INTERNATIONAL JOURNAL OF SCIENTIFIC PROGRESS AND RESEARCH (IJSPR) ISSN: 2349-4689
Volume-17, Number - 01, 2015

An Analysis of Image Denoising Methods & Applications

Subhash Kumar[1], Prof. Kamal Niwaria[2] Dr. Manish Trivedi[3]
[1]M-Tech Research Scholar, [2]Research Guide, [3]HOD
Department of Electronics & Communication, RKDF IST, Bhopal

Abstract- In this research paper we have reviewed the applications and analyzed the wavelets applications. These are increasingly being used in scientific and engineering fields; traditional wavelets do well only at representing point singularities, as they ignore the geometric properties of structures and do not exploit the regularity of edges. Thus, de-noising, wavelet based compression or structure extraction become computationally inefficient for geometric features with line and surface singularities. For ex, when we download compressed image or video, we mostly find a mosaic phenomenon. The mosaic phenomenon comes from the poor ability of wavelets to handle line singularities. In fluid mechanics, discrete wavelet thresholding mostly leads to oscillations along edges of the coherent eddies, and to the deterioration of the vortex tube structures, which later can cause an unphysical leak of energy into neighboring scales producing an artificial "cascade" of energy.

Keywords- Image Denoising, Wavelet Transform.

I. INTRODUCTION

The term wavelet thresholding is defined as decomposition of the data of image into wavelet coefficients, comparing the detailed coefficients having a given threshold value, and minimizing these coefficients close to zero to remove the effect of noise in the data. Then image is reconstructed from modified coefficients. This is also known as inverse discrete wavelet transform. At the time of thresholding, a wavelet coefficient is compared to the given threshold and is set to zero if its magnitude is less than the threshold otherwise, it is then retained or modified depending on the thresholding rule. Thresholding distinguishes between coefficients due to noise and the ones consisting of important signal information. The selection of a threshold is an important point of interest. It plays an important role in the removal of noise in the images because de-noising most frequently produces smoothed images, by reducing the sharpness of the image. Care should be taken to preserve the edges of the de-noised image. Various methods for wavelet thresholding exists, which rely on the choice of a threshold value. Typically used methods for image noise removal include Sureshrink, VisuShrink and BayesShrink. It is necessary to know about the two generic categories of thresholding. These are hard thresholding and soft thresholding. The hard-thresholding TH is given as

$$TH = \begin{cases} x \; for \; |x| \geq t \\ 0 \; in \; all \; other \; region \end{cases}$$

where t is the threshold value. A plot of TH is shown in Figure below

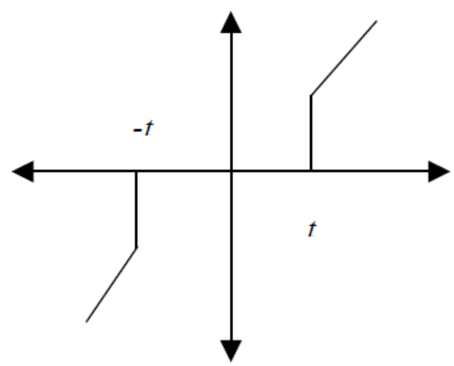

Fig 1 Hard thresholding

Therefore, all coefficients whose magnitude is greater than the selected threshold value T remains same and the others with magnitudes smaller than t are set to zero. It creates a region around 0 where the coefficients are considered to be negligible.

Soft thresholding is that where the coefficients with greater than the threshold are shrunk towards zero after comparing them to the threshold value. It is defined as below

$$T_s = \begin{cases} sign\,(x)(|x| - t) \; for \; |x| > t \\ 0 \qquad in \; all \; other \; region \end{cases}$$

Practically, it can be seen that the soft method is much better and yields more visually pleasant images. This is because the hard method is discontinuous and yields abrupt artifacts in the images recovered. Also, the soft method yields a smaller MSE (minimum mean squared error) compared to hard form of thresholding.

