Master MVA
Image Denoising

Experimental Report 3

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Exploring Patch Similarity in an Image

- **Description of the paper**

This paper is a description of a demo created to study the concepts of self-similarity and the Gaussianity of a group of similar patches extracted from an image. Here, similarity is considered as the repeatability of information found in several segments of an image. It is computed using the L2 distance in the neighborhood of the patch. Using a user-selected patch, we can extract all similar patches and explore their similarity characteristics using the histogram and log-histogram of the closest patches. By applying PCA and EM, extracting the principal components of these similarities, we can understand the Gaussianity and test the mixture Gaussianity. The principal component projection histogram and the Anderson-Darling normality test are also two techniques used to verify the Gaussianity of the set of patches.

Moreover, this paper analyzes three different types of patches that are considered the most relevant one: the edge, highly textured patches, and naturally textured patches. Indeed, it explores the information determined from similar patches to study their sparsity, Gaussianity, variability, Gaussian mixing pattern, etc.

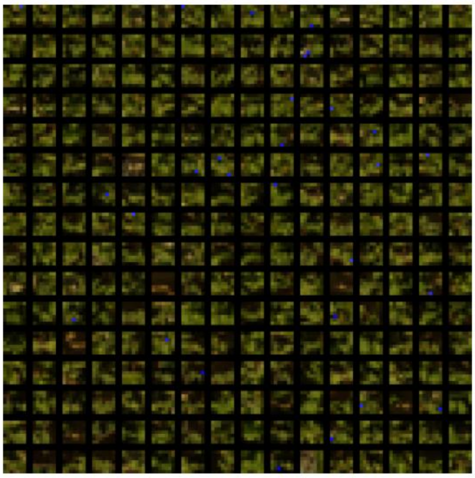
I will work on these three different patterns using these images:

Natural Textured Patch (1)

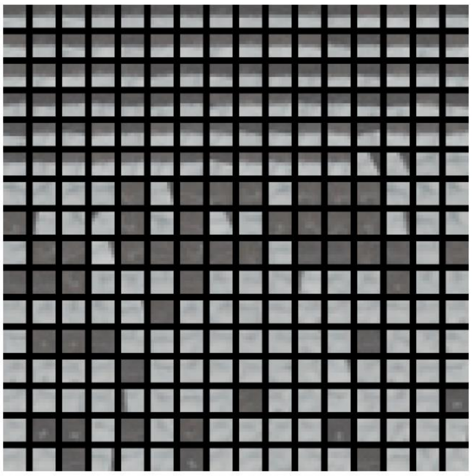
Highly Textured Patch (2)

Edge Patch (3)

❖ **The behavior of a set of patches similar to a selected patch in an image**



Similar patches (1)



Similar patches (2)

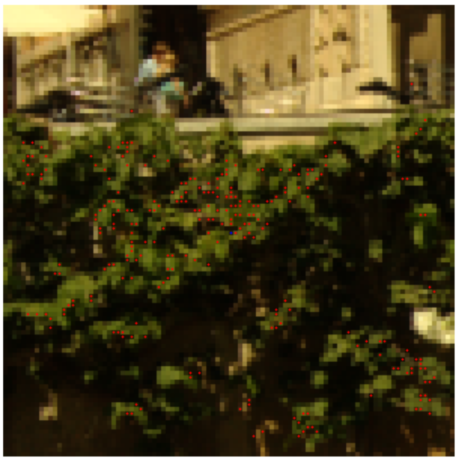
Similar patches (3)

From these results, we can say that the set of similar patches has many patterns. By choosing a natural structured image, we can notice that the patches are different and each one describes a new different part of the vegetation. All these patches describe globally the same information, namely the leaf region, but in a different way.

For the edge image, we notice that only the first closest patches are similar to edges, the others show homogeneous patches. In fact, in the vicinity of the edge, this image shows many edge-like structures. This additional information near the edge will affect the selection of similarities, this is due to our choice of "canny points" for the extraction method which lead to extracts patches that correspond to all relevant structures in the image.

For the highly textured image, we can notice that almost all patches are similar to each other. All patches show two green lines that correspond to the shape of the window. It is possible that there is an offset between these patches of about a few pixels. This is due to the sampling problem that affects the self-similarity of the observed patches.

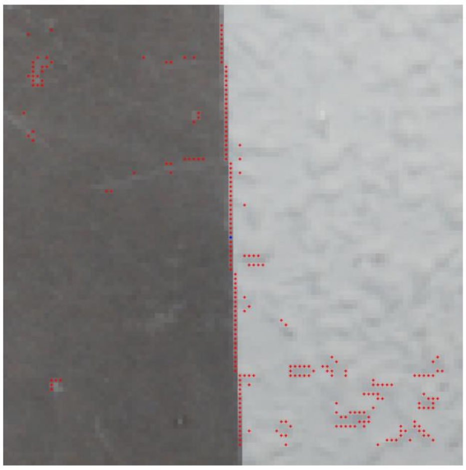
❖ **Studying the self-similarity of an image**



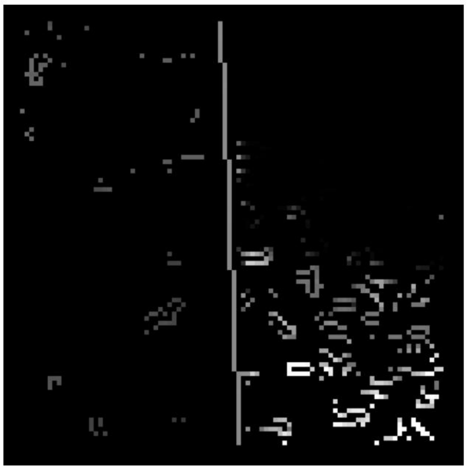
Closest Patches (centers)

Patches closest to closest (histogram)

Since many shapes are repeated in the natural structured image, similar sets of patches will be detected scattered along the vegetation. These sets of patches represent the natural structures in a similar way. From the previous plots, we can notice that the centers of the closest patches are detected in the whole neighborhood of the patch. By exploring the sets of closest patches, we notice that they have many common centers. Thus, we can say that these patches can form a total set of clusters without losing coherence. This result is also noticed from the histogram of the closest patches. The highest bins in the histogram correspond to leaves. It also shows consistency in the bins. Then, we can say that in the natural structured image, the sets of closest patches do not differ too much between each other. Thus, these sets are consistent and self-similar.



