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Texture Preserving Image Denoising Based On Patches Reordering

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Abstract: Presently a number of image denoising techniques utilize patch information and interrelations between them to remove the noise. Although the ways of establishing the relations between patches may greatly differ depending upon the characteristics of noise and image. Furthermore the ordering of patches requires the estimation noise-free value of patch which require heavy calculations. This paper presents an efficient approach to order the patch in a required sequence using the neural network. The neural network presents a coarse approximation of noise-free values of the patch.After that the weighted median filter is used to perform the smoothing operation which performs the final denoising. Finally the simulation of the proposed algorithm shows that the proposed scheme achieves much better results than many of state-of-the-art techniques.

Keywords: Image Denoising, Patch Ordering, Neural Network, Median Filter,

1. INTRODUCTION

Recently, many image denoising techniques already presented works on the basis of the relations between neighborhood patches. Each one uses the different approach to estimate the relations between patches. Like weighted averaging of pixels, bunching the patches into disjoint sets and treating every set in a different ways etc. But the most popular one is creating a delegate dictionary for the patches and utilizing it form relations among the patches.

However every proposal uses the different ways of measuring relations between the patches the basic idea behind the all patch based technique remains the same. This idea states that each patch taken from the image might find comparative ones at somewhere else in the image. In more general term we can say that, the image patches are expected to display an exceedingly organized geometrical frame in space framed by image.

This explanation describes why, non-local means can accomplish better results through joint treatment of comparative patches.

In this paper we set out an efficient approach to reduce the calculation time required for establishing relations between the patches, and on the other hand, we presented a weighted filter by utilizing the pdf of the image pixels.

The rest of the paper is organized as follows: the Section 2 presents the literature review. Section 3 presents the basic concept of the patch based scheme can perform denoising using patch ordering and averaging In Section 4presents a brief overview of neural network. In the section 5 experimental results are presented followed by the conclusion and future scope in section 6.

2. LITERATURE REVIEW

It has already been discussed in [4][5] that a number of the spatial domain denoising techniques are already presented in earlier work, like the bilateral filter [6], NLM (nonlocal means) [7], and optimal filtrations [8]. Broadly speaking, these denoising methods inherently share the same patch interrelations [9],differing mainly in the way the interrelation is calculated. Like in [1] [2] authors, use a wavelet domain to uncover complex relationship between patches of wavelet coefficients with patches from nearby spatial positions, at different orientations, and scales. On the other way, there are studies of image statistical properties which try to estimate an “optimal” set of linear vectors in the space defined by the image data. The patch searching methods have also been shownto have some modified versions. Such that presented in [17] for the nonlocal means(NLM) filter where an iterative version of NLM is motivated from considering an equivalent variational framework using gradient descent. Adaptation of the NLM filter in a variational framework for image denoising and segmentation has also been done in [10] [11]. Learning a suitable basis function to describe image patches is another concept in same field. Use of such basis functions to describe geometric structure has been previously explored leading to the invention of curvelets[14], contourlets [15], bandelets [16], etc. All these tools allow learning of a suitable basis to describe the image, especially the intricate edge and texture regions. Many other linear and nonlinear methods have been also proposed to solve this problem. One of the earlier methods to achieve considerable success in this domain was the bilateral filter, proposed in [6]. While this method received broad attention in the image processing and computer vision communities, it fails to perform well in the presence of strong noise. A wavelet domain denoising technique based on scale mixture of Gaussians (GSM) proposed in [12] was considered to be better than all other techniques at the time of its introduction. In [7] proposed a simple patch-based technique which exploits the occurrence of repeating structures in a given image to perform a weighted averaging of pixels with similar structures to remove the noise. In [8], noticeably enhanced a localized version of this procedure using an iterative structure where the variance of the intensity estimation at each pixel location is used to compute the weights and the region of interest for the averaging process. A more recent technique named BM3D[13], works on the same conceptof using similar patches throughout the image to perform denoising.

