” procedure, while soft thresholding, shrinks coefficients above the threshold whether positive or negative (it only considers the absolute value) [11]. Hard thresholding may seem to be natural, but the continual nature of soft thresholding has advantages like making algorithms more understand-



(a) Hard-thresholding (b) Soft-thresholding

Figure 2: Thresholdings.

able in the mathematical sense. Also, at times there is a possibility that actual sharp noise coefficients may pass the hard threshold and will end up appearing as unwanted blobs in the output. Soft thresholding does not allow or contribute towards such false structures.

Wavelet coefficients have varying magnitudes but the ones with larger magnitude are correlated with the most noticeable features in the image data. Based on these magnitudes, thresholding can be performed on the wavelet coefficients of the images in the wavelet domain to denoise them and once that is done, they can be converted back into the spatial domain by applying inverse transform. When the magnitude of the wavelet coefficient is too small it is difficult to get rid of noise component, but while the magnitude of the wavelet coefficient is too large it will again not perform moderately and will eliminate useful signal components. There are a variety of ways to determine the threshold value T [10]. Depending on whether or not the threshold value T changes across the various levels of decomposition in the wavelet domain and spatial locations, the thresholding can be classified [10] in the following types:

1. Global Threshold

   A single threshold is used for all the coefficients across all scale space.

2. Level-Dependent Threshold

   Multiple threshold values are selected for each decomposition level in the wavelet domain.

3. Spatial Adaptive Threshold estimate

   Every wavelet coefficient has its individual and sometimes unique properties.

The threshold values depend on the local properties of the individual wavelet coefficients and vary spatially in the wavelet domain.

We have used the threshold settings manager to obtain the threshold value and specified the method of thresholding as ‘penalhi’ that uses the Birgé-Massart strategy for determining thresholds depending on several different parameters. The alpha used by this method is 5*(3*alpha+1)/8. Alpha is the sparsity parameter used for compressing or denoising data, specified as a positive scalar greater than 1 and less than 10.

4 Conclusion

We have implemented and tested the Wavelet Shrinkage denoising algorithm on noisy images. We figured that it is easier to denoise images in the wavelet domain as compared to the spatial domain. The wavelet filter to select is a crucial decision to make since the results would majorly depend on it. Thresholding works differently in the wavelet domain. Soft thresholding works better than hard thresholding, in the sense that it gives better visual results. But we have anyway run the hard thresholding technique as well and included those results. We also tested the bilateral filtering method that preserves edges while removing noise, but those results did not turn out to be as good as the Wavelet Shrinkage algorithm results either.

5 References

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Figure 3: Denoising on a Grayscale picture.

Figure 4: Denoising using Bi-Lateral Transform.