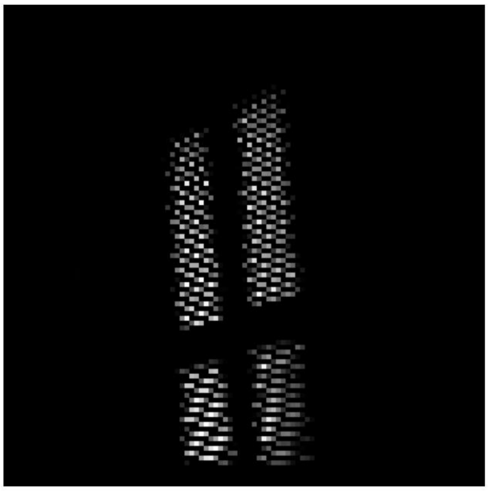
Closest Patches (centers)



Patches closest to closest (histogram)

In the region of the edge, one can notice the presence of other remarkable structures and forms. These additional structures will affect the detection of the closest patches. From the demo, we can notice that the set of centers of the patches closest to the first one is totally different from those of the set of patches closest to the last patch. In fact, the first closest patches contain centers especially along the edge shifted by one pixel vertically. However, the patches closest to the last patch contain centers of the structures on the wall near the book. Hence, we can say that the sets of similar patches have a very big variation, and the patches vary a lot. This result is also detected in the histogram of the closest patches because there are many structures detected with high intensity which do not correspond to the edge. Here, the histogram aligns with the line and with other structures in the image. This result helps us to conclude that we cannot extend the clusters, otherwise we will lose the self-consistency between patches.

Closest Patches (centers)



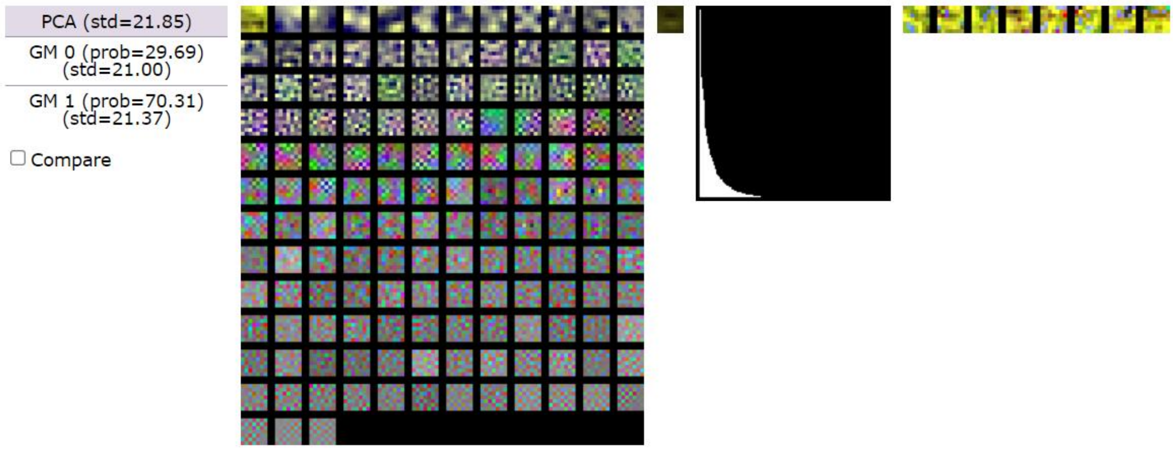
Patches closest to closest (histogram)

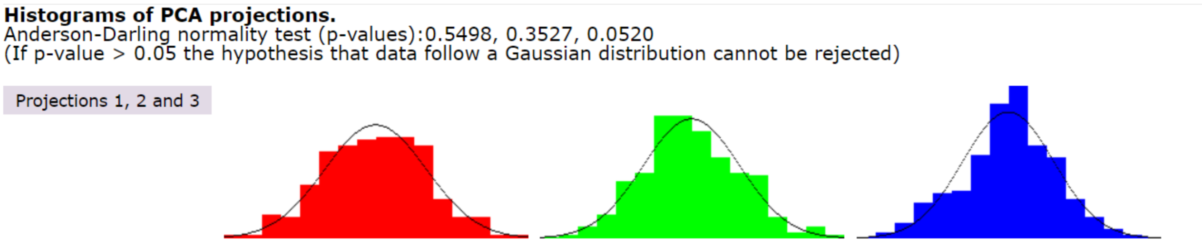
All the closest patches share almost the same centers. These patches describe the same structure as the initial centered patch. They correspond to the repeated shape of the window. We can also notice some changes in position. Moreover, the histogram presents the detected centers. These centers are aligned very well with the shape of the window in the original image. We can therefore say that these patches are in agreement, and we can form a complete cluster without losing the coherence between the patches. The group of patches is complete to represent all the different details of the window.

- **Study the validity of the hypothesis of Gaussianity of a set of similar patches**

In this part, we will investigate whether the group of similar patches is well represented by a single PCA or by a Gaussian mixture model.