3. Problem Statement Image Denoising

Let Y be an image of size $N_1 \times N_2$where $N_1 N_2 = N$, andlet Z be its noisy version

$$Z = Y + V, \dots \dots \dots \dots \dots \dots \dots ..(1)$$

$Vdenotes$ an additive white Gaussian noise independent of $Y$with zero mean and varianceσ^2. Also, let z and y be the column stacked representations of $Z$and Y, respectively. In order to reconstruct the original y from the noisy observation z we need a permutations matrixP_k of size $N \times N$ which arranges the elements of z in the order of their distances after that it is pass through an averaging filter H which produces the smoothed version ofz^s. Now the denoised y matrix is recovered by applying the inverse permutation $P_k^{-1}$to theresult.

The above discussed concept has three main limitations. First, Arrangement of z in a given order is a very time consuming process. Second it is considered that the rearranged elements of z have same order as of $y$which is, practically not possible because z is already corrupted by the noise. Thirdly the tuning the weights of averaging filters. Our goal is to overcome these limitations.

4. Weighted Average Filter

Basically the Average Filter Replace each pixel by the average of pixels in a window surrounding this pixel. The size of window is decided based on the trade-off between noise removal and detail preserving: as the larger window can remove noise more effectively, but also blur the details (like edges) opposite of this is true for smaller window size.

100	100	100	100	100
100	200	205	203	100
100	195	200	200	100
100	200	205	195	100
100	100	100	100	100

100	100	100	100	100
100	144	167	145	100
100	167	200	168	100
100	144	166	144	100
100	100	100	100	100

Figure 1: Demonstration of 3X3 window size Averaging Filter.

However the weighted averaging filter works differently as Instead of averaging all the pixel values in the window, give the closerby pixels higher weighting, and far-away pixels lower weighting.

$$g(m,n) = \sum_{l=-L}^{L} \sum_{k=-L}^{L} h(k,l) s(m-k, n-l), \dots \dots ..(2)$$

This type of operation for arbitrary weighting matrices is generally called “2-D convolution or filtering”. When all the weights are positive, it corresponds to weighted average. Weighted average filter retains low frequency and suppresses high frequency or act as low-pass filter.

$\frac{1}{16} \times$

1	2	1
2	4	2
1	2	1

100	100	100	100	100
100	156	176	158	100
100	174	201	175	100
100	156	175	156	100
100	100	100	100	100

Figure 2: Demonstration of 3X3 weighted window (Left) Weighted Averaging Filter.

5. Artificial Neural Network

An artificial neural network is an interconnected group of nodes (which is generally a summing operator), similar to the vast network of neurons in a brain. There are many type of ANN’s are available but for present case we prefer MLP.

A multi-layer perceptron (MLP) is a nonlinear function that maps vector-valued input via several hidden layers to vector-valued output. For instance, an MLP with two hidden layers can be written as [18],

$$f(x) = b_3 + W_3 \tanh(b_2 + W_2\, tanh(b_1 + W_1 x)) , ..(3)$$

The weight matrices W_1, W_2, W_3 and vector-valued biasesb_1, b_2, b_3 parameterize the MLP, the function tanh operatescomponent-wise. The architecture of an MLP is definedby the number of hidden layers and by the layer sizes.

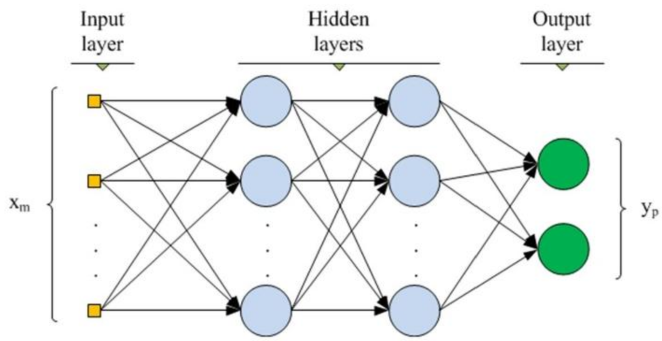

Figure 3: Structure of the MLP Neural Network.

