

# Effect of Correlation between Non-Local Means Patch Dissimilarities on Search Region Adaptation for Improved Image Denoising

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**Abstract**— In this paper we refer to the correlation analysis between the Non-Local Means (NLM) dissimilarity elements within a given search region. This analysis is required for a more accurate determination of a model-based adaptive search region that we introduced earlier. We explore three levels of correlation according to the degree of patches overlap and explain how this analysis can be used in our model-based NLM approach.

**Index Terms**—Non-Local Means, Dissimilarity correlation, Adaptive search region.

## I. INTRODUCTION

In recent years, patch-based methods have drawn much attention in the image processing community. In 2005, Buades et al. [2] introduced the Non-Local Means (NLM) denoising algorithm, which takes advantage of image redundancy by comparing local neighborhoods within a defined search region. Each pixel value is estimated as a weighted average of all other pixels in the search region. These pixels are each assigned a weight that is proportional to the similarity between their local neighborhood and the reference pixel local neighborhood.

The search region is usually a rectangular neighborhood, centered at the pixel of interest (POI), which may include pixels whose original gray value do not match the original value of the POI. Consequently, their participation in the averaging process degrades denoising performance. To eliminate their effect, researchers (e.g., [5],[7]) suggest creating an adaptive search-region, which excludes those dissimilar pixels. These methods involve heuristics and threshold setting, thus require parameter setting. Moreover, they restrict the search region to be contiguous, which may be inappropriate for regions that contain texture.

In [1], we presented a novel model-based method, which defines a set of similar pixels to the POI, from the initial search region, using the statistical distribution of the NLM dissimilarity measure values. We refer to the dissimilarity measure that characterizes the NLM method as a random variable and base our proposed approach on the variance of the dissimilarity elements associated with the pixels included in the adaptive search region. In addition, we suggested adapting the NLM patch-kernel to local structure. Our proposed approach was compared to the standard NLM and to other methods that use NLM combined with an adaptive search region, and was found to provide better denoising results both visually and quantitatively.

The statistical model, presented in [1], was developed under the simplifying assumption that the dissimilarity elements in a given search region are not correlated. In this paper, we explore the correlation between the dissimilarity values of patches in a given search region and its effect on the model-based scheme presented in [1]. The correlation analysis is important since it affects the variance of the dissimilarity elements, thus affecting the threshold that determines the adaptive search region. The reason that such a correlation exists is that the dissimilarities of all the patches in a given search region are computed with respect to the same reference patch. Furthermore, some patches may overlap each other and/or the mutual reference patch itself, contributing further to the correlation. We compare in this work the performance of the two schemes-with and without correlation consideration.

The remainder of this paper is as follows. Section II briefly describes the NLM method. The proposed adaptive method is concisely described in Section III. Section IV introduces the correlation analysis for different cases of patch overlap. Section V presents experimental results that compare the two schemes – with and without correlation consideration. Finally, Section VII presents a summary and concluding remark.

## II. NON-LOCAL MEANS IMAGE DENOISING

This section presents a brief overview of the non-local means method [2]. Let  $X$  and  $Y$  be the original and the observed noisy images, respectively. It is assumed that the original image is corrupted by Additive White Gaussian Noise (AWGN)  $N$  with a zero mean and a known standard deviation  $\sigma_n$ , such that

$$Y = X + N, \quad N \sim \mathcal{N}(0, \sigma_n^2) \quad (1)$$

Each pixel in the restored image is derived as the weighted average of all gray values within a defined search region:

$$\hat{X}_i = \sum_{j \in S_i} w_{i,j} Y_j, \quad (2)$$

where  $i$  represents a pixel index, and  $S_i$  refers to a rectangular search region of size  $M \times M$  centered at pixel  $i$ . The normalized weights, which can be referred to as similarity probabilities, are defined as:

$$w_{i,j} = \frac{1}{W_i} \exp\left(-\frac{d_i(j)}{h^2}\right), \quad j \in S_i, \quad (3)$$

such that  $W_i = \sum_{j \in S_i} w_{i,j}$  is a weight normalization factor,  $d_i(j)$  is the dissimilarity measure, and  $h$  is the weight smoothing parameter that is typically controlled manually in the algorithm and set globally. Choosing a very small  $h$  leads to noisy results almost identical to the input, while a very large  $h$  gives an overly-smoothed image. The NLM dissimilarity measure  $d_i(j)$  is defined over the corresponding similarity patches as:

$$d_i(j) = \left\| Y(A_i) - Y(A_j) \right\|_{2,a}^2 = \sum_{\substack{m \in A_i, l \in A_j, \\ l \in [1, p^2]}} \alpha_k (Y_m - Y_l)^2, \quad (4)$$

where  $Y(A_i)$  defines a vector of neighborhood pixel values and  $A_i$  represents a square similarity patch of size  $p \times p$  centered at pixel  $i$  ( $p < M$ ). The similarity patches may overlap within a given  $S_i$ . The vector norm is simply the Euclidean distance, weighted by a Gaussian kernel of zero mean and variance  $a$  with coefficients  $\alpha_k, k \in [1, p^2]$ , such that  $\sum_{k=1}^{p^2} \alpha_k = 1$ . In practice, instead of a Gaussian kernel, simpler kernels are used; a Uniform kernel (which assigns the same weights to all the pixels within the similarity patch), whose corresponding dissimilarity measure is denoted  $d_i^U(j)$ , and a Box kernel [1] whose corresponding dissimilarity measure is denoted  $d_i^B(j)$ .

In this paper, the similarity patch is set to be  $5 \times 5$  ( $p=5$ ) and the search region is set to  $11 \times 11$  ( $M=11$ ), as suggested in [6].

### III. MODEL-BASED ADAPTIVE SEARCH REGION

This section concisely describes the two main innovations of our earlier suggested method [1].

#### A. Search Region Pixel Classification

The NLM search region is usually a rectangular neighborhood, centered at the pixel of interest (POI), which may include pixels whose original gray value do not match the value of the original central pixel. Consequently, their participation in the averaging process degrades the denoising performance. To eliminate their effect, researchers (e.g., [5],[7]) suggest creating an adaptive search-region, which excludes those dissimilar pixels. These adaptive approaches suggest to partition the given search region into two groups, based on pixels' similarity to the POI. These approaches are parameter-dependent or restrict the set of similar pixels to the POI to be contiguous. In [1], we too propose to partition the search region of a given pixel  $i$  ( $S_i$ ) into two sets: a set of similar pixels (with respect to the reference pixel, denoted  $S_i^S$ ) and a complement set of dissimilar pixels, denoted  $S_i^D$ . However, unlike some of the earlier approaches, the set is not restricted to be contiguous, and the partition is determined on the basis of a statistical model of the NLM dissimilarity measure. Similarly to the other approaches, the weighted averaging is applied only to the pixels in the set  $S_i^S$ .

Our basic assumption relies on the fact that the normalized dissimilarity measure, for any patch-kernel being used (see eqn. (4)), for pixels included in the set  $S_i^S$ , is characterized with a *Chi-Square* distribution with  $p^2$  degrees of freedom that can be approximated as a *Normal* distribution, for  $p^2 \gg 1$ , as sum of  $p^2$  independent normal variables. Consequently, the following applies for a general patch-kernel:

$$\frac{d_i^G(j)}{2\sigma_n^2} \sim \mathbb{N}\left(1, 2\sum_{k=1}^{p^2} \alpha_k^2\right) \quad (5)$$

For the particular case of the Uniform patch-kernel,  $\sum_{k=1}^{p^2} \alpha_k^2 = p^{-2}$ , thus

$$\frac{d_i^U(j)}{2\sigma_n^2} \sim \mathbb{N}(1, 2p^{-2}) \quad (6)$$

Pixels that are not included in the set  $S_i^S$  are characterized with a normalized dissimilarity whose mean is larger than 1 and variance is larger than  $2\sum_{k=1}^{p^2} \alpha_k^2$  (as explained in [1]).

We propose to classify the initial search region  $S_i$  based on the distribution of the normalized dissimilarity measure. In this manner, we follow the next steps, using the Uniform patch-kernel:

- 1) Compute the normalized dissimilarity measure for all pixels  $j \in S_i$ , to obtain  $d_i^U(j)/2\sigma_n^2$ .
- 2) Sort the normalized dissimilarities in an ascending order.
- 3) Compute *Accumulated* variance: start with the two smallest dissimilarities and compute their variance. Then, add another dissimilarity element from the sorted list.
- 4) Continue with accumulated variance computation until the variance of the elements accumulated so far exceeds the theoretical variance threshold of  $2p^{-2}$  (see eqn. (6)).

The pixels whose elements were accumulated constitute the set  $S_i^S$ .

#### B. Patch-Kernel Type adaptation

Simulations suggest that the Uniform patch-kernel is more adequate for smooth regions, whereas the Box patch-kernel is more adequate for texture or edges. Consequently, we suggest combining the use of these two kernels based on local structure.