Image 1:

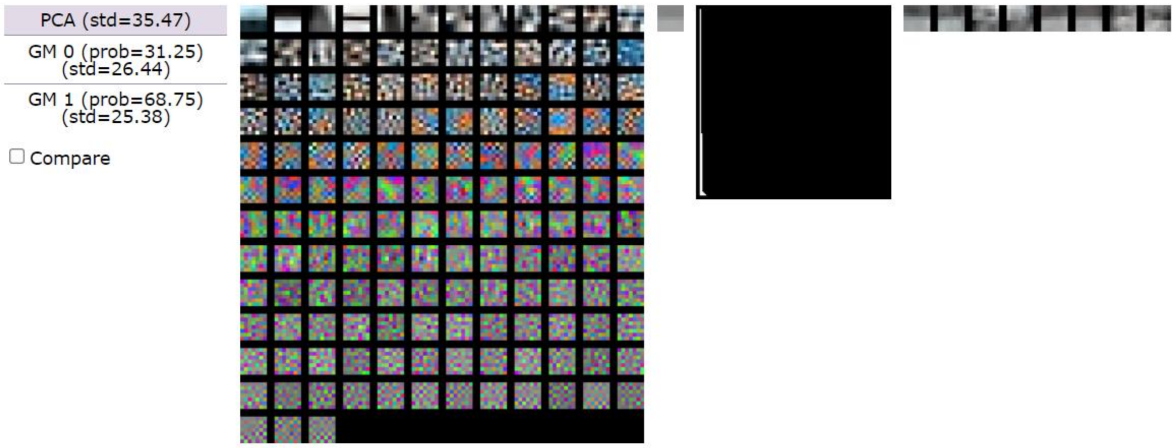


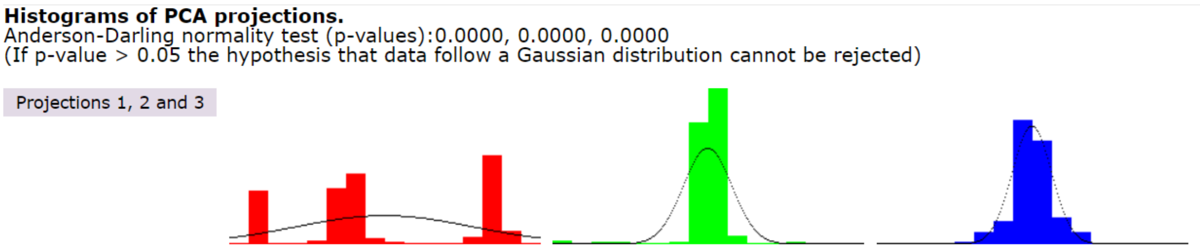


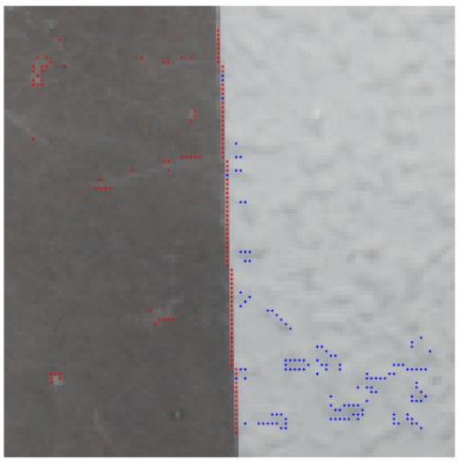
Patches GM closest (centers)

Here, the PCA representation is not sparse. Indeed, its spectrum shows a wide range of values. Thus, the sparsity is not verified. In addition, the spectra of the Gaussians are very close to that of the PCA, and the standard deviations are 21 and 21.37 which means that the variability of the two Gaussians is the same. Thus, the two Gaussians are redundant and therefore only one Gaussian distribution is able to describe the appearance. Furthermore, the Anderson-Darling normality test shows that we cannot reject the hypothesis that the data follow a Gaussian distribution. In the Gaussian mixture of the closest patches image, we can notice that the two Gaussians cover the whole neighborhood. Thus, we can conclude that the natural structure patches are approximately Gaussian.

Image 2:







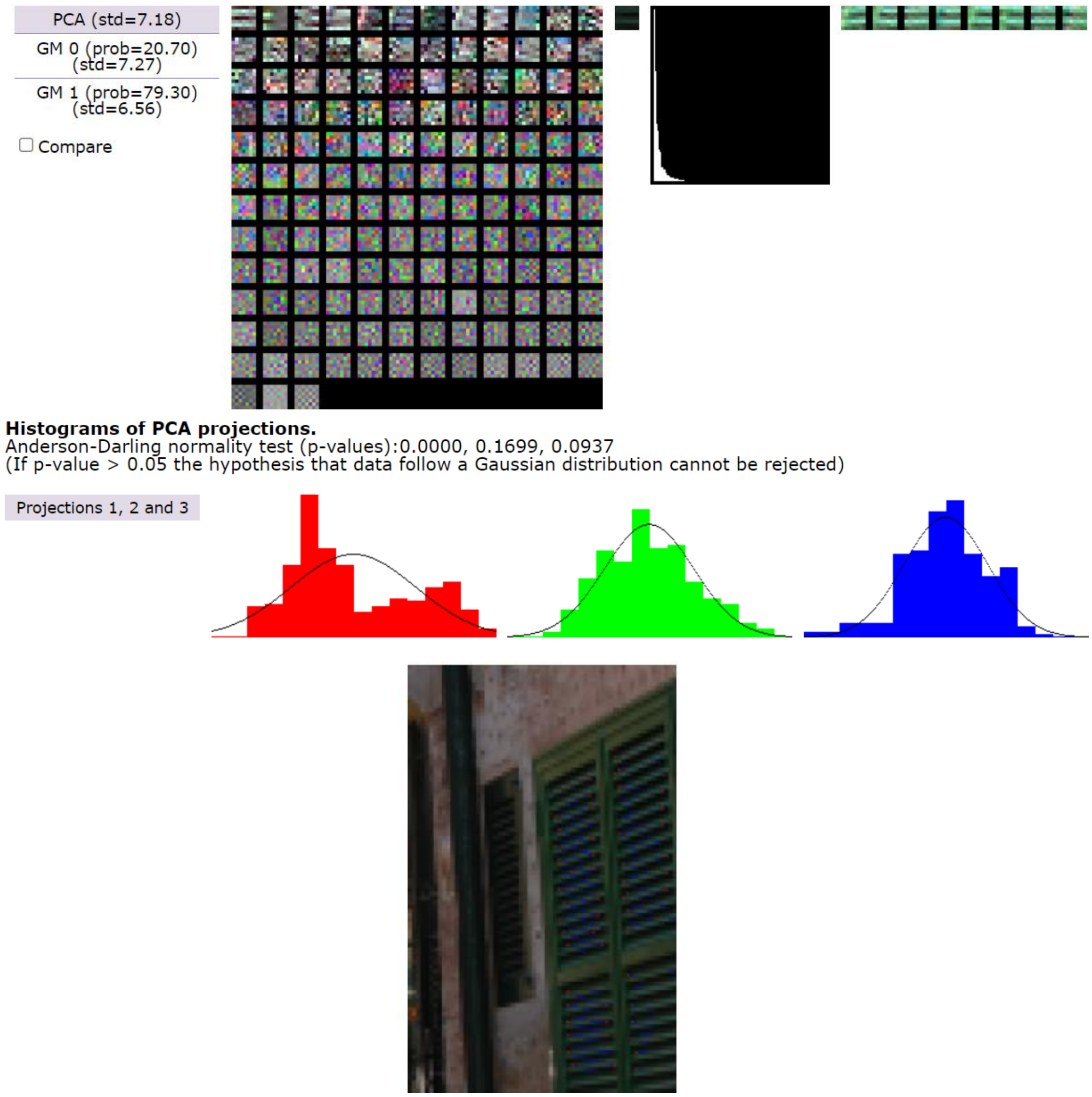
Patches GM closest (centers)