For instance, a (256,2000,1000,10)-MLP has two hidden layers. The input layer is 256-dimensional, i.e. $x \in< 256$. Thevector $v_1 = tanh(b_1 + W_1 x)$ of the first hidden layer is2000-dimensional, the vector $v_2 = tanh(b_2 + W_2 v_1)$ ofthe second hidden layer is 1000-dimensional, and the vector$f(x)$ of the output layer is 10-dimensional. Commonly, an MLP is also called feed-forward neural network.

6. Proposed Algorithm

The algorithm starts by training the neural network for that:

Step 1: We randomly pick a clean patch x froman image dataset.

Step 2: Generate a corresponding noisy patch$y$ by corrupting x with noise, for instance with additivewhite Gaussian (AWG) noise.

Step 3: The MLP parameters arethen updated by the back-propagation algorithm minimizing the quadratic error between the mapped noisy patch$y = f(x)$ and the clean patch x, i.e. minimizing$(f(x) - x)^2$.

Step 4: To denoise images, we decompose a given noisy imageinto overlapping patches and denoise each patch y separately. The denoised image is obtained by placing the denoised patches x at the locations of their noisy counterparts.

Step 5: Now we start the Patch Ordering based Filtration. For which we divide the pre-filtered noisy image into n1*n2 patches.

Step 6: After that we calculate the distance between all patches formed in step 5.

Step 7: Now sort the patches according to the distance calculated above and form a matrix.

Step 8: Apply the Gaussian weighted averaging filter on the matrix formed in step 7.

Step 9: Now construct denoised image from this matrix by performing the inverse operations.

7. Simulation Results

The proposed algorithm is implemented in MATLAB and tested for different types of images corrupted by AWGN noise of different variance and the results obtained are presented as follows:

Figure 4: Test images taken for the analysis (1) Baboon, (2) Lena, (3) Boat, (4) Hill.

Table 1; Comparison for Baboon Image

Noise (σ^2)	10	20	50	80	100
Previous [19]	30.2015	28.1254	22.1182	13.2172	8.0287
Proposed	30.9188	29.3036	23.3547	17.3823	12.5213

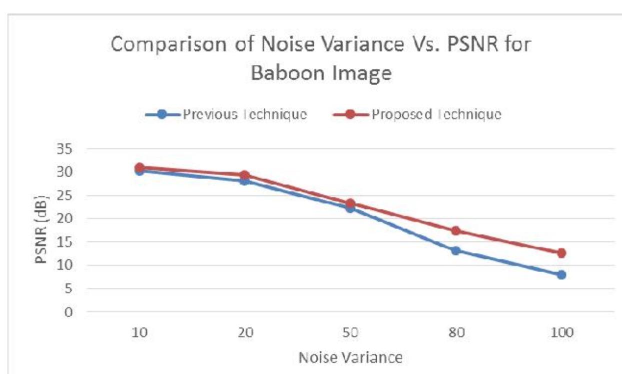

Figure 5: Plot for the Table 1 (Baboon Image)

Table 2; Comparison for Lena Image

Noise (σ^2)	10	20	50	80	100
Previous [19]	35.6122	33.6148	25.3349	14.3724	8.5118
Proposed	36.2811	34.2619	26.9181	19.1098	13.2104

