An Inspection on PSNR and MSE Decomposition of De-noised segmented Images

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Abstract: In this project, we deliberate an image pixel decomposition technique that a new framework for noise reduction methods has been is described. The model calculates the test components of the image to be processed in a moving frame that encodes its particular geometry. De-noised image quality has also been traditionally measured in terms of the MSE or its offshoots. However, none of these metrics takes the structural fidelity of the image into account. We investigate the structural changes that occur during the de-noising process and attempt to study and estimated PSNR and MSE for six different images. The strategy we develop is to de-noise the workings of the image in the moving frame in the sequence to preserve its local geometry, which would have been more exaggerated if handling the image directly. Investigates on a total image database tested with several de-noising methods show that this framework can provide best results than de-noising the image directly, both in terms of PSNR and Structural similarity index metrics

Key words : SSIM, MSE, PSNR, Noise, Denoise, index metrics

1. INTRODUCTION

Denoising an image is a fundamental task for modifying defects produced during the acquisition of the real world scene and its limitation on a display, due to physical and technological condition.To a great extent, these patch based methods outperformed the denoising models that existed at that time.Since then, a number of patch-based methods have been developed, comprising the majority of the current state-of-theart denoising methods. We refer the reader to the paper of Lebrun et al. [17] for a complete description of the denoising problem, as well as a detailed analysis and comparison of state-of-the-art denoising methods. It has been shown by Levin and Nadler and Chaterjee and Milanfar that the current state-of-the-art denoising methods are close to optimal when applied to natural images. Nonetheless, there is still room for improvement in several directions. For instance, while these methods manage to correctly remove most of the noise, they tend to not properly recover some of the image details. The main aim is to eliminate the noise of an image while preserving its important features. The image de-noising technique is enhanced carefully by taking into account of the local geometry (direction of gradients and level-lines) image to process. The image quality metrics Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM) index are figured at each stage of image being processed. PSNR is a good measurable for comparing restoration results for the same image. Higher the PSNR value, the better corrupted image has been recreated to match the original image and the better the reconstructive algorithm. Take a colour image as input and add Gaussian noise of zero mean and variance 0.01 to it to create the noisy image. Apply Non-Local Means (NLM) algorithm to the noisy image and Vectorial Total Variation (VTV) de-noising method is applied to the NLM processed image. We construct four different a colour image as input and add Gaussian noise of zero mean and variance 0.01 to it to create the noisy image. Apply Non-Local Means (NLM) algorithm to the noisy image and Vectorial Total Variation (VTV) de-noising concept is applied to the NLM apporach image.Based on the observation that the curvature of the level-lines of a gray-level image is less affected by the noise than the intensity values of the image (assuming that the image has been corrupted by additive Gaussian noise), they conjectured that it can be easier to recover the curvature of the clean image than the clean image itself. Experiments involving 4 different denoising methods: TV denoising performed through gradient descent [5] and Bregman iterative algorithm [2], orientation matching using smooth unit tangents [7], NLM [8] and BM3D [3], confirmed that applying a denoising method on the curvature of the noisy image and then reconstructing an image from the denoised curvature provides a better approximation to the clean image (in terms of PSNR and Q-Index metrics) than applying this denoising method directly on the noisy image.