The first observation one can make is that the PCA spectrum is very sparse. Moreover, the PCA has an extremely sparse representation. We can notice that only the first 5 representations are not sparse. This result may be explained by the fact that the clusters of canny patches on edges are "sparse". Therefore, we can say that the PCA covers only a low dimension, which implies the non-normality of the patches.

Moreover, the standard deviation of the overall PCA is completely different from those of the Gaussian mixtures, which are themselves different. This indicates that the Gaussian distributions are not redundant with different means and variances. We can also notice that all the p-values of the distribution of the projected patches are less than the value 0.05, which leads us to reject the Gaussianity of the patches. We can conclude that the patches of the edge structure are not gaussian, but they are high dimensional.

Here we can notice that the Gaussian mixture pattern covers two different parts of the centers. One of the Gaussian contains the edge and the other is related to the shapes on the wall. We can notice that the Gaussian that contains the edge is grouped with the centers on the book, so the edge is considered as part of the book. Maybe if we increase the number of gaussians, we will get that each distribution describe a specific shape. We will try this in the next part by studying the role of the number of Gaussian.

Image 3:



Patches GM closest (centers)

In this example, we can see that the spectrum of the PCA is sparse with a standard deviation equal to 7.18. Only few first components are not sparse. We can notice also that the gaussians have different means and variations. Using the Anderson-Darling test, we found that the p-value of the first direction is less than 0.05. Thus, the gaussian distribution hypothesis in this example is rejected. We can conclude that the highly structure patches are not gaussian.

Each Gaussian in the Gaussian mixture image corresponds to a set of centers. The red points correspond to the extreme parts of the shape. On the other hand, the blue points cover the whole shape of the window. Here, the two Gaussians are not redundant, and we can say that we cannot represent the whole structure with a single Gaussian. Moreover, maybe two Gaussians are not enough to study the pattern of these highly structured shapes. We need to increase their number and study the behavior of centers in each cluster.

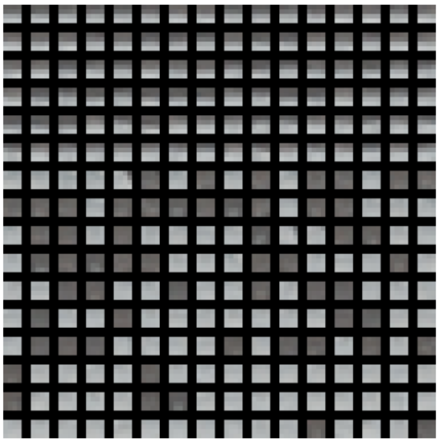
❖ Parameter Interpretation

Search window size:

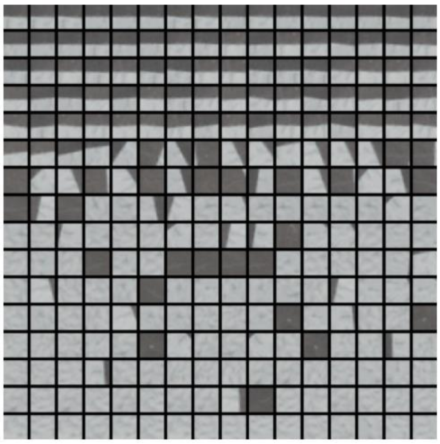
This parameter controls the search step. By choosing a large value, we can expand the search for similar patches. This parameter should be fixed according to the problem. In some cases, it is sufficient to search for local parts to find similarities.