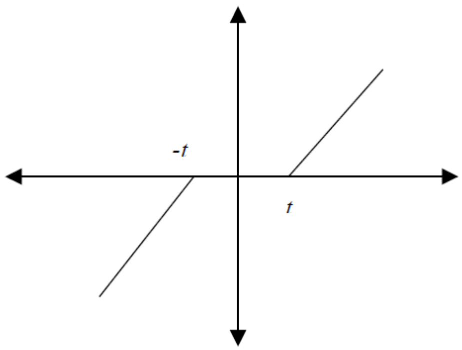

Fig 2 Soft Thresholding

II. IMAGE DENOISING METHODS

Multi Resolution Bilateral Filter Framework

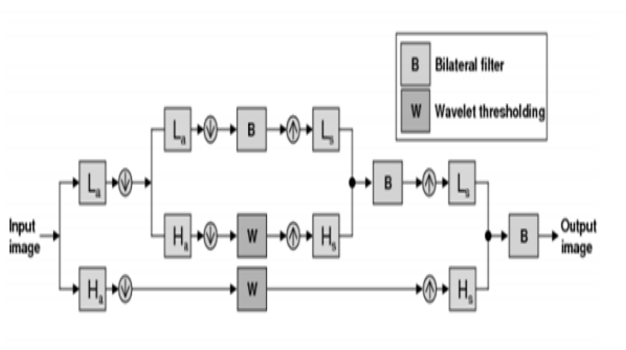

Fig 3 Framework of multi resolution bilateral filter.

As we have discussed in previously, image noise is not necessarily white and may have different spatial frequency (fine-grain and coarse-grain) characteristics. Multi resolution analysis has been proven to be an important tool for eliminating noise in signals; it is possible to distinguish between noise and image information better at one resolution level than another. To put the bilateral filter in a multi resolution framework: Referring to Figure 3.8, a signal is decomposed into its frequency sub-bands with wavelet decomposition. As the signal is reconstructed back, bilateral filtering is applied to the approximation sub-bands. Unlike the standard single-level bilateral filtering, this multi resolution bilateral filtering has the potential of eliminating low-frequency noise components. (This will become evident in our experiments with real data.) Bilateral filtering works in approximation sub-bands; in addition, it is possible to apply wavelet thresholding to the detail sub-bands, where some noise components can be identified and removed effectively. This new image denoising framework combines bilateral filtering and wavelet thresholding.

Denoising Filter Method

Bilateral Filter

There are two parameters that control the behavior of the bilateral filter [1]. σ_d & σ_r characterize the spatial and intensity domain behaviors, respectively. In case of image denoising applications, the question of selecting optimal parameter values has not been answered from a theoretical perspective; to the best of our knowledge, there is no empirical study on this issue either. In this section, I provide an empirical study of optimal parameter values as a function of noise variance. To understand the relationship among σ_d, σ_r and the noise standard deviation σ_n. Zero-mean white Gaussian noise was added to some standard test images and the bilateral filter was applied for different values of the parameters σ_d and σ_r .

Denoising Filter Method

Fast Bilateral Filter

In Porikli's constant time bilateral filter, he applied Taylor expansion to the Gaussian spatial filter. Since for constant spatial filter, the response of bilateral filter can be written as the summation of the integral histogram, a bilateral filter can be interpreted as the weighted sum of the spatial filtered responses of the powers of the original image. So he used a box filter to compute the 2D spatial linear filter in constant time O(1) by using an integral image.

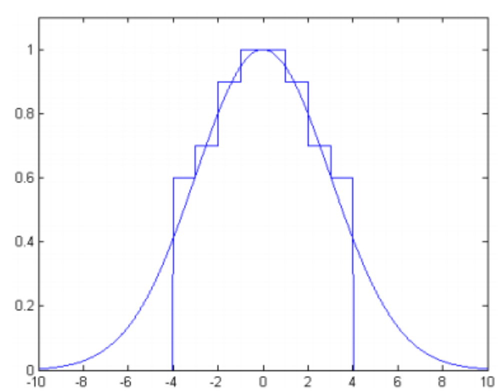

Figure 3.9 Multiple boxes filters and Gaussian filter

Based on the method provided by Porikli, we can find that he only use one box filter to approximate the Gaussian filter. So I extend one box filter to multiple box filters which can be more precise and close to the Gaussian. The weight of each box depends on the area of each box. The summation of the area of every box should be equal to the area of the Gaussian. The multiple boxes filter is shown in Figure 3.9.

Non-wavelet Approaches

Denoising images can be achieved by a spatial averaging of nearby pixels. This method removes noise but creates blur. Henceforth, neighborhood filters, which perform an average of neighboring pixels under the condition that their grey level is close enough to the one of the pixel in restoration, creates shocks and staircasing effects. Buades et al. [15] performed an asymptotic analysis of neighborhood filters as the size of the neighborhood shrinks to zero. His paper proved that these filters are asymptotically equivalent to the

Perona-Malik equation [16], one of the first nonlinear PDE proposed for image restoration. In continuation, he proposed an extremely simple variant of the neighborhood filter using a linear regression instead of an average. By analyzing its subjacent PDE, the artifacts can be eliminated. Elad et al. [19] addressed his approach based on sparse and redundant representations over a trained dictionary. The proposed algorithm denoised the image, while simultaneously training a dictionary on its corrupted content using the K-SVD algorithm. As the dictionary training algorithm is limited in handling small image patches, the author extended its deployment to arbitrary image sizes by defining a global image prior that forces sparsity over patches in every location in the image.