2. PROPOSED METHODOLOGY

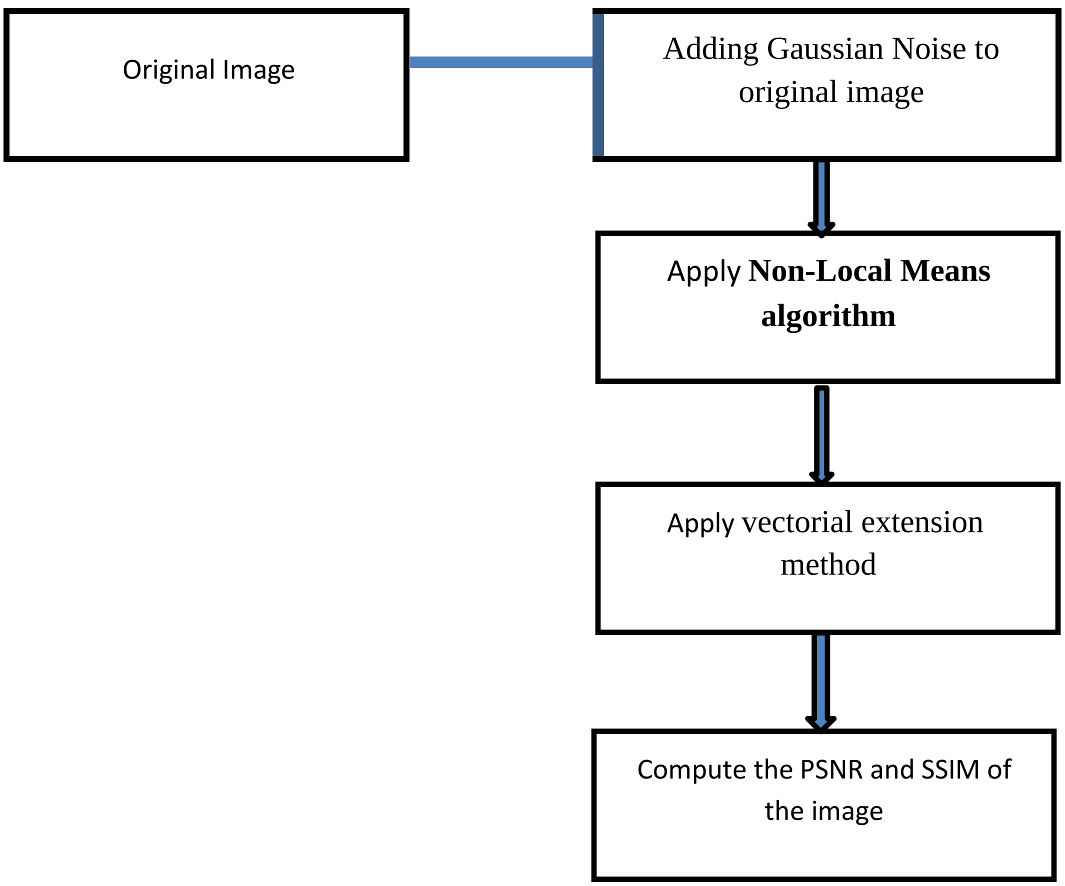

Fig 1: Block Diagram of the proposed work

i) Adding Gaussian Noise- The first step is taking a colour image and adding Gaussian noise of default mean value zero and variance 0.01. The noise free image is reserved as input image to de-noise by adding noise and apply input noise elimination algorithm. The purpose of adding noise to noise-free image is to compute the PSNR and SSIM quality calculation metrics of the

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image. The PSNR value of noise free image will be infinity so the image is approached with additive noise and the PSNR value is calculated by comparing input image and the image treated with Gaussian noise. SSIM for colour image is calculated by taking mean SSIM of each colour channel path. After adding Gaussian noise to the input image, the image with noisy pixels is displayed.
ii) Applying Non-Local Means Algorithm- Non-Local Means methods estimate every pixel intensity based on information from the whole image thereby exploiting the presence of similar patterns and features in image. The weights w(i, j) depend on the similarity between the neighborhoods centered at positions iand j. The weighting function is defined as follows :

$$w(i,\ j) = Exp\left(\frac{\|y_1 - y_2\|^2}{2h^2}\right) \quad (1)$$

The Euclidean distance between the pixel intensities yi and yj measures distance between the center sample iand the j-thsample,h is the filter parameter.The NL-means not only compares the grey level in a single point but the geometrical configuration in a whole neighborhood.