Patch size:

By increasing the patch size, we take into account more elements in the patch. For an image with natural structure, a large patch size will not affect the similarity result because the vegetation structures are very similar. However, for the edge patch, choosing a smaller patch will improve the similarities. This is an example of edge structure patch:



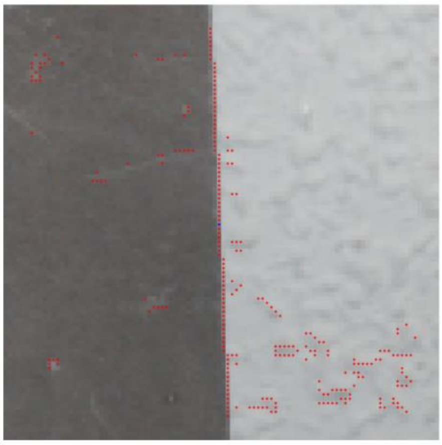
Patch size 4 × 4

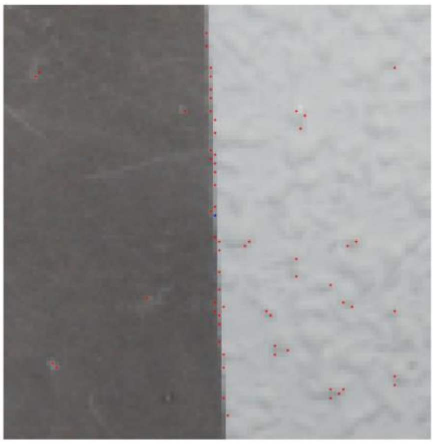


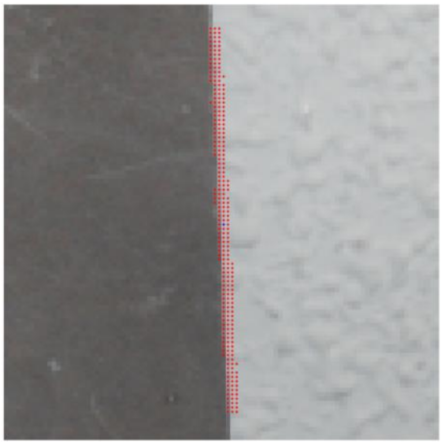
Patch size 16 × 16

Extraction methods:

- "All points": explores an arbitrary group of points to search for patches that are similar to it.
- "Canny points" / "Harris points": these methods are used to select only relevant information in images that are considered to be centered on a visible structure. In addition, the “Canny points” leads to a more reliable normalization by orientation.


Canny points

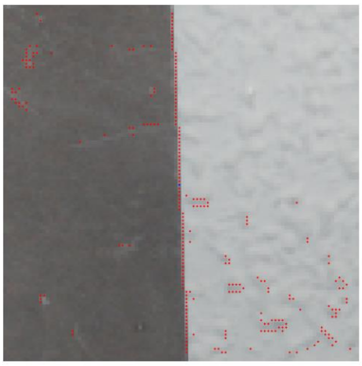

Harris points

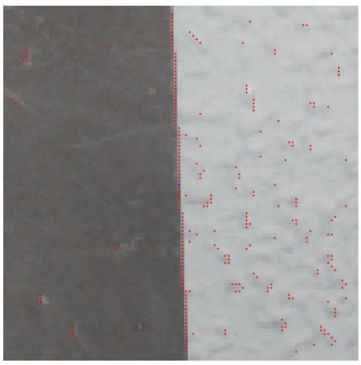

All points

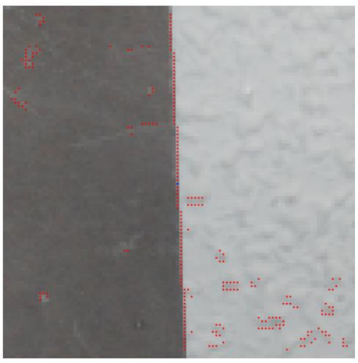
From these graphs, we can see that each type of point gives a particular pattern. “Canny points” are detected around edges and corners. “Harris points” are located in areas of sharp change. On the other hand, for the “all points” method, the centers are aligned as a thick line. This is due to the sampling effect.

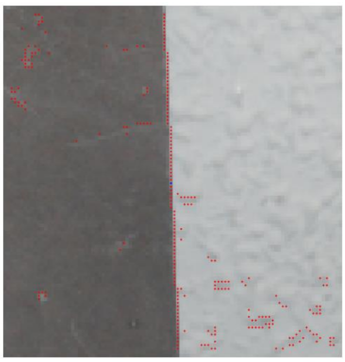
Normalize Orientation / Normalize Mean / Normalize Variance:

These buttons are used to select whether or not to normalize orientation, mean and variance. Normalization of orientation is used so that the similarity detection remains unchanged for a rotated patch.


No / No / No


No / Yes / No


Yes / No / No


No / No / Yes

By changing these parameters for the same patch and fixing all other parameters, we can see that the centers of the closest patches have changed. There are variations in the homogeneous regions and the centers on the edge remain unchanged.

Number of closest patches:

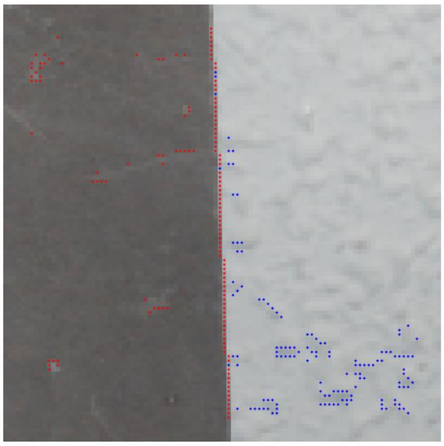
This controls the number of closest patches to be studied.

Vector projection orientation:

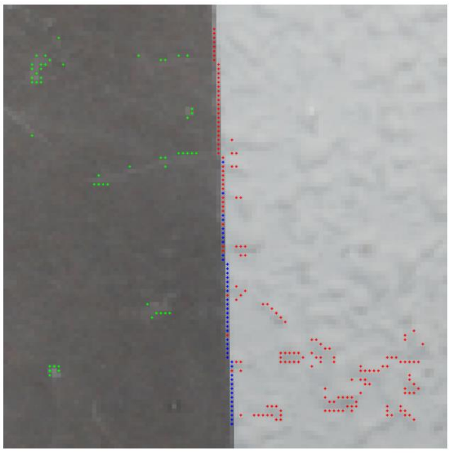
This panel helps us to choose on each eigenvector the patches will be projected. This will help us to understand the patches and their main direction.