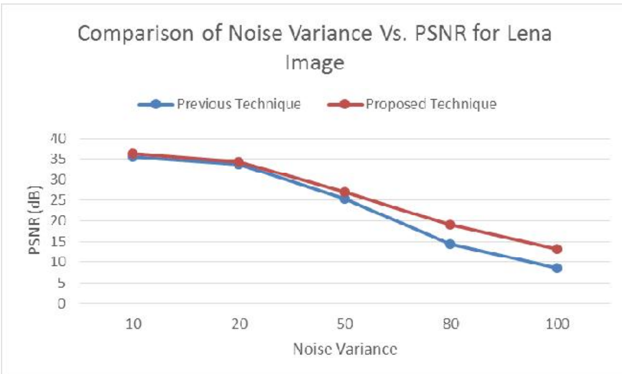

Figure 6: Plot for the Table 2 (Lena Image)

Table 3; Comparison for Boat Image

Noise (σ^2)	10	20	50	80	100
Previous [19]	35.9267	33.1167	25.4362	15.1058	8.2173
Proposed	36.7193	34.3121	26.2033	19.7236	13.1192

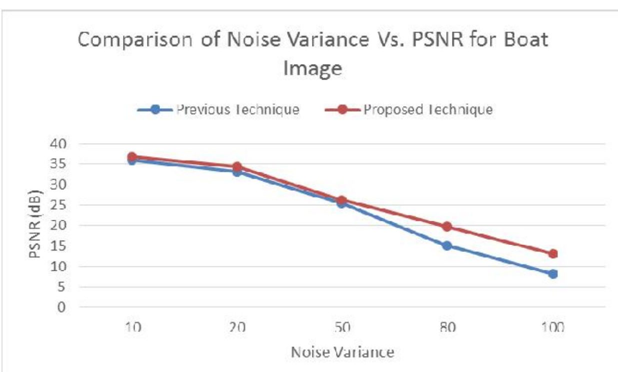

Figure 7: Plot for the Table 3 (Boat Image)

Table 4; Comparison for Hill Image

Noise (σ^2)	10	20	50	80	100
Previous [19]	33.2851	32.921	25.2152	15.7105	8.1127
Proposed	34.8207	33.0783	27.0173	19.1154	13.1411

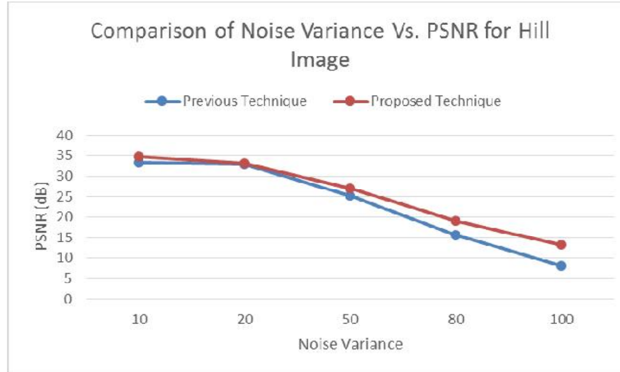

Figure 7: Plot for the Table 3 (Hill Image)

8. Conclusion

In this paper, we presented a patch based image denoising technique based on MLP artificial neural network and weighted average filtration. The MLP based pre-filtration helps in proper reordering of patches without much complexity and computational overhead. The weighted Average filtering preserves the texture information and avoid the blurring and fading. The simulation results shows that the proposed technique provides the good overall performance for all types of images and outperforms the previous [19] technique by noticeable margin, also the proposed algorithm reduces the computational complexity required by previous algorithm. Because it estimates the exact values of noisy pixels in pre-filtrations stage which eliminates the need of excessive searching throughout the image and hence reordering is performed quickly. In future this work could be to extend by selecting the more complex MLP structure and higher numbers of training images. Furthermore the algorithm can be modified to work with other types on noises.

REFERENCES

[1] Wegmann, B. and Zetzsche, C. "Statistical dependence between orientation filter outputs used in human vision basedimage code". Proc. SPIE Visual Comm. and Image Processing, 1990, vol. 1360. Lausanne, Switzerland, pp. 909–922.

