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THE NOISE CLINIC: A UNIVERSAL BLIND DENOISING ALGORITHM

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ABSTRACT

Most papers on denoising methods assume a white Gaussian noise model. Yet in most images handled by the public or by scientific users, the noise model is unknown and is not white, because of the various processes applied to the image before it reaches the user: scanning, demosaicing, compression, deconvolution, etc. To cope with this wide ranging problem, we propose a blind multiscale denoising algorithm working for noise which is simultaneously signal and frequency dependent. On noisy images coming from diverse sources (JPEG, scans of old photographs,) we show perceptually convincing results. This algorithm is compared to the state-of-the-art and it is also validated on images with white noise.

Key words-blind denoising, multiscale algorithm, noise estimation, denoising

1. INTRODUCTION

Denoising is probably the operation with the highest impact to improve image quality. Indeed the presence of noise hides image details and limits other image improvements such as contrast enhancement or color balance. Our goal here is to provide a "blind" multiscale image denoising method. Its denoising part is preceded by an accurate noise estimate made from the image itself. Our main motivation comes from the fact that most image users in science and technology do not actually dispose of both the raw image and the noise model. While their image is not necessarily fully denoised, it has generally undergone several frequency and signal distortions. This helplessness of image users can be observed in the IPOL journal's archives of six papers analysing recent or emblematic denoising methods (NL-means [1], DCT denoising [2], TV denoising [3], K-SVD [4], BM3D [5] and NL-Bayes [6]). These online papers demos allow users to upload noisefree images, to add the noise, and denoise them. Yet it appears that a majority of the tens of thousands of images submitted by the readers had colored noise. Only from this fact comes clear that the demand for image denoising exceeds widely the white noise case. "Blind" methods are required for a good diffusion of state-of-the-art image processing methods among other scientific disciplines. Scanned old photographs have chemical noise, JPEG images are the result of a strong quantization on DCT coefficients making the noise frequency dependent. Augmented light cameras create a blurry noise. In medical images, frequency domain hardware of software operations on the noisy samples are frequent.

This leads us to assume the general noise model must be (at least) signal and frequency dependent. This assumption is for example compatible with noise in JPEG images, which is the result of a (signal dependent) Poisson noise which has generally undergone a demosaicking, a gamma correction and a color balance quantization of its DCT coefficients.

The literature on blind denoising approach is surprisingly scarce. It has been studied by Javier Portilla [7], [8], Tamer Rabie [9] and by Liu, Freeman, Szeliski and Kang [10]. For this purpose, Portilla modified his state-of-the-art denoising algorithm BLS-GSM and adapted it to deal with homogeneous, Gaussian or mesokurtotic noise, which provides the only state-of-the-art (and reproducible) blind denoising algorithm to our knowledge. Liu, Freeman, Szeliski and Kang proposed a unified framework for JPEG image for two tasks: 1) automatic estimation and 2), removal of colored noise from a single image. The paper proposed by Rabie works only for Gaussian noise, where the blind denoising filter is based on the theory of robust statistics. Our plan follows from the above considerations. Section 2 explains how to adapt a denoising algorithm (here NL-Bayes) to the general noise model. The noise estimation procedure is sketched in Section 3. Section 4 gives the multiscale denoising procedure and summarizes the blind denoising method. Some results on real noisy images with unknown preprocessing and comparison with the state-of-the-art algorithm of [7] are presented in Section 5.

USING NL-BAYES

We chose the NL-Bayes algorithm because it can be applied with a general noise covariance matrix, that can be made signal and scale dependent. Let P˜ be a reference patch extracted from the image, and P(P˜) the set of patches Q˜ similar to P˜. NL-Bayes assumes that the patches similar to a given patch follow a Gaussian model. Assuming that the noise on these patches is also Gaussian and that we know its covariance matrix, a "basic" estimate of the denoised patch P is obtained by Bayes' formula

$$P\mathbf{basic} = \overline{\tilde{P}} + \left[\mathbf{C}_{\tilde{P}} - \mathbf{C}_n\right] \mathbf{C}_{\tilde{P}}^{-1} \left(\tilde{P} - \overline{\tilde{P}}\right) \qquad (1)$$

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where P˜ is the average of patches similar to P˜, $\mathbf{C}_n$ is the covariance matrix of the noise and $\mathbf{C}_{P}$˜ is the covariance matrix of the patches similar to P˜. (For pure Gaussian signalindependent noise, we simply have $\mathbf{C}_n = \sigma^2\mathbf{I}$.) The above formula is optimal if $\mathbf{C}_{P}$˜ is exactly known, but this covariance matrix can only be estimated on the set of similar noisy patches.

