Global Non Local Means Algorithm For Image Denoising

Authors

Meera Mohan¹, Dhanya Venugopal²

1. PG Scholar, Department Of Cse, Musaliar College Of Engineering And Technology, Pathanamthitta, Kerala, India,
2. Assistant Professor, Department Of Cse, Musaliar College Of Engineering And Technology, Pathanamthitta, Kerala, India,

EMAIL: meerajarahul@gmail.com, dhanyacs@gmail.com

ABSTRACT

Images are often corrupted by noise during the acquisition process. Denoising aims at eliminating this measurement noise while trying to preserve important signal features such as texture and edges. Over the past few decades, a large variety of algorithms has been developed for that purpose. They can be roughly categorized into linear denoising methods such as Wiener filtering and smoothing splines, variation and patch based methods. The patch-based methods are based on patch matching, and the main problem that affect their performance is the ability to reliably find sufficiently similar patches. But when the number of patches grows, it will reduce the likelihood of finding sufficiently close matches. The total effect is that the patch based methods are good overall, their performance goes slow in the case of bigger images due to complexity. In this global non local means algorithm all pixels in the image can be estimated for finding every other pixel. In this an approximation has been carried out using the Nyström method. Using these, we demonstrate that this global filter can be used in an effective way. Hence, our approach can effectively enhance the performance of existing filters.

KeyWords: Image Denoising, Non Local Means, Wiener filtering, Nyström Extension

1. INTRODUCTION

Image denoising has been studied for decades in computer vision, image processing and statistical signal processing. This problem not only provides a good platform to examine natural image models and signal separation algorithms, but also becomes an important part to digital image acquiring systems to enhance image qualities. The model for denoising can be described as

\[ m = c + e \]
where vectors c and m denote the image and its noisy observation, respectively. There exist a number of denoising algorithms to estimate z from y, and in general most of these methods can be considered as patch-based filters. In the case of denoising techniques such as Gaussian filter[1], Anistropic PDE, Rudin Osher Fatemi TV, SUSAN filter[2], Wiener filter, Wavelets, DUDE, bilateral [3][4] each pixel can be estimated by the fusing of “similar” neighbourhood pixels; The patch-based methods like BM3D [5] and PLOW [6] denoise by grouping of similar patches together.. Matching of similar patches is a complex task in patch based methods.. Specially, for images that can be well represented by locally sparse transform, the shrinkage operator performs well. The performance of the patch-based filtering will be affected by the scarcity of similar patches. Patch-based Wiener filter that exploits patch redundancy can be used for image denoising. The framework uses both geometrically and photometrically similar patches to estimate the different filter parameters. The challenge of any image denoising algorithm is to suppress noise while producing sharp images without loss of finer details.

The Nyström method’s various applications such as manifold learning, segmentation of images, and image editing. In the global approach only a part of the matrix has been used. A gaussian filter smoothes an image by calculating weighted averages in a filter box. The blurring is controlled by two parameters:

1) The box size, described by (2·n+1) pixels in one direction
2) The radius r.

The simplest method for noise removal is Gaussian filtering, which is equivalent to solving an isotropic heat diffusion equation, a second order linear PDE[7]. Compared to simple Gaussian filtering, anisotropic diffusion smooth out noise while keeping edges. However, it tends to over-blur the image and sharpen the boundary with many texture details lost. More advanced partial differential equations (PDEs) have been developed so that a specific regularization process is designed for a given (user-defined) underlying local smoothing geometry, preserving more texture details than the classical anisotropic diffusion methods.

All these methods rely on some explicit or implicit assumptions about the true (noise-free) signal in order to separate it properly from the random noise. In particular, the transform-domain denoising methods typically assume that the true signal can be well approximated by a linear combination of few basis elements. That is, the signal is sparsely represented in the transform domain. Hence, by preserving the few high-magnitude transform coefficients that convey mostly the true-signal energy and discarding the rest which are mainly due to noise, the true signal can be effectively estimated. The sparsity of the representation depends on both the transform and the true-signal’s properties. The multiresolution transforms can achieve good sparsity[8][9][10] for spatially localized details, such as edges and singularities.

Kernel based methods[11][12] have recently been used widely in image denoising. Tuning the parameters of these algorithms directly affects their performance. In this paper, an iterative method is proposed which
optimizes the performance of any kernel based denoising algorithm in the mean-squared error (MSE) sense, even with arbitrary parameters.

Denoising using wavelet[13][14][15] is effective because its able to capture the energy of a signal in few energy transform values. This wavelet denoising[16][17][18] presents the Haar and Daubechie transform to remove the Gaussian noise using Global and Adaptive thresholding technique.

The block diagram of the proposed framework for denoising mainly colour images is illustrated in Fig. 1.

```
INPUT IMAGE

↓

NYSTROM EXTENSION

↓

FILTER APPROXIMATION

↓

FILTER OPTIMIZATION

↓

OUTPUT IMAGE
```

**Fig 1:** Flow Of The Proposed Denoising Algorithm

Algorithm: Filter approximation
Input: Matrix subblocks.
Output: Approximated eigen vectors.

**Nystrom method:**
1. Eigen decomposition of the sub block of similarity matrix
2. First p leading eigen vectors are approximated.