[2] Simoncelli, E.P. "Modeling the joint statistics of images in the wavelet domain". In Proc. SPIE, 44th Annual Meeting, 1999, vol. 3813.Denver, CO. pp. 188–195.

[3] Huang, J. and Mumford, D. "Statistics of natural images and models". In Proc. of IEEE Conf. on Computer Vision and PatternRecognition1999.

[4] H. Takeda, S. Farsiu, and P. Milanfar, "Higher order bilateral filters and their properties," in Proc. SPIE Conf. Computational Imaging V, Feb.2007, vol. 6498, p. 64980S.

[5] H. J. Seo and P. Milanfar, "Video denoising using higher order optimalspace-time adaptation," in Proc. IEEE Int. Conf. Acoustics,

Speech andSignal Processing, Las Vegas, NV, Apr. 2008, pp. 1249–1252.

[6] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in Proc. 6th Int. Conf. Computer Vision, Washington, DC, Jan.1998, pp. 839–846.

[7] A. Buades, B. Coll, and J.-M. Morel, "A non-local algorithm for image denoising," in Proc. IEEE Conf. Computer Vision and Pattern Recognition, Washington, DC, Oct. 2005, vol. 2, pp. 60–65.

[8] C. Kervrann and J. Boulanger, "Optimal spatial adaptation for patchbased image denoising," IEEE Trans. Image Process., vol. 15, no. 10,pp. 2866–2878, Oct. 2006.

[9] H. Takeda, S. Farsiu, and P. Milanfar, "Kernel regression for imageprocessing and reconstruction," IEEE Trans. Image Process., vol. 16,no. 2, pp. 349–366, Feb. 2007.

[10] G. Gilboa and S. Osher, "Nonlocal linear image regularization and supervised segmentation," SIAM Multiscale Model. Simul., vol. 6, no. 2,pp. 595–630, Jul. 2007.

[11] D. Barash, "A fundamental relationship between bilateral filtering,adaptive smoothing, and the nonlinear diffusion equation," IEEETrans. Pattern Anal. Mach. Intell., vol. 24, no. 6, pp. 844–847, Jun.2002.

[12] J. Portilla, V. Strela, M. J. Wainwright, and E. P. Simoncelli, "Imagedenoising using a scale mixture of Gaussians in the wavelet domain,"IEEE Trans. Image Process., vol. 12, no. 11, pp. 1338–1351, Nov.2003.

[13] K. Dabov, A. Foi, V. Katkovnik, and K. O. Egiazarian, "Image denoising by sparse 3-D transform-domain collaborative filtering," IEEETrans. Image Process., vol. 16, no. 8, pp. 2080–2095, Aug. 2007.

[14] E. Candes and D. Donoho, "Curvelets—A surprisingly effective non-adaptive representation for objects with edges," in Curves and Surfaces, A. Cohen, C. Rabut, and L. Schumaker, Eds. Nashville, TN: Vanderbilt Univ. Press, 2000, pp. 105–120.

[15] M. N. Do and M. Vetterli, "The contourlet transform: An efficient directional multi resolution image representation," IEEE Trans. Image Process., vol. 14, no. 12, pp. 2091–2106, Dec. 2005.

[16] E. L. Pennec and S. Mallat, "Sparse geometric image representation with bandelets," IEEE Trans. Image Process., vol. 14, no. 4, pp.423–438, Apr. 2005.

[17] Xin Li "Patch-Based Image Interpolation: Algorithms andApplications",citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.141.1512.

[18] Harold C. Burger, Christian J. Schuler, and Stefan Harmeling "Image denoising: Can plain Neural Networks compete with BM3D?",Max Planck Institute for Intelligent Systems, Tubingen, Germany. http://people.tuebingen.mpg.de/burger/neural_denoising/.

[19] Idan Ram, Michael Elad, and Israel Cohen, "Image Processing Using Smooth Ordering of its Patches", IEEE Transactions on Image Processing, Vol. 22, No. 7, July 2013.