© 2017 IJSRST | Volume 3 | Issue 2 | Print ISSN: 2395-6011 | Online ISSN: 2395-602X

National Conference on Advances in Engineering and Applied Science (NCAEAS)
16th February 2017
In association with
International Journal of Scientific Research in Science and Technology

Research Article on Image Denoising

Sangita Kulkarni, Prof. Anil Bavaskar

Department of VLSI Engineering