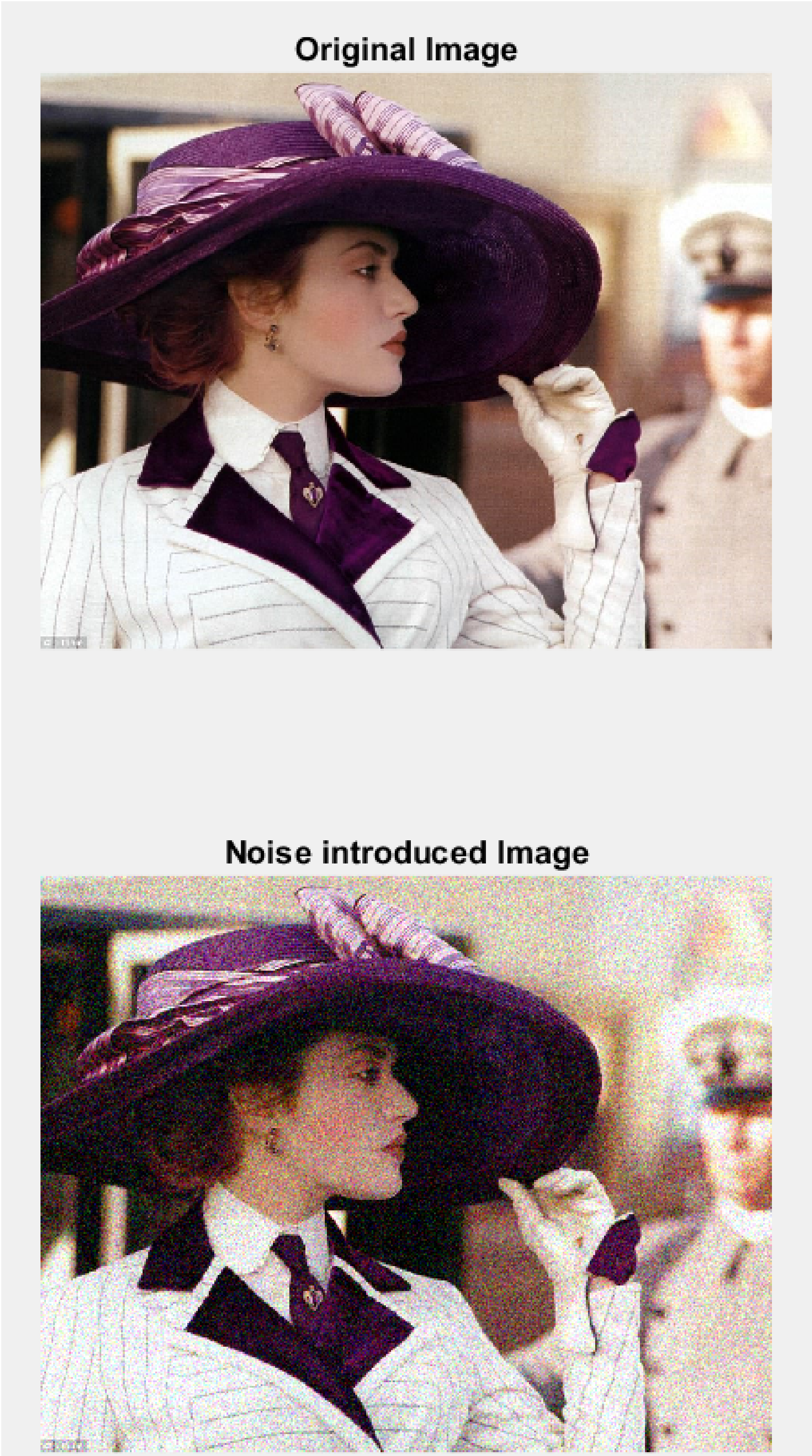

Figure 5: Denoising on Color pictures: Original vs Noisy

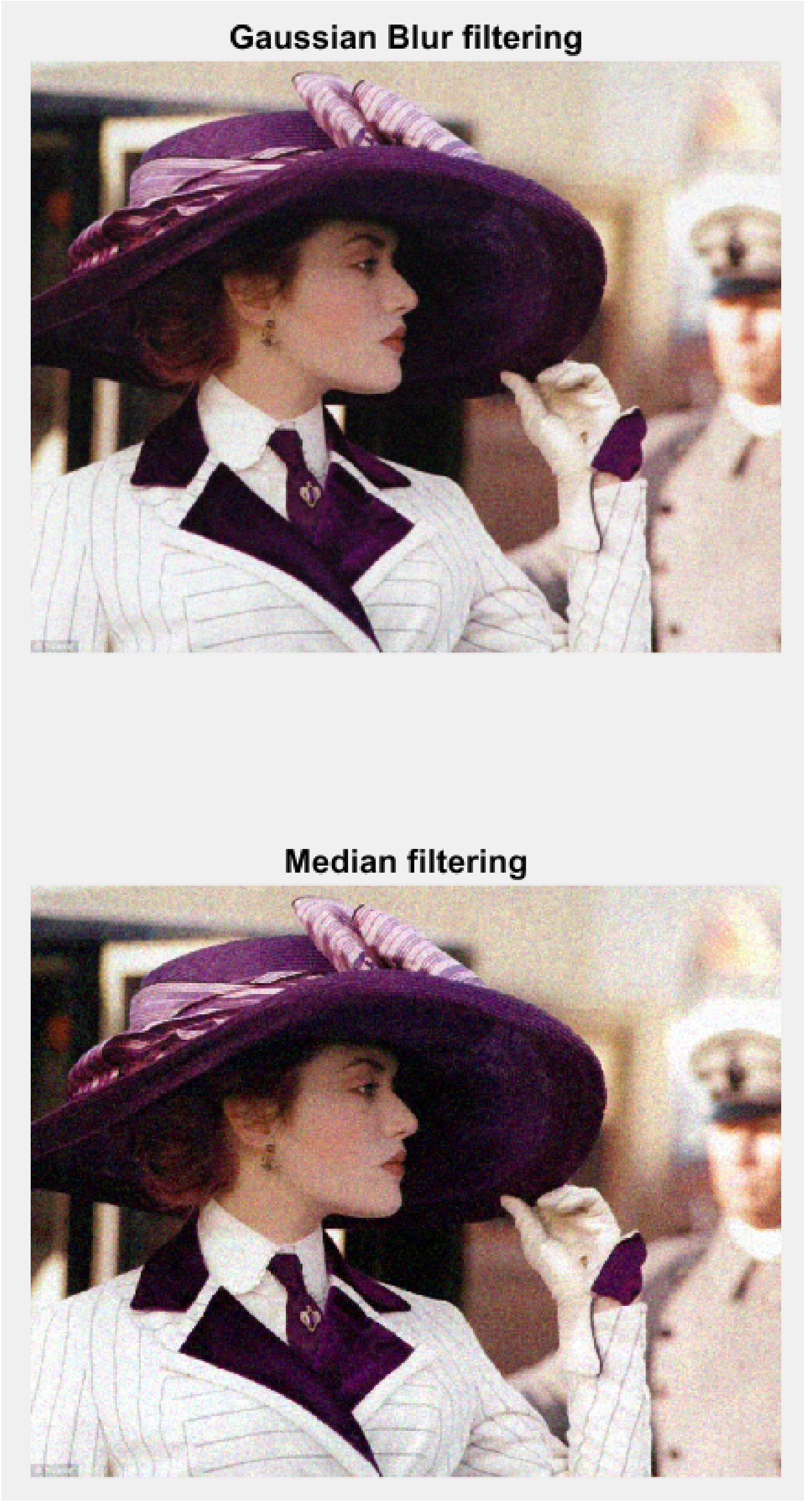