The vectorial TV approach supports a common edge direction for all channels, comprises important invariance properties and comes with a dual formulation that allows for stable and exact minimization schemes.For functions, the vectorial total variation equals the integral over the largest singular value of the derivative matrix, the VTV-based denoising model to these components using again the vectorial extension of Chambolle's projection algorithm. Compute the PSNR and SSIM metrics of the processed images at each stage and the quality of the image is improved depending upon the metric values obtained.Compute the PSNR and SSIM metrics of the processed images at each stage and the quality of the image is improved depending upon the metric values obtained.

iii) Applying Vectorial Total Variation method- Denoising is performed as an infinite-dimensional minimization problem, where the search space is all Bounded Variation (BV) images.SplitBregman is a flexible algorithm for solving non-differentiable convex minimization problems, and it is especially efficient for problems with Total Variation (TV) regularization.Total Variation is approxiamated by summing the vector magnitude over all pixels.The split Bregman ides is to apply operator splitting and use Bregman iteration to solve the resulting constrained minimization. Where ui,jis the summing vector magnitude, δ is positive parameter fi,j is the observed pixel values. The problem is solved by an alternating direction method i.e., in each step minimizing either d or u while keeping the other variable fixed.The sub-problem is solved for all Bregmaniteration.Selecting the penality parameter is a important role where u and d converges quickly.

3. IMAGE QUALITY MEASUREMENT

There are basically two classes of objective quality assessment of images. The first are the mathematically defined measures such as the mean square error (MSE), peak signal to noise ratio (PSNR), root mean square error (RMSE) and signal to noise ratio (SNR). The second class of measurement methods depend on the characteristics of the human visual system (HVS) in an attempt to incorporate perceptual quality measures. Of the two methods the mathematically defined measures are most widely used. This is because of simplicity of implementation. Most error sensitivity methods are based on the mean square error (MSE). In most cases, they are equivalent metrics. The MSE is parameter free, inexpensive to compute and the samples in an image are assumed to be independent. The MSE offers a clear physical meaning.

4. ERROR SENSITIVITY METHODS

4.1. MEAN SQUARED ERROR (*MSE*).

In statistics, the mean squared error (MSE) of an estimator (of a procedure for estimating an unobserved quantity) measures the average of the squares of the errors—that is, the average squared difference between the estimated values and what is estimated. MSE is a risk function, corresponding to the expected value of the squared error loss. The fact that MSE is almost always strictly positive (and not zero) is because of randomness or because the estimator does not account for information that could produce a more accurate estimate.The dominant error-sensitivity measurement tool has been the mean square error. There are variations of the MSE that are also in use as we mentioned. The MSE is used as a signal fidelity measure. The goal of signal fidelity measure is to compare two signals by providing a quantitative score to determine the level of error or distortion between them. The MSE between two signals Yi and Yj is

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_j)^2 \tag{2}$$

4.2. PEAK SIGNAL-TO-NOISE RATIO (PSNR) CALCULATION

Peak signal-to-noise ratio, often abbreviated **PSNR**, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \tag{3}$$

The PSNR is defined as in db

$$\mathbf{PSNR} = \mathbf{10} - \mathbf{Log}_{\mathbf{10}}\left(\frac{\mathbf{MAXI}^{\mathbf{2}}}{\mathbf{MSE}}\right) \tag{4}$$

$$\mathbf{PSNR} = 20 - \mathbf{Log}_{\mathbf{10}}\left(\frac{\mathbf{MAX_I}}{\sqrt{\mathbf{MSE}}}\right) \tag{5}$$

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. More generally, when samples are represented using linear PCM with B bits per sample, MAX_I is 2^B-1.PSNR is most commonly used to measure the quality of reconstruction of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs, PSNR is an approximation to human perception of reconstruction quality.Typical values for the PSNR in lossy image and video compression are between 30 and 50 dB, provided the bit depth is 8 bits, where higher is better. For 16-bit data typical values for the PSNR are between 60 and 80 dB.[3][4] Acceptable values for wireless transmission quality loss are considered to be about 20 dB to 25 Db. .In the absence of noise, the two images *I* and *K* are identical, and thus the MSE is zero. In this case the PSNR is infinite (or undefined, see Division by zero).

5. PSNR AND MSE SCORES FOR TOTAL VARIATION DENOISED IMAGES

Different pixel image are identified and eliminates the noise and the imporved version are described in details one by one shown in fig 1.1 to 6.2. the fig.1.1,2.1,3.1,4.1,5.1 and 6.1 are noise included image.

The improved and de-noised images are shown in 1.2,2.2,3.2,4.2,5.2,and 6.2. Order statistic filters are spatial filters whose response is based on ranking the values of the ixels contained in the image area delineated by the filter. The result of the ordering determines the ilter response. The median filter is an order statistic filter. It replaces the pixel value by the median intensity values in the neighbourhood of that pixel.