After computing the adaptive search region, we derive its normalized cardinality  $r_i = |S_i^S|/M^2$ , where  $|S_i^S|$  refers to the cardinality of the adaptive search region of pixel  $i$  and  $M^2$  is the initial size of the search region. We classify the matrix  $R$ , whose elements are  $r_i$ , into two clusters using *K-Means*, each of them is associated with a designated centroid. The pixels associated with the larger centroid value are considered part of a smooth region, thus their weights are computed using the

Uniform patch-kernel. On the other hand, the pixels associated with the smaller centroid value are considered part of a texture or edge region, thus their weights are computed using the Box patch-kernel.

This adaptation improves the preservation of edges and texture and decreases granularity of smooth regions.

#### IV. CORRELATION BETWEEN DISSIMILARITIES

The statistical model in the previous section was developed under the simplifying assumption that the dissimilarity elements in a given search region  $S_i$  are not correlated. It is important to state that other works, e.g., [7], [8], do not relate to any source of correlation between the dissimilarity elements and its effect on their statistical properties.

In this section we consider the correlation between normalized dissimilarities of patches in a given search region and its effect on the model-based scheme. The reason that such a correlation exists is that the dissimilarities of all the patches in a given search region are computed with respect to the same reference patch  $A_i$ . Furthermore, some patches may overlap each other and/or the mutual reference patch itself, contributing further to the correlation. To simplify the analysis, we first consider the correlation due to the mutual reference patch (Case 1), assuming no patch overlaps. Then we add the effect of overlap between patches, but not with the reference patch (Case 2), and finally we address the most general case in which overlapping patches may also overlap the reference patch (Case 3). By arranging the dissimilarities in a vector form, we express the correlation between the vector elements via its covariance matrix and apply the results to derive the statistical properties of the empirical (estimated) variance used in the proposed model-based denoising scheme ([1], [9]). For simplicity, the following analysis is based on dissimilarities computed using the Uniform path-kernel.

##### A. Case 1: Correlation between dissimilarities of patches that do not overlap each other, nor the reference patch

This case is illustrated in Fig. 1(a). In this figure, the reference patch is denoted  $A_i$  and some two compared patches denoted  $A_j, A_k$  for  $j, k \in S_i$ . The patches satisfy the no-overlap criterion:  $\forall j, k \in S_i, j \neq k : A_j \cap A_k = \emptyset, A_j \cap A_i = \emptyset, A_k \cap A_i = \emptyset$ . This means that these patches do not overlap each other, or the reference patch. By definition, the normalized dissimilarity of a patch is computed with respect to the reference patch, thus the reference patch serves as a mutual member that adds a source of correlation between dissimilarities of different compared patches. The distribution of the dissimilarity measure remains *Chi-Square* and can be approximated by a *Normal* distribution. The covariance matrix of the normalized dissimilarity elements  $\tilde{\mathbf{d}}_i^U$ , arranged in a vector form, is as follows [9]:

$$C_{\tilde{\mathbf{d}}_i^U} = E[\tilde{\mathbf{d}}_i^U (\tilde{\mathbf{d}}_i^U)^T] = p^{-2} \begin{bmatrix} 2 & 0.5 & \dots & 0.5 \\ 0.5 & 2 & \dots & 0.5 \\ | & | & | & | \\ 0.5 & \dots & \dots & 2 \end{bmatrix} \quad (7)$$

The off-diagonal elements of the respective covariance matrix refer to the cross-variance between the vectorized dissimilarity elements.

The estimated variance of the normalized dissimilarities, for this case, is affected by the correlation term that appears in eqn. (7) and its statistical analysis is required for setting the accumulated variance threshold, as explained in section III. The sorting process deals with a set of normalized dissimilarity elements of size  $L$ ,  $L \in [2, |S_i|]$ . The set of sorted elements associated with  $S_i$  is referred to as a vector  $\tilde{\mathbf{d}}_i^U$  with elements  $\tilde{d}_i(\psi_i^L(m))$ , where  $m \in [1, L]$  and  $\psi_i^L \subseteq S_i$  is a sub-set of the global indices of the pixels that are included in the search region and satisfy the no-overlap constraint, sorted in order of increasing dissimilarity value.