Figure 6: Denoising on Color pictures: Local Averaging vs Median Filtering

Figure 7: Denoising on Color pictures: Soft vs Hard Thresholding

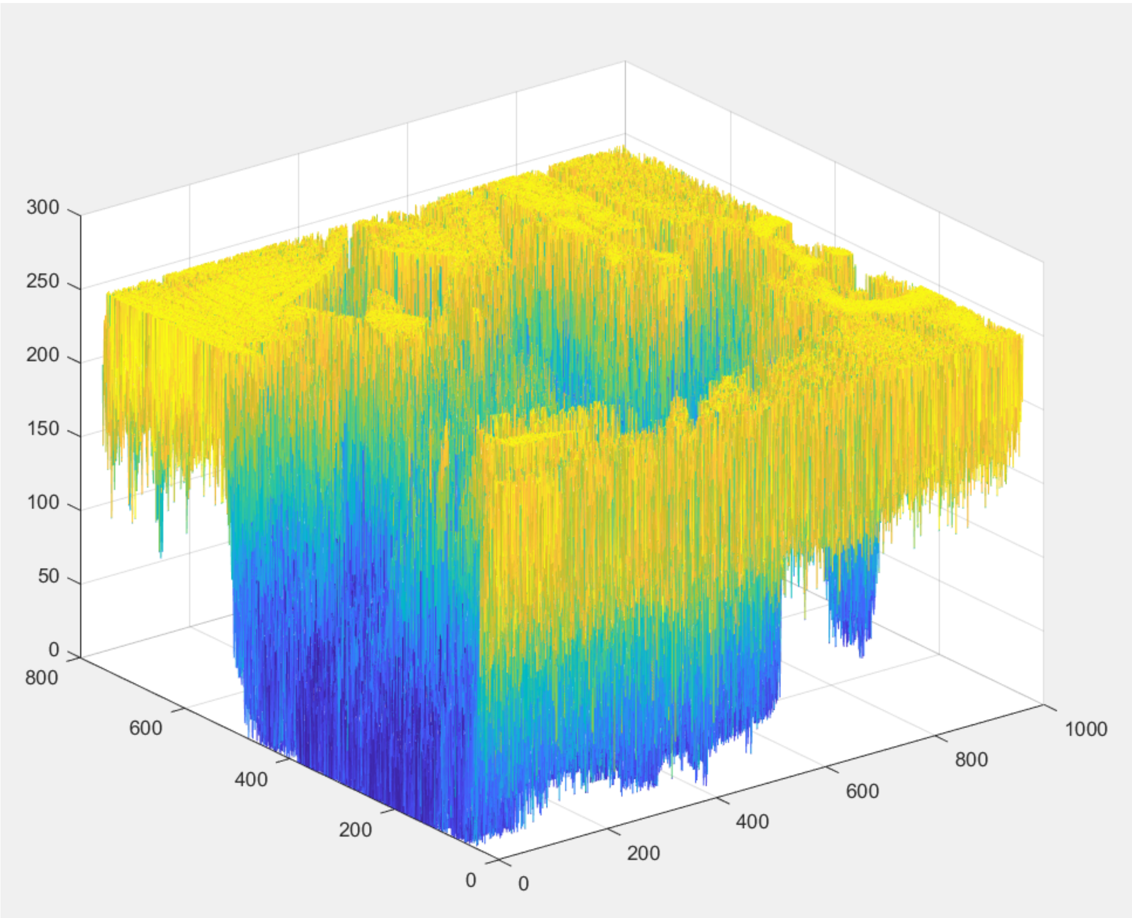

Figure 8: Wavelet Surface before Denoising.

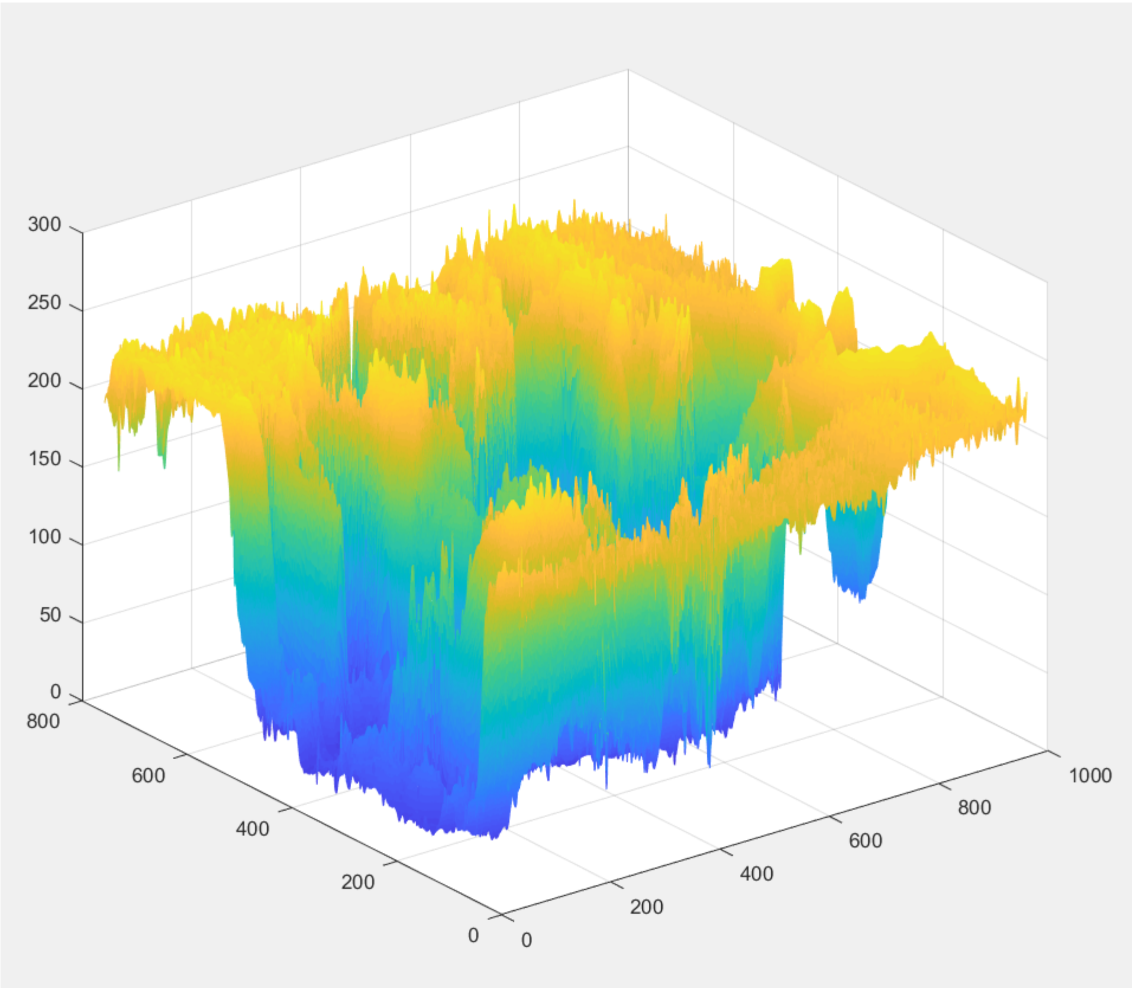

Figure 9: Wavelet Surface after Denoising.