Tested image 1

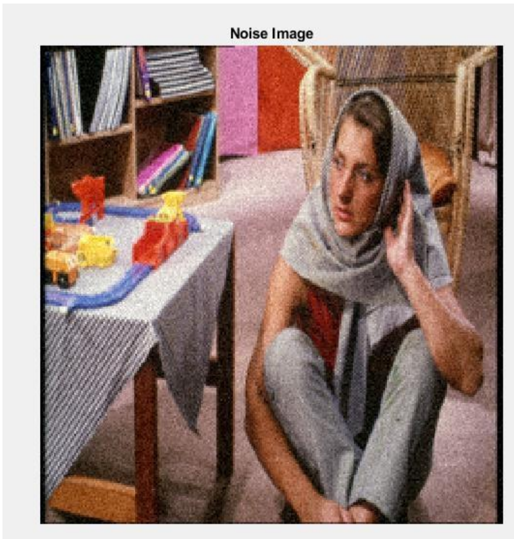
<table>
<tr><th>Noise image</th><th>De-Noise image</th></tr>
<tr><td>

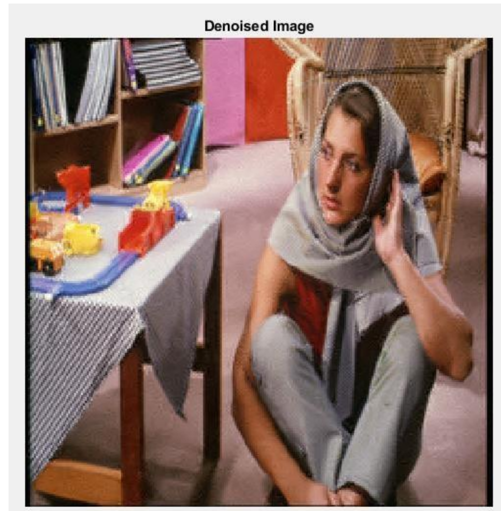
Fig 1.1: Noise image</td><td>\\


Fig 1.2: De-Noise image</td></tr>
</table>

Table 1.1 PSNR and MSE Framework

Components	De-noised Image
Peak Signal-To-Noise Ratio (Psnr) Calculation (PSNR)	35.2872
Mean Squared Error (*MSE*).	19.2681

Table 1.2 simulated parameter

Components	Calculated Value
Normalized Absolute Error	0.04671
Average Difference	0.089722
Maximum Difference	34.6667
Structural Content	0.99925