The estimated (empirical) unbiased variance of a set of  $L$  dissimilarity elements (constituting  $\tilde{\mathbf{d}}_i^U$ ) is defined as:

$$\hat{V} = \frac{1}{L-1} \sum_{m=1}^L (\tilde{d}_i(\psi_i^L(m)) - \hat{B})^2, \quad (8)$$

where  $\hat{B} = \frac{1}{L} \sum_{m=1}^L \tilde{d}_i(\psi_i^L(m))$  is the estimated mean of the corresponding vector elements. Since the (unsorted) elements of  $\tilde{\mathbf{d}}_i^U$  are distributed normally, as expressed by eqn. (6), the estimated mean  $\hat{B}$  is a *Normal* random variable, being a sum of *Normal* random variables. The statistical properties of the estimated mean variable at the variance threshold crossover point (section III) are as follows [9]:

$$\hat{B} \sim \mathcal{N}\left(1, \frac{L+3}{2Lp^2}\right) \quad (9)$$

As can be seen, the variance of the estimated mean is not decaying to zero for large  $L$  values. This is due to the non-zero correlation between the normalized dissimilarity elements. After establishing the statistical properties of the estimated mean for the threshold crossing point, we derive the properties of the estimated variance. The estimated variance is not distributed *Chi-Square* since the dissimilarity elements are correlated. Therefore, we do not know its distribution type, but we can derive its mean and variance at the threshold crossing point, which are [9]:

$$E[\hat{V}] = \frac{3}{2p^2}, \quad Var[\hat{V}] = \frac{9}{2p^4} \frac{1}{L-1} \quad (10)$$

Section V explains the need to estimate the variance of the empirical variance.

The correlation, in this case, causes a decrease in the mean of the estimated variance, as expected. Its value decreases from  $2p^{-2}$  (eqn. (6)) to  $1.5p^{-2}$ .

##### B. Case 2: Correlation between dissimilarities of patches that overlap each other, but not the reference patch

We discuss here the case of similarity patches that overlap each other, but not the reference patch, as illustrated in Fig. 1(b). The compared patches satisfy the following overlap criterion:  $\forall j, k \in S_i, j \neq k : A_j \cap A_k \neq \emptyset, A_j \cap A_i = \emptyset, A_k \cap A_i = \emptyset$ . As in Case 1, the reference patch  $A_i$  serves as a mutual

member in the dissimilarity between itself and the compared patches, thus inducing correlation between the corresponding dissimilarity elements. In this case, however, there is yet another source of correlation that stems from patches overlap. The distribution of the patch dissimilarity elements remains *Chi-Square* and can be approximated by a *Normal* distribution, as presented in eqn. (6). The covariance matrix obtained for the dissimilarity elements arranged in a vector form is [9]:

$$C_{\tilde{d}_i^U} = \mathbb{E}[\tilde{d}_i^U (\tilde{d}_i^U)^T] = p^{-2} \begin{bmatrix} 2 & 0.5 & \dots & 0.5 \\ 0.5 & 2 & \dots & 0.5 \\ | & | & | & | \\ 0.5 & \dots & \dots & 2 \end{bmatrix} + 0.5O, \quad (11)$$

where

$$O = \begin{bmatrix} 0 & \dots & \dots & |O_{\psi_i^L(1)\psi_i^L(L)}| \\ |O_{\psi_i^L(1)\psi_i^L(2)}| & \dots & \dots & | \\ | & | & | & | \\ |O_{\psi_i^L(L)\psi_i^L(1)}| & \dots & \dots & 0 \end{bmatrix}_{L \times L} \quad (12)$$

$O$  is a matrix obtained due to patches overlap and whose diagonal elements are all zero. The off-diagonal elements refer the region of overlap between compared patches. For example,  $|O_{\psi_i^L(1)\psi_i^L(L)}|$  is the cardinality of the overlap region between the similarity patch associated with the smallest dissimilarity  $\psi_i^L(1)$  and the last element in the sorted list  $\psi_i^L$ . The off-diagonal elements of the respective covariance matrix (eqns. (11), (12)) refer to the cross-variance between the vectorized dissimilarity elements.