Seeing nevertheless the above basic estimation as an "oracle", equation (1) yields to the second step of NL-Bayes,

$$P^{\text{final}} = \overline{P}^{\text{basic}} + \mathbf{C}_{\tilde{P}}^{\text{basic}} \left[\mathbf{C}_{\tilde{P}}^{\text{basic}} - \mathbf{C}_n\right]^{-1} \left(\tilde{P} - \overline{P}^{\text{basic}}\right) \quad (2),$$

where $\mathbf{C}^{\text{basic}}$P˜ is a better covariance matrix estimated on the denoised patches of the first step.

Adapt NL-Bayes to signal dependent noise was easy. It only requires the additional knowledge of an estimated covariance matrix for the noise $\mathbf{C}_{ni}$, which we assume to depend only on the patch average intensity **i**.

NOISE ESTIMATION

Most noise estimation algorithms capable of estimating the noise variance according to the frequency can be easily adapted to measure signal-dependent noise [11]. For the Noise Clinic we adapted an existing method by Ponamarenko et al. [12] to estimate the noise variance at each frequency.

Description of the Algorithm The algorithm can be summarized as follows:

1. Extract from the input image (of size $N_x \times N_y$ pixels) all possible $M = (N_x - w + 1)(N_y - w + 1)$ overlapping $w \times w$ blocks (with w = 4) and compute its 2D orthonormal DCT-II.
2. Set L = ∅ (the empty set).
3. For each DCT block m_1,

a. Look for the block m_2 that minimizes $\text{PMSE}_{m1,m2}$ (Eq. (3)). Consider only those blocks whose horizontal and vertical distance with respect to m_1 belongs to the interval $[r_1,r_2] = [4,14]$.

b. Add block m_1 and its PMSE, $[m_1, \text{PMSE}_{m1,m2}]$, to list L.

1. Compute the mean of each block[1].
2. Classify the elements of list L into disjoint bins according to the intensity of the blocks [11]. Each bin contains (with the exception of the last) 42000 elements.

Then, for each bin,

1. Consider the set Sp made by the blocks inside the current bin whose PMSE is below the p-quantile, with p = 0.005.
2. Assign to the current bin the intensity **i** as the median of the means of the blocks that belong to the bin[2].
3. $[i, j] \in [0, w-1]^2, [i, j] \neq$For each frequency [i,j] with [0,0],

a. Compute the (biased[3]) variance of the noise at the current bin and frequency [i,j] using the MAD estimator (Eq. (4)).

b. Correct the biased variance and obtain the finalestimate $\tilde{\sigma}_{\mathbf{i}}[i,j] = 1.967\hat{\sigma}_{\mathbf{i}}[i,j] - 0.2777$.

PMSEm1,m2 :=

$$\frac{1}{w^2} \sum_{i=0}^{w} \sum_{j=0}^{w} (m_1[i,j] - m_2[i,j])^2 (w^2 + 1 - i - j)^2. \quad (3)$$

σˆ[i,j] = MAD(Sp)

$=\text{median}_k\, [|Sp[k][i,j]) - \text{median}_l(Sp[l][i,j])|]$.

How to Obtain the Covariance Matrix At this point, we will suppose that for any given intensity **i**, the multi-frequency noise estimate has provided us with $k^2 \times k^2$ matrices.

$$\mathbf{M_i} = \mathbb{E}\left(\mathcal{D}N_{\mathbf{i}}\,(\mathcal{D}N_{\mathbf{i}})^t\right) = \left(\tilde{\sigma}_{\mathbf{i}}[i,j]\right)_{i,j} \quad (5)$$

- This operation is fast since the mean of the block can be obtained by dividing into *w* the value of the coefficient at frequency [0,0].
- The means of the blocks have been already computed in step 4.
- The estimate is biased because of the MAD estimator and because the variance is measured using a finite number of samples from L.
- Note that with this approach it is not possible to estimate the STD of the noise frequency [0,0]. However, since the complete algorithm is multiscale (see Sec. 4), the missed information about the low frequencies of the noise is later recovered when the noise is estimated at the next scale.