Tested image 2

Noise image	De-Noise image

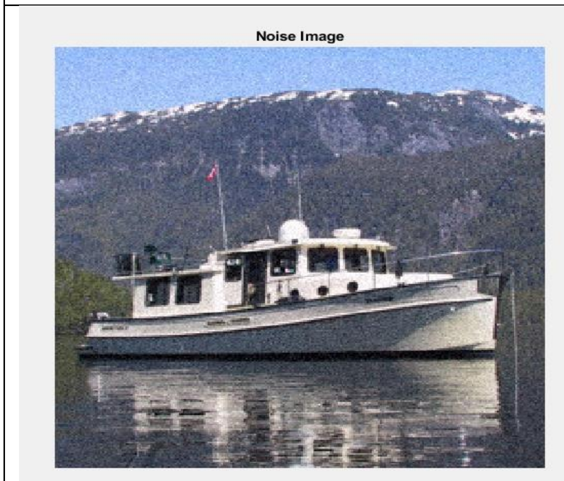


Fig 2.1: Noise image

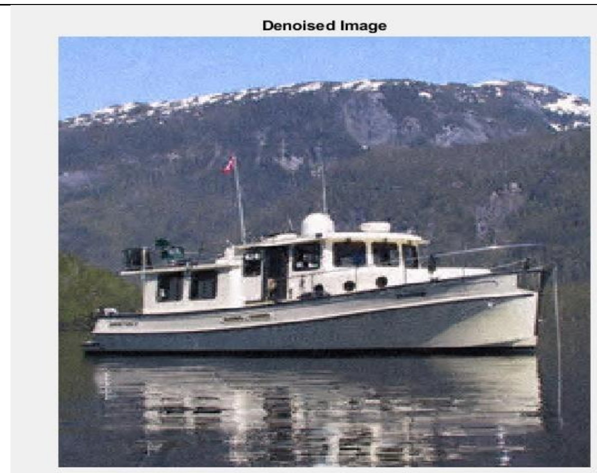


Fig 2.2: De-Noise image

Table 2.1 PSNR and MSE Framework

Components	De-noised Image
Peak Signal-To-Noise Ratio (Psnr) Calculation (PSNR)	34.3372
Mean Squared Error (*MSE*).	24.0177

Table 2.2 simulated parameter

Components	Calculated Value
Normalized Absolute Error	0.046692
Average Difference	0.19461
Maximum Difference	35.3333
Structural Content	1.0033

Tested image 3

Noise image	De-Noise image

Fig 3.1: Noise image

Fig 3.2: De-Noise image

Table 3.1 PSNR and MSE Framework

Components	De-noised Image
Peak Signal-To-Noise Ratio (Psnr) Calculation (PSNR)	37.1779
Mean Squared Error (*MSE*).	12.4568

Table 3.2 simulated parameter

Components	Calculated Value
Normalized Absolute Error	0.02362
Average Difference	0.17678
Maximum Difference	33
Structural Content	1.003

Tested image 4

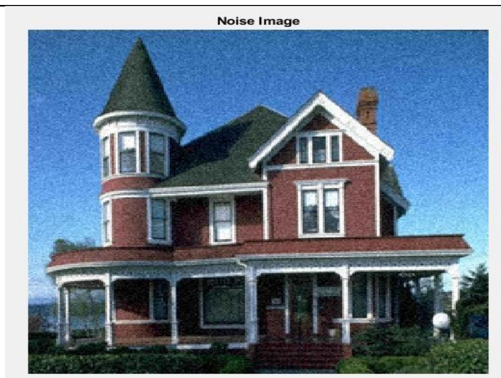
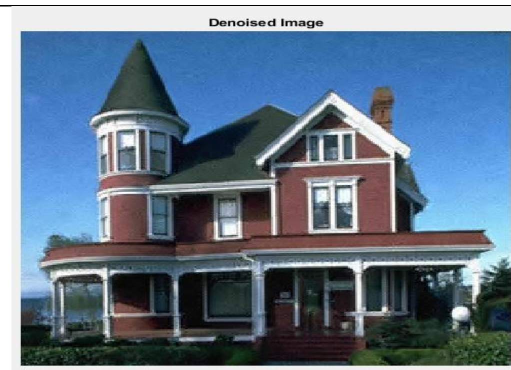
Noise image	De-Noise image
 Fig 4.1: Noise image	 Fig 4.2: De-Noise image

Table 4.1 PSNR and MSE Framework

Components	De-noised Image
Peak Signal-To-Noise Ratio (Psnr) Calculation (PSNR)	**35.7272**
Mean Squared Error (*MSE*).	**17.4138**

Table 4.2 simulated parameter

Components	Calculated Value
Normalized Absolute Error	**0.045054**
Average Difference	**0.061269**
Maximum Difference	**35.3333**
Structural Content	**1.001**

Tested image 5

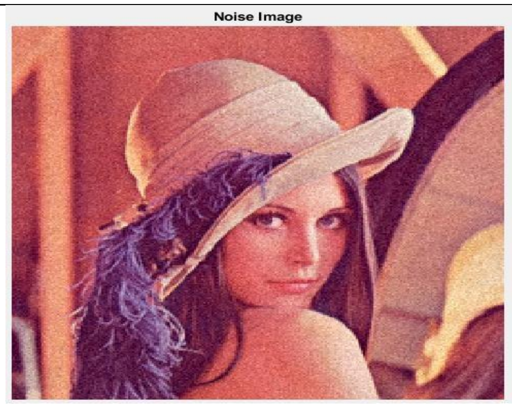
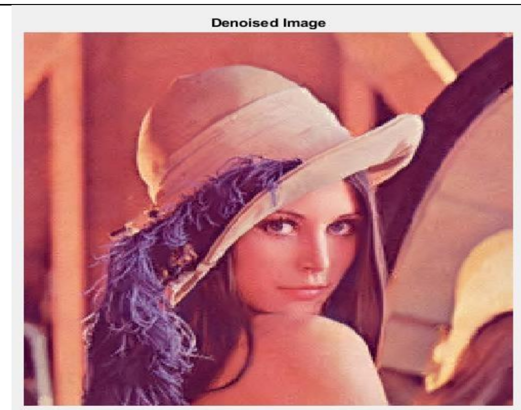
Noise image	De-Noise image
 Fig 5.1: Noise image	 Fig 5.2: De-Noise image