Kernel regression is also a popular state-of-the-art method for image denoising. Takeda et al. [20] made contact with the field of nonparametric statistics and adapt kernel regression ideas for use in image denoising, upscaling, interpolation, fusion, and more. They established key relationships with some popular existing methods and show how several of these algorithms, including the recently popularized bilateral filter, are special cases of the proposed framework. Especially they proposed the iterative steering regression which has a better performance than the bilateral filter for the elimination of both Gaussian white noises and real noise.

Patch-based approach is proposed by Kervrann et al. The method is based on a point-wise selection of small image patches of fixed size in the variable neighborhood of each pixel. Associate with each pixel the weighted sum of data points within an adaptive neighborhood in a manner that it balances the accuracy of approximation and the stochastic error at each spatial position. By introducing spatial adaptivity, they extend the Non-local means filter which can be considered as an extension of bilateral filtering to image patches. So they propose a nearly parameter-free algorithm for image denoising.

One of the best methods in non-wavelet pattern is called sparse 3D transform domain collaborative filtering (BM3D) by Dabov et al. Their strategy is based on an enhanced sparse representation in transform domain. The enhancement of the sparsity is achieved by grouping similar 2D image fragments (e.g. blocks) into 3D data arrays called "groups".
Collaborative filtering is a special procedure developed to deal with these 3D groups. The result is a 3D estimate that consists of the jointly filtered grouped image blocks. By attenuating the noise, the collaborative filtering reveals even the finest details shared by grouped blocks and at the same time it preserves the essential unique features of each individual block.

III. LITERATURE REVIEW

In the literature, there are numerous methods proposed to reduce compression artifacts. Some methods are introduced as a part of the encoding process, such as the lapped transform. Since these methods require modification of the codec, alternative post-processing methods, which do not require any codec changes, have become main focus in the area. The post-processing methods can be categorized into two: enhancement based algorithms and restoration based algorithms. Enhancement based algorithms try to improve the perceptual quality without an explicit optimization process; on the other hand, restoration based algorithms try to recover the original image based on some optimization criteria. Another
way of categorizing these methods is spatial domain vs. transform domain, depending on
which domain the image is processed. There are methods that use both domains. An example of the enhancement based algorithms is by Apostolopoulos et al., where the blockiness is first detected based on the number of zero DCT coefficients in each block, and then applying 1D median filter to reduce block discontinuities and 2D median filter to reduce mosquito artifacts.

A restoration based algorithm is proposed by Katsaggelos via the Bayesian approach. They used the hierarchical Bayesian paradigm to the reconstruction of block discrete cosine transform (BDCT) compressed images and the estimation of the required parameters. Then derive expressions for the iterative evaluation of these parameters applying the evidence analysis within the hierarchical Bayesian paradigm. This method allows for the combination of parameters estimated at the coder and decoder.

Another restoration base method is POCS (projection onto convex sets) by Liew et al. POCS method is presented for the suppression of blocking and ringing artifacts in a compressed image that contains homogeneous regions. In their paper, a new family of convex smoothness constraint sets is introduced, using the uniformity property of image regions. This set of constraints allows different degrees of smoothing in different regions of the image, while preserving the image edges. The regions are segmented using the fuzzy c-means algorithm, which allows ambiguous pixels to be left unclassified.

Wu et al. proposed the post-filter using the DCT coefficients of shifted blocks to deblock and preserve the details. For each block, its DC value and DC values of the surrounding eight neighbor blocks are exploited to predict low frequency AC coefficients. Those predicted AC coefficients allow inferring spatial characteristics of a block before quantization stage in the encoding system. They are used to classify each block into either of two categories, low-activity and high-activity block. In the following post-processing stage, two kinds of low pass filters are adaptively applied according to the classified result on each block. It allows for strong low pass filtering in low-activity regions where the blocking artifacts are most noticeable, whereas it allows for weak low pass filtering in high-activity regions to reduce ringing noise as well as blocking artifacts without introducing undesired blur.