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where D is the matrix of the discrete cosine transform (DCT) of size $k^2 \times k^2$ and $N_{\mathbf{i}}$ denotes the k×k stochastic noise patch model at intensity **i**. From equation (5) and the definition of the covariance matrix of the noise, it comes for a given intensity **i** that

$$\mathbf{C}^{n}_{\mathbf{i}} = Cov(N_{\mathbf{i}}) = \mathbb{E}\left(N_{\mathbf{i}} N_{\mathbf{i}}^{t}\right) = \mathcal{D}^{t}\mathbf{M}_{\mathbf{i}}\mathcal{D}.$$

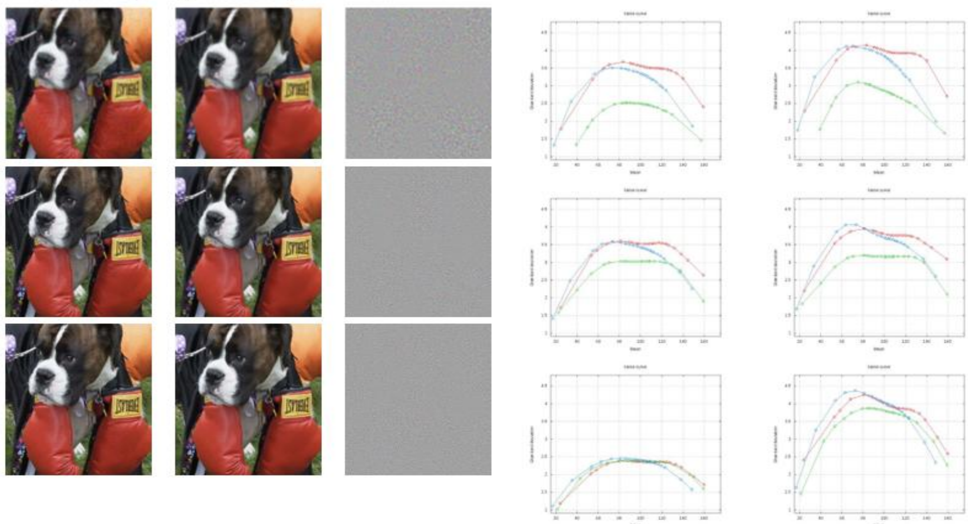

Fig. 1. Result of the Noise Clinic at each scale. From top to bottom: scale 2, scale 1 and scale 0. From left to right: noisy image, denoised image, difference image. The noise in a JPEG image is mainly present in low scales.

THE MULTISCALE NOISE CLINIC

The state-of-the-art denoising algorithms such that DDID (Knaus et al. [13]), BM3D (Dabov et al. [14]), NL-means (Buades et al. [15]), K-SVD (Mairal et al. [16], [17]), Wiener filters applied on DCT (Yaroslavsky et al. [18], [19]) or on wavelet transform (Donoho et al. [20]) or even the total variation minimization (Rudin et al. [21]) achieve good results for moderate white noise. Yet for large low frequency noise, many artifacts inherent to each method start appearing. A natural idea to deal with low frequency noise is to involve a multiscale procedure, which promises three improvements: 1) it favors a better patch comparison, 2) at larger scales the noise decreases, 3) subsampling the image before denoising amounts to enlarge the real size of the neighborhood.

Down and Up Sampling The sub-sampling is done by averaging four samples in the higher scale without any overlapping. As there are four ways to do it (depending on the starting pixel), the four sub-sampled images are kept to avoid aliasing. Then the noise estimation may work with the same amount of pixels at every scale. As the four sub-images are shifted by $\pm\frac{1}{2}$ in both coordinate directions, the up-sampling of higher scale pixels is done by averaging their four neighbors, each one belonging to each sub-image.

Fig. 1 illustrates a multiscale denoising result, where it is apparent that noise remains mainly at lower scales.

Noise Estimation The proposed algorithm has been develFig. 2. Average noise curves for the image in Fig. 1. From left to right: low frequencies, high frequencies. From top to bottom: scale 2, scale 1, scale 0. Instead of being divided by two at each scale (as it should happen with white noise), the noise grows in lower scales, where JPEG has not removed it.

oped to deal with a broad variety of noise as illustrated in Fig. 2. The noise covariance matrices must be estimated at each scale and signal value. Fig. 2 shows an example of average noise curves over high and low frequencies for a three scales noise estimation.