Similarly to Case 1, we need to analyze the statistical properties of the estimated mean variable, at the threshold crossover point, in order to analyze the properties of the estimated variance, required to set the variance threshold. Consequently, the estimated mean  $\hat{B}$  is distributed normally with the following properties [9]:

$$\hat{B} \sim \mathbb{N}\left(1, \frac{L+3}{2Lp^2} + \frac{1}{2L(L-1)p^4} \sum_{k=1}^L \sum_{s=1, s \neq k}^L |O_{\psi_i^L(k)\psi_i^L(s)}|\right) \quad (13)$$

The mean of the empirical variance is derived as [9]:

$$\mathbb{E}[\hat{V}] = \frac{3}{2p^2} - \frac{1}{2L(L-1)p^4} \sum_{k=1}^L \sum_{s=1, s \neq k}^L |O_{\psi_i^L(k)\psi_i^L(s)}| \quad (14)$$

The variance of the estimated variance  $Var[\hat{V}]$ , in this case, involves a complicated development due to the complicated form of the covariance matrix (see eqns. (12),(13)). It can be seen from eqn. (14) that the correlation term due to the overlap between the patches themselves causes a decrease in the mean of the estimated variance, compared to its mean in Case 1. This decrease, however, is relatively small since it is proportional to  $p^{-4} \ll 1$ . Moreover, this overlap term has to be computed for each explored sub-set in each search region, which makes the computation impractical ([9]).

### C. Case 3: Correlation between dissimilarities of patches that overlap each other and the reference patch

We finally discuss here the most general case of similarity patches that overlap each other as well as the reference patch,

as illustrated in Fig. 1(c). In this figure, the selected compared patches  $A_j, A_k, j, k \in S_i$  overlap each other, and each one of them also overlaps the reference patch  $A_i$ , satisfying the overlap criterion:  $\forall j, k \in S_i^S, j \neq k: A_j \cap A_k \neq \emptyset, A_j \cap A_i \neq \emptyset, A_k \cap A_i \neq \emptyset$ .

Here we get an additional source of correlation, as compared to the two previous cases, which is the overlap of the compared patches with the reference patch. In this case, the distribution of patch dissimilarity is not *Chi-Square* anymore because not all the elements in the summation defining it (see eqn. (4)) are independent, in contrast to what was assumed by Buades et al. [3] and Thacker et al. [8]. The mean and variance of the normalized dissimilarity measure for a Uniform patch-kernel are obtained as [9]:

$$\mathbb{E}[\tilde{d}_i(j)] = 1, \quad Var[\tilde{d}_i(j)] = \frac{2}{p^2} + \frac{|O_{i,j}|}{p^4}, \quad (15)$$

where  $O_{i,j}$  is the set of pixels associated with the overlap between the similarity patch  $A_j$  and the reference patch  $A_i$  and the cardinality of the set is denoted  $|O_{i,j}|$ . The cross-variance term (off-diagonal elements of the covariance matrix), is given by [9]:

$$Cov(\tilde{d}_i(j), \tilde{d}_i(k)) = \frac{1}{2p^2} + \frac{1}{2p^4} (|O_{i,j}| + |O_{i,k}| + |O_{j,k}|) + \begin{cases} |O_{i,j}|p^{-4} & \text{if } |O_{i,j}| = |O_{i,k}| \\ 0 & \text{Otherwise} \end{cases} \quad (16)$$

Similar to Case 2, the additional terms are very small and their computation is even more complex (a detailed analysis can be found in [9], section 5.3 and Appendices B.3, C.3). Hence, in the experimental results below we present only the correlation effect related to case 1.

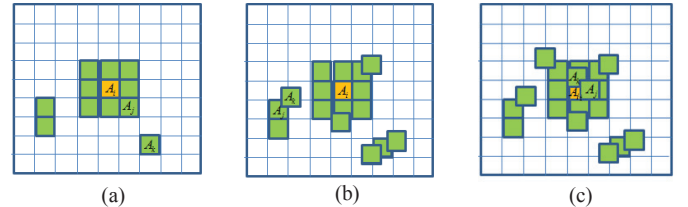


Fig. 1: Schematic presentation of the three cases. (a) Case 1, (b) Case 2, (c) Case 3.

## V. EXPERIMENTAL RESULTS

This section discusses the performance of the correlation-dependent model-based scheme, introduced in section IV, and compares it to the model-based scheme introduced in [1], and to the standard NLM, applied with either the Uniform or the Box patch-kernels. The difference between the first two schemes is based on the effect of the correlation between the dissimilarities, within a given search region, on the estimated variance based on Case 1 (eqn. (10)) and the no-correlation model (eqn. (5)), with the following NLM parameters:  $p = 5, M = 11, h = \sigma_n$ .

At the beginning of the variance accumulation process (see section III), the number of accumulated elements  $L (L < |S_i^S|)$  is relatively small. Consequently, the empirical variance

computation is not reliable, as further explained in [9], section 3.5. In order to compensate for this lack of robustness, we suggest modifying the threshold that sets the adaptive search region as follows:

$$TH^G = E[\hat{V}] + f \cdot STD[\hat{V}], \quad (17)$$

where the factor  $f$  is set empirically and was chosen to be 0 for the no-correlation scheme and 2 for the correlation-dependent scheme of Case 1 [9].