Number of Gaussians:

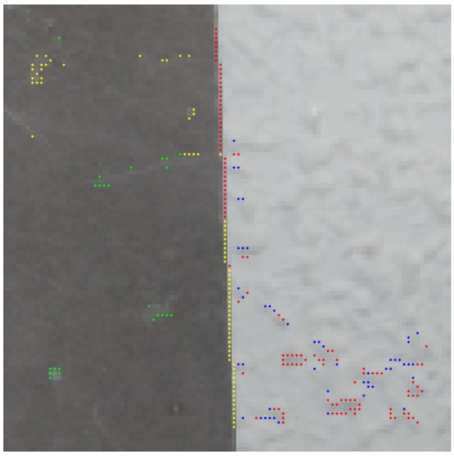
Changing the number of gaussian is important especially when we are going to study the Gaussianity of patches.



2 Gaussians



3 Gaussians



4 Gaussians

After changing the number of Gaussians, we can notice that each distribution corresponds to a specific pattern of the centers. But, by increasing the number, we did not find a single Gaussian that uniquely describes the edge in this case.

Implementation of the “Non-Local Bayes” (NL-Bayes) Image Denoising Algorithm

❖ Description of NL-Bayes:

The NL-Bayes method is one of the relevant algorithms for image denoising, used especially for color images. This method is an extension of the NL-Means algorithm. The improvement of this method consists in replacing the calculation of the weighted average of similar patches to determine the estimate by the attribution of a Gaussian distribution to the patch. This distribution is parameterized by an empirical mean and variance. Then, it uses these values to compute the estimate of the patch in the sense of the Bayesian minimum mean square error. Moreover, this method is similar to the BM3D method. They follow the same steps. We can also say that this method is faster on small patches and for small and medium amount of noise because it only requires the inversion of a matrix, and it uses an acceleration trick to not use as reference patch the patches already used in denoising.

The NL-Bayes method is divided into two steps. Each step is divided into 3 main parts. The first part is dedicated to the search for similar patches. These patches will then be grouped in a 3D block to be used in denoising. The main improvement of this method is realized in the second part. First, an estimate of the noise is computed. Then, depending on its value, two cases arise. For a low value, the patch is considered as homogeneous, and it is then estimated with the average of similar patches. In the opposite case, it is considered as a multi-structured patch. This structure is then approximated with a Gaussian distribution whose parameters are calculated empirically. The last part is the aggregation which is used to group all overlapping patches that contain redundant information.

The second step follows the same strategy as the first step. The only difference between these two steps is that the second one uses the estimated patches calculated in the first step. These estimated patches seem to improve the mean and variance of the estimated Gaussian distribution. That is, this step improves the denoising performance.

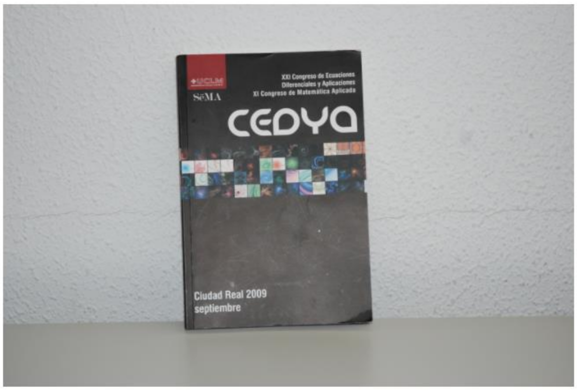
The Bayesian approach can also help to define a new approach which is the NL-PCA. The idea of this method is to perform the PCA on the 3D block. This method is also very close to the BM3D method, the only change is in the collaborative filtering by changing the linear transformation with the PCA.

❖ The homogeneous Criteria:

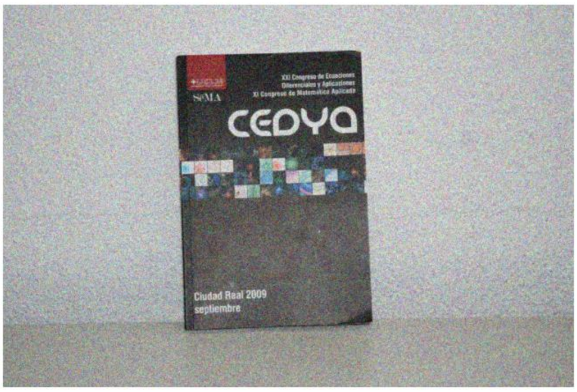
σ/PSNR	Without / Without	With / Without	Without / With	With / With
20	35.2517	36.1523	35.7525	35.8289
30	32.6905	34.6592	34.4234	34.5203
50	31.6157	33.4333	33.0493	32.9637

In this part, we tried to change the parameter of the homogeneous area criterion in both steps and for different noise values. We found that for a small value of noise, the algorithm performs better in estimating the denoised image. By increasing the noise value, the performance decreases. We also found that the best results are in the case where we chose to use the homogeneous criteria in the first step and not to use it in the second step for all different noise values. This means that taking the homogeneous region into account in the first step flattens the image and reduces an important amount of noise. Then, in the second step, without taking this assumption into account, the algorithm will build the fine details lost in the first step. In the next experiments, we will choose this choice for the homogeneous criteria.