IV. CONCLUSION

The noise may come from a noise source present in the vicinity of image capturing location or may be introduced due to imperfection inherent in the image capturing devices like cameras. For example, lenses may be misaligned, focal length may be weak, scattering and other adverse conditions may be present in the atmosphere, etc. This makes careful study of noise and noise approximation an essential ingredient of image denoising. This leads to selection of proper noise model for image processing system. In this review work we have studied and analyzed the research study by considering methods based on machine learning to be the best adaptive representations for natural images. We have analyzed that the better results than conventional representation models for the tasks of image denoising and deblurring would be achieved.

REFERENCES

[1]. M. Elad and M. Aharon, “Image denoising via learned dictionaries and sparse representation,” Proc. IEEE Computer Vision and Pattern Recognition, June 2006.

[2]. M. Elad J. Mairal and G. Sapiro, “Sparse representation for color image restoration,” IEEE Trans. Image Processing, vol. 17, no. 1, pp.53–69, January 2008.

[3]. M. Elad and M. Aharon, “Image denoising via sparse and redundant representations over learned dictionaries,” IEEE Trans. Image Processing, vol. 54, pp. 3736–3745, 2006.

[4]. H. Takeda, S. Farsiu and P. Milanfar, “Deblurring Using Regularized Locally Adaptive Kernel Regression,” IEEE Trans. Image Processing, vol.17, no. 4, pp. 550-563. April 2008.

[5]. P. Perona and J. Malik, “Scale-space and edge detection using anistropic diffusion,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 12, no. 7, pp. 629–639, July 1990.

[6]. D. L. Donoho and I. M. Johnstone, “Ideal spatial adaptation by wavelet shrinkage,” Biometrika, vol. 81, no. 3, pp. 425–455, 1994.

[7]. D. L. Donoho, I. M. Johnstone, G. Kerkyacharian, and D. Picard, “Wavelet shrinkage: Asymptopian,” Journal of Royal Statistics Society, Series B, vol. 57, no. 2, pp. 301–369, 1995.

[8]. S. G. Chang, B. Yu, and M. Vetterli, “Adaptive wavelet thresholding for image denoising and compression,” IEEE Trans. Image Processing, vol. 9, no. 9, pp. 1532–1546, September 2000.

[9]. L. Sendur and I. W. Selesnick, “Bivariate shrinkage functions for wavelet-based denoising exploiting interscale dependency,” IEEE Trans. Signal Processing, vol. 50, no. 11, pp. 2744–2756, November 2002.

[10]. A. Pizurica and W. Philips, “Estimating the probability of the presence of a signal of interest in multiresolution single- and multiband image denoising,” IEEE Trans. Image Processing, vol. 15, no. 3, pp. 654–665, March 2006.

[11]. J. Portilla, V. Strela, M. J. Wainwright, and E. P. Simoncelli, “Image denoising using scale mixtures of gaussians in the wavelet domain,” IEEE Trans. Image Processing, vol. 12, no. 11, pp. 1338–1351, November 2003.

[12]. F. Luisier, T. Blu, and M. Unser, “A new sure approach to image denoising: Inter-scale orthonormal wavelet thresholding,” IEEE Trans. Image Processing, vol. 16, no. 3, pp. 593–606, March 2007.

[13]. A. Buades, B. Coll, and J. Morel, “Neighborhood filters and pde’s,” Technical Report 2005-04, CMLA.

[14]. F. Luisier, T. Blu, and M. Unser, “A new sure approach to image denoising: Inter-scale orthonormal wavelet thresholding,” IEEE Trans. Image Processing, vol. 16, no. 3, pp. 593–606, March 2007.

[15]. A. Buades, B. Coll, and J. Morel, “Neighborhood filters and pde’s,” Technical Report 2005-04, CMLA.

[16]. P. Perona and J. Malik, “Scale-space and edge detection using anistropic diffusion,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 12, no. 7, pp. 629–639, July 1990.

[17]. M. Elad and M. Aharon, “Image denoising via learned dictionaries and sparse representation,” Proc. IEEE Computer Vision and Pattern Recognition, June 2006.

[18]. M. Elad J. Mairal and G. Sapiro, “Sparse representation for color image restoration,” IEEE Trans. Image Processing, vol. 17, no. 1, pp.53 69, January 2008.

[19]. M. Elad and M. Aharon, “Image denoising via sparse and redundant representations over learned dictionaries,” IEEE Trans. Image Processing, vol. 54, pp. 3736–3745, 2006.

[20]. H. Takeda, S. Farsiu and P. Milanfar, “Deblurring Using Regularized Locally Adaptive Kernel Regression,” IEEE Trans. Image Processing, vol.17, no. 4, pp. 550-563. April 2008.