**Sinkhorn Algorithm**
Row = ones(n,1)
For i=1 to iteration
Column and row normalizations can be done.
End
For i=1 to p
Sub blocks of the filter matrix can be generated
End

Orthogonalization
1. Generate another symmetric matrix using the sub block of filter matrix.
2. Eigen decomposition has been carried out
3. Eigen vectors are approximated

2. APPROXIMATION OF FILTER
Since we need orthogonal eigen vectors, an orthogonalization procedure is used to obtain an orthonormal approximation for eigen-decomposition of filter. The proposed method can be applied to both colour and grayscale images. In the case of proposed method the denoising of real images can be done in a more effective way. Here we mainly focus on denoising of colour images. Different methods can be used in denoising colour images.

2.1. Nystrom Approximation
Instead of taking into account all the entries. Having p pixels in a sampled subimage 1, we can compute the m × m kernel matrix \( K_1 \) which represents the similarity weights of pixels in 1. We also define the subimage 2 containing the rest of \((n-m)\) pixels, followed by the m×(n–m) matrix \( K_{12} \), which contains the kernel weights between pixels in 1 and 2. The similarity matrix \( K_m \) in block form is therefore

\[
K_m = \begin{bmatrix} K_1 & K_{12} \\ K_{12}^T & K_2 \end{bmatrix}
\]  \( \text{(1)} \)

where \( K_2 \) denotes the \((n-m) \times (n-m)\) similarity weights between pixels of the sub image 2. Then the following approximation for the first \( p \) eigenvectors of \( K \)

\[
\phi = \begin{bmatrix} \phi_1 \\ K_{12}^T \phi_1 \pi_1^{-1} \end{bmatrix}
\]  \( \text{(2)} \)

Then the approximated similarity matrix will be \( \tilde{K} = \phi \pi_1 \phi^T \)

The important aspect of the Nyström approximation is the sampling procedure in which the columns (or rows) of the original matrix have been selected.
3.2. Sinkhorn
The filter \( W \) can be represented as the row-normalized form of the kernel matrix. The matrix can be approximated using, using Sinkhorn’s algorithm. Based on this method. Symmetric matrix can be generated. Instead, as can be seen in Algorithm. Symmetric matrix can be approximated as below

\[
W_{\text{symmetric}} = \begin{bmatrix} W_1 & W_{12} \\ W_{12}^T & W_2 \end{bmatrix}
\]

(3)

These eigen vectors does not have orthonomal property So orthogonaliation is needed.

3.3. Orthogonalization
Using the sub matrices the \( W \) in and \( W/2 \) in hand, here we can approximate the orthogonalized eigenvectors. For any positive definite matrix, the orthogonalized approximated eigenvectors can be solved in one step. The square root of the first sub matrix has been taken. We can express \( G = W_1 + W_1^{-1/2}W_{12}W_{12}^T W_1^{-1/2} \) and the eigen decomposition of this symmetric matrix as \( G = V_0 S_0 V_0^T \). The the approximated symmetric matrix can be diagonalized and in which vectors are represented as

\[
\tilde{V} = \begin{bmatrix} W_1 \\ W_{12} \end{bmatrix} W_1^{-1/2} S_0 \tilde{V}_0^{-1/2}.
\]

The the filter approximation can be done. The above three methods gives us an approximation of the filter eigen values and vectors.

3.4 Permutation
In order to identify the noise in the image and to get the probability on random noise we do permutation on the filtered eigen vectors. Shuffling the filtered eigen vectors is the important task in this phase.

3. COLOUR IMAGE DENOISING
Different methods can be used in colour image denoising.

They are

3.1 Method 1
After converting the image in rgb form to yuv colour space monte carlo, non local means and global filter are applied to all the three channels of yuv.

3.2 Method 2
Nonlocal means and global filter are applied to y,u and v.

3.3 Method 3
Weights are computed from y channel and applied to u and v colour space.

3.4 Method 4
Weights are computed from y channel and Gaussian filter applied to u and v colour space.
4. EXPERIMENTAL RESULTS AND DISCUSSION

Rather than the PSNR improvement, visual quality of the proposed global method also is enhanced compared to the NLM filter. As it can be seen, both edges and smooth features of the image are preserved better than the other methods. The method can be better used for colour image denoising.

![Noisy image (std deviation=40)](image1)

**Fig-2:** Noisy image (std deviation=40)

![Prefiltered output by NLM](image2)

**Fig-3:** Prefiltered output by NLM

![Output by proposed method](image3)

**Fig-4:** Output by proposed method

The experimental results showing denoising in real noise using method 2 and 3 is shown in fig 5-10.
**Fig-5:** noisy image

**Fig-6:** prefiltered image

**Fig-7:** output by proposed method (method2)
Fig 8: Noisy image

Fig 9: Prefiltered image

Fig 10: Output by proposed method (method 3)
A comparison between different methods used in color image denoising is shown below.

**Fig-7:** comparison of different methods in colour denoising

**Chart-1:** Time Complexity of different methods in colour denoising

5. CONCLUSION

The global approach goes beyond performance of non-local patch-based processing, which we have shown here to be inherently limited. In our method, a global filter has been used which uses all the pixels in the input image for denoising every single pixel. By exploiting the Nyström extension, computational cost and storage complexity can be reduced. At the same time, the experimental results show that the proposed approach is the best among the existing filters in terms of both PSNR and visual quality.

REFERENCES


[17] Applying the Haar Wavelet Transform to time series information