Table 5.1 PSNR and MSE Framework

Components	De-noised Image
Peak Signal-To-Noise Ratio (Psnr) Calculation (PSNR)	**36.7035**
Mean Squared Error (*MSE*).	**13.8947**

Table 5.2 simulated parameter

Components	Calculated Value
Normalized Absolute Error	**0.033386**
Average Difference	**0.061269**
Maximum Difference	**37.3333**
Structural Content	**1.0006**

Tested image 6

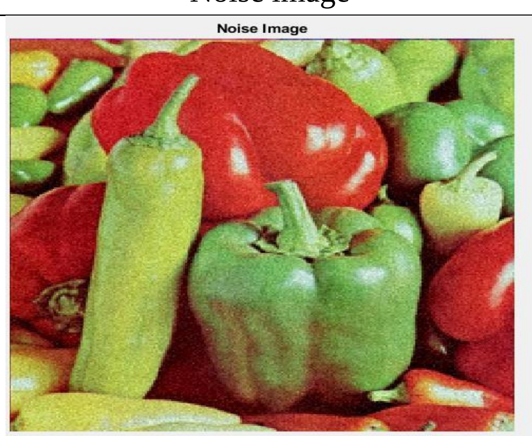
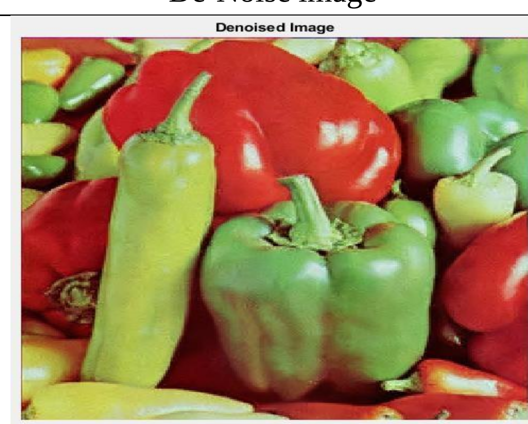
Noise image	De-Noise image
 Fig 6.1: Noise image	 Fig 6.2: De-Noise image

Table 5.1 PSNR and MSE Framework

Components	De-noised Image
Peak Signal-To-Noise Ratio (Psnr) Calculation (PSNR)	36.5262
Mean Squared Error (*MSE*).	14.4979

Table 5.2 simulated parameter

Components	Calculated Value
Normalized Absolute Error	0.042648
Average Difference	0.16044
Maximum Difference	35.3333
Structural Content	0.99886

6. Conclusion

In this Project, we have established a context that enables any denoising method to take more into explanation the local geometry of the image to be denoised by preserving the affecting frame describing the graph of a scaled version of the image. Experiments with the VTV-based denoising method,NLM and BM3D algorithms on both gray-level and color images tested over the Kodak database showed that our strategy systematically improves the denoising method it is applied to, in terms of PSNR and SSIM metrics. The PSNR is commonly used for the purpose of describing denoised image quality. But the PSNR depends on the dynamic range and the MSE of the image. If two images with different dynamic ranges are corrupted with the same amount of noise,the resulting PSNR value will be different because of the difference in dynamic ranges.In the proposed strategy for denoising, we either combine the components into a single vector-valued function to which we apply a denoising method (VTV) or treat them separately applying the same denoising method but with different parameters (NLM and BM3D). However, as the components have different geometric meaning, one shall wonder whether they should not rather be denoised with different denoising methods, and we are currently investigating that point.

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