The whole Noise Clinic is summarized in Algorithm 1.

2. RESULTS AND COMPARISONS

A comparison with blind BLS-GSM introduced in [7] and [8] is shown in Fig. 3 on some images with different kinds and values for the noise, extracted from [8]. Whereas for the left image the Noise Clinic better succeed to remove all the low frequency noise than blind BLS-GSM while preserving details, it re-enforces the strong structured noise in the right image, whereas blind BLS-GSM remarkably removes it. However one can argue that this structured noise may be seen and treated as detail belonging to the image. Results over an old photography and a JPEG image are given in Fig. 4. Both noisy images present a huge amount of noise with artifacts, but the Noise Clinic manages to remove a lot of it, while well preserving details and structure of the image.

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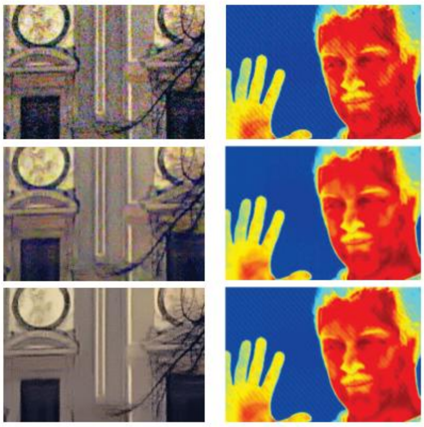

Algorithm 1 Noise Clinic Algorithm

Input : Noisy image $\tilde{u}_0$, Number of scales N

Output : Denoised image $\hat{u}_0$

Part 1 : Getting the image scale pyramid

for each scale $s = 1$ to $N-1$ do

Let $\{\tilde{u}^k_{s-1}\}$ be the previously set of noisy sub-images

for $k = 1$ to 4^{s-1} do

Down-sample $\tilde{u}^k_{s-1}$ into 4 sub-images and save details

$$\tilde{d}^k_{s-1} = \tilde{u}^k_{s-1} - U \{\tilde{u}_s^{4(k-1)+i}\}^k_{i\in[[14]]}$$

end for

if $s = N-1$ then

Set $\{\tilde{v}^k_{N-1}\}_k = \{\tilde{u}^k_{N-1}\}_k$

end if

end for

Part 2 : Estimating the noise and denoising the pyramid

for $s = N-1$ to 0 do

Estimate the noise covariance matrices over $\{\tilde{v}^k_s\}_k$.

Denoise $\{\tilde{v}^k_s\}_k$ with the NL-Bayes algorithm by using noise covariance matrices $\{D^t \mathbf{M}_i D\}_i$ to get $\{\hat{u}^k_s\}_k$.

if $s > 0$ then

for $k = 1$ to 4^{s-1} do

Fig. 3. Results of Blind BLS-GSM and of our blind denoising algorithm on different images from [8]. From Top to bottom: noisy image, Blind BSL-GSM result, Noise Clinic result.

Fig. 4. Results of Blind BLS-GSM and of our blind denoising algorithm over noisy images. From Top to bottom : noisy image, Blind BSL-GSM result, Noise Clinic result.

Up-sample $\{\hat{u}_s^{4(k-1)+i}\}_{i\in[[1,4]]}$ and add the saved details $\tilde{d}^k_{s-1}$ to get $\tilde{v}^k_{s-1}$.

end for else $\hat{u}_0 = \hat{u}_0^1$

end if

end for

3. CONCLUSION, LIMITATIONS

The presented Noise Clinic brings together state-of-the-art methods for denoising and noise estimation and a multiscale procedure to create a simple and effective blind denoising algorithm. The power of the proposed method lies in the fact that very few assumptions on the nature of the noise are done, which allows the Noise Clinic to give good results on almost any natural image, even if it has been modified by destructive applications such as JPEG compression. This power is strengthened by the multi-scale approach which efficiently removes low-frequency noise while preserving tiny details. This method does not apply to images having impulse or multiplicative noise. Also, our local noise estimation procedure did not detect the strength of the fully structured noise present in the second infrared image of Fig. 3. Nevertheless, our trials on very numerous images indicate that the assumed noise model is sufficient for most JPEG images. A general entropybased noise level estimator has been proposed in [22], which may work for any sort of noise. Unfortunately it delivers a noise level but not a noise model. So we could not use it for noise estimation.

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