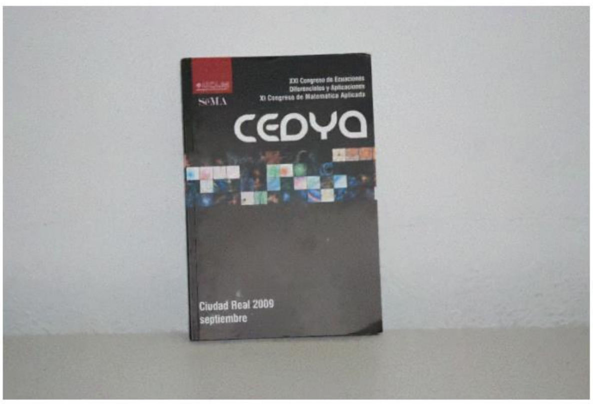
❖ First experiment for $\sigma = 30$:



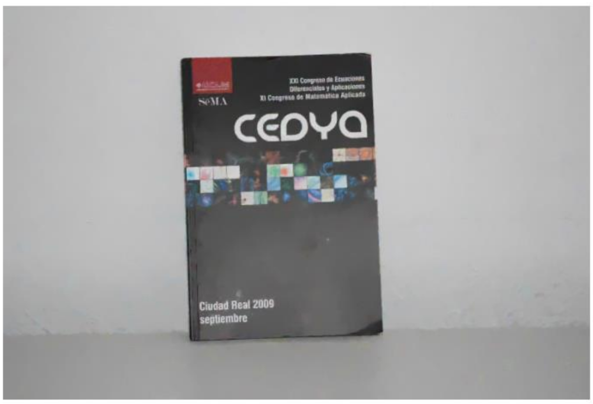
Original Image



Noisy Image



Basic Image ; PSNR = 34.4973 dB



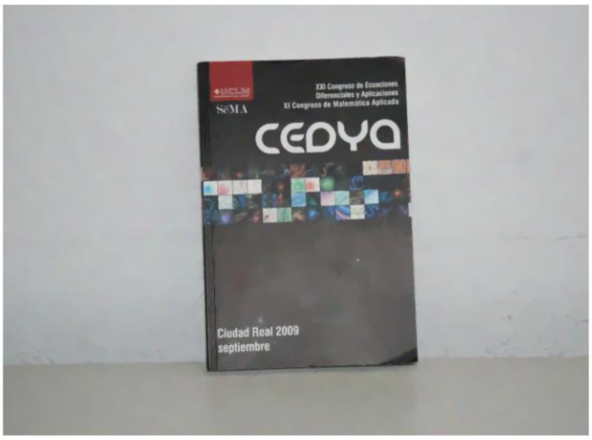
Denoised Image ; PSNR = 34.674 dB

Difference Image

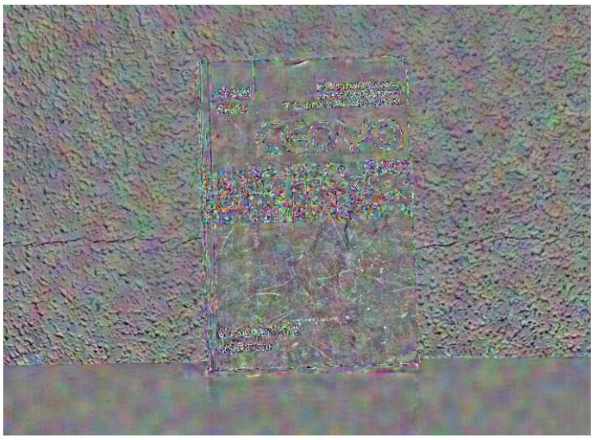
This method successfully denoised an image with a significant amount of noise. Indeed, it gives PSNR values for both steps above 30 dB. In addition, the overall appearance of the image is well constructed, especially in regions with sharp color changes, edges, and text areas. However, the difference image contains a lot of color and structures visible from the original image. These structures mainly describe the fine details of the wall and the structure of the book such as the small pictures. These regions are highly textured regions. Thus, the algorithm is not able to differentiate between noise and forms. We can also notice that the floor region is colored in the difference image. Maybe, this is because this region is close in intensity to the wall and then the algorithm uses patches that do not correspond to the ground region to denoise it. Also, curves and lines in the homogeneous region are not reconstructed. This algorithm in the first step eliminates these details because of the homogeneity criterion. That is, these details will be considered as part of the homogeneous regions.

When we compare the results of the first and the second methods, it is clear that the second method has improved the quality of the denoised image. From a visual perspective, the denoised image is closer to the original image.

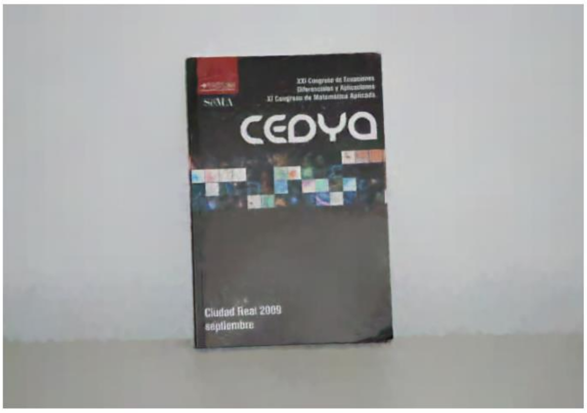
❖ Changing the value of the noise:

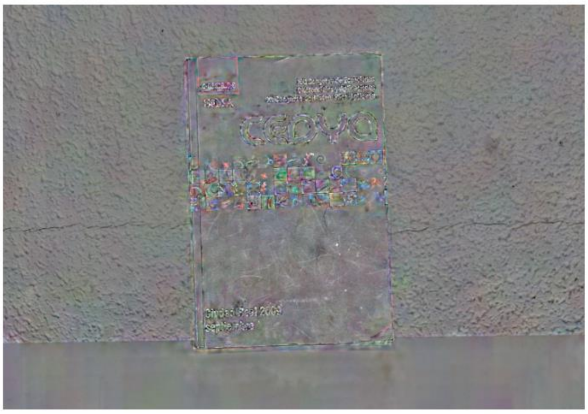


Denoised Image ; σ = 50



Difference Image


Denoised Image ; σ = 20


Difference Image

σ / PSNR	PSNR of first step	Final PSNR
20	35.9039	36.1126
30	34.4973	34.674
50	32.4125	33.4309

In this part, we changed the noise values to study whether the algorithm still performs well with a large amount of noise or not. We notice that the algorithm performs better when the noise is low. Indeed, in the difference image, with a noise value equal to 20, the image becomes grayer, and the book cover becomes indistinguishable. Only in the part of the pictures, there are some artifacts because this region is a multi-textured. So, it is difficult to build it with this algorithm. For a high value of noise, the denoising results are acceptable. However, many structures become visible in the difference image. Also, there are some ringing artifacts created especially around edges.