The following table presents the comparison results for different selected images and various noise levels. As was shown in [1], the no-correlation scheme is characterized by better denoising results, compared to the standard NLM, both visually and in terms of PSNR and SSIM. The correlation-dependent model-based scheme is slightly better than its simplified version, mainly PSNR-wise. The PSNR difference, for the images and noise conditions presented in the table, is maximum 0.04 dB, and is not noticeable visually.

TABLE I. QUANTITATIVE COMPARISON

Image	Noise STD	NLM w. Uniform		NLM w. Box		No-Correlation ( $f=0$ )	Correlation-Dependent ( $f=2$ )
		PSNR[dB]/SSIM	PSNR[dB]/SSIM	PSNR[dB]/SSIM	PSNR[dB]/SSIM	PSNR[dB]/SSIM	PSNR[dB]/SSIM
Lena	20	30.11 / 0.87	30.25 / 0.87	30.48 / 0.88	<b>30.51 / 0.88</b>		
Baboon	20	24.78 / 0.69	25.54 / 0.74	25.62 / 0.75	<b>25.64 / 0.75</b>		
Barbara	30	26.92 / 0.8	26.94 / 0.8	27.16 / 0.81	<b>27.18 / 0.81</b>		
Pirate	15	30.55 / 0.84	31.02 / 0.85	31.08 / 0.85	<b>31.12 / 0.85</b>		

Fig. 2 presents a performance comparison between the two model-based schemes and the standard NLM with the Uniform patch-kernel, as a function of noise level. The displayed curves are the result of averaging over ten explored natural images. As observed from the results presented in Table I, the correlation-dependent scheme is only slightly better, PSNR-wise, than the basic (no-correlation) model-based scheme. It is more pronounced at low noise levels. The two schemes are better than the standard NLM applied using either the Box or the Uniform patch-kernel.

## VI. CONCLUSION

In this work, we have analyzed and explored the effect of the correlation between the dissimilarity elements, within a given search region, on the variance threshold that is used to set the adaptive search region, according to [1]. The correlation is analyzed based on the degree of overlap between the corresponding patches. We have shown that the correlation-dependent model can be simplified if we neglect the overlap terms (eqn. (14)) that are impractical to compute. Moreover, based on the experimental results, there is no quantitative significant difference between the two schemes. This implies that computational complexity can be reduced, while preserving denoising results in terms of PSNR/SSIM and visibility.

BM3D [4] is considered to be the state-of-the-art denoising approach that achieves the best performance over other reported image denoising algorithms. However, it is computationally expensive and requires multiple parameters

setting. We suggest integrating our adaptive search region method (with no-correlation consideration) in the grouping stage of the first phase of the BM3D scheme, and by that decrease the computational complexity while preserving the quality of the denoising results. Refer to [9], Chapter 7, for more details. The overall reduction achieved in our simulations is 4.5% on average.

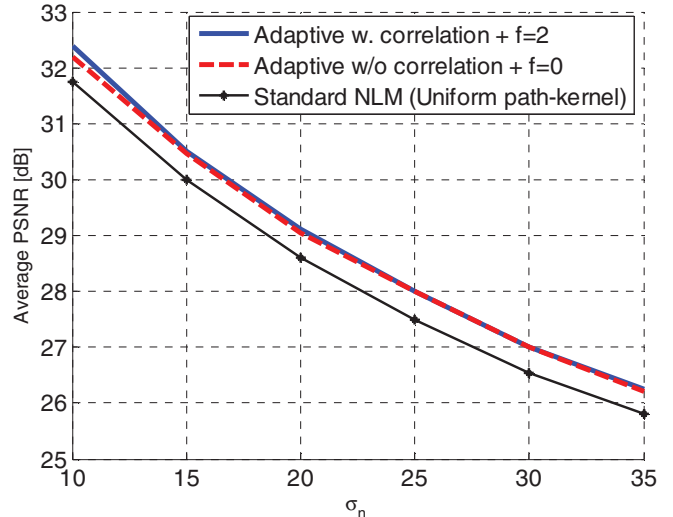


Fig. 2: Comparison between three NLM schemes: the blue curve refers to the correlation-dependent scheme with  $f=2$ , the dashed red curve refers to the no-correlation scheme with  $f=0$ , and the black curve refers to the standard NLM using the Uniform patch-kernel.

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