❖ Comparison between BM3D and NL-Bayes:

By studying this paper, we found that these two methods are very similar in their structure, but they differ in some steps.

- The pre-processing step:

Both methods can be applied to both color and grayscale images. To do this, they use the transformation of color space from RGB to luminance-chrominance space. The luminance channel is then used to determine the 3D block and the order of similarities. The same order is then used for the other channels.
As the assembly is done on a single channel, these methods use the same principles on gray scale images.

- The grouping step:

Both methods use the luminance channel to group the patches. The similarity is calculated using only luminance channel in the first step. In the second step, the NL-

Means uses the estimated channels to calculate the distances. In contrast, the BM3D uses the estimated channels and luminance channel.

- Collaborative filtering:

Both methods use the result of the first step to improve the performance. The main difference in collaborative filtering is that the NL-Bayes method uses a Bayesian approach to calculate the estimate. The BM3D method uses a linear transformation and hard thresholding to compute the estimate in the first step and Wiener filtering in the second step. In addition, the NL-Means differentiate between the homogeneous and non-homogeneous regions by comparing the noise in the patch to the value of the original noise.

- Aggregation:

This step is identical for both methods. The only difference is that the aggregation in the NL-Bayes method is not weighted, which is not the case for the BM3D method.

- Acceleration option:

The NL-Means method has an acceleration option. To do so, the method does not take as reference the patches used to denoise other patches.

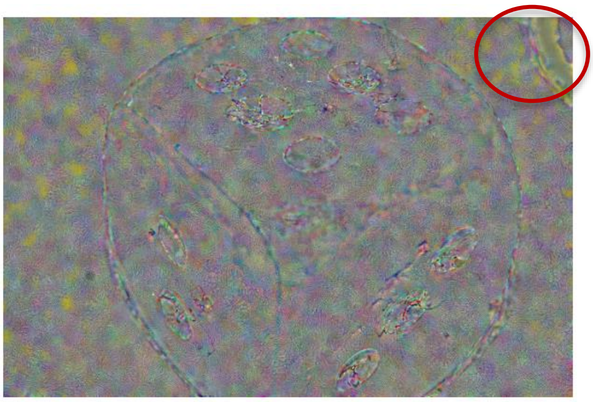
1- ($\sigma = 30$)

NL-Bayes Basic Image
PSNR = 31.0059 dB

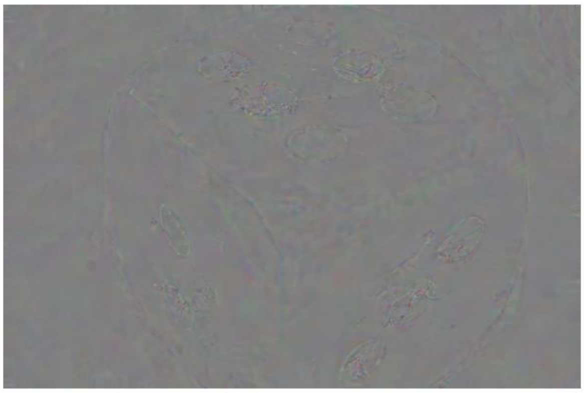
BM3D Basic Image
PSNR = 36.1133 dB

NL-Bayes Denoised Image
PSNR = 33.9651 dB

BM3D Denosied Image
PSNR = 37.9111 dB



NL-Bayes Difference Image



BM3D Difference Image

We notice that the result of the BM3D method is better than that of the NL-Bayes method. Indeed, the two BM3D steps give the best PSNR for the same noise value. The NL-Bayes method has more artifacts in the background region especially in the region circled in red, which is not the case with BM3D. In addition, the NL-Bayes difference image shows a lot of colors, and the general appearance of the original image is still visible. On the other hand, the BM3D difference image is completely gray. We can hardly detect the shapes that are present in the original image.

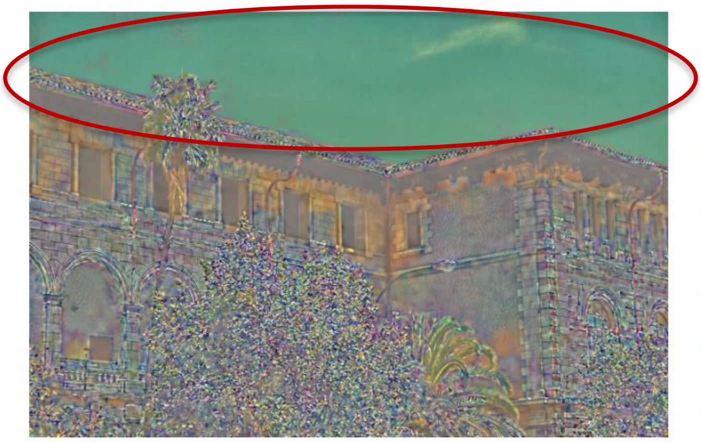
2- (σ = 50)

NL-Bayes Basic Image
PSNR = 25.9048 dB

BM3D Basic Image
PSNR = 26.9494 dB

NL-Bayes Denoised Image
PSNR = 26.7756 dB

BM3D Basic Image
PSNR = 27.5218 dB



NL-Bayes Difference Image

BM3D Difference Image

From these results, we can notice that the BM3D method obtains the best performance for both steps, even when we increase the noise value. Moreover, we can notice that the PSNR values of the BM3D method are always higher than those of the NL-Means method. For the first step, the NL-Means method gives a better visual performance than the BM3D which has a lot of artifacts especially in the sky region. For the second step, the BM3D method gives better visual results. The denoised image becomes similar to the original image only some artifacts are created in the highly textured areas. On the other hand, the NL-Means give worser results. We can notice this from the difference image as it contains a lot of colors. Moreover, the color of the sky which is circled in red has completely changed but it contains less artifacts than the image of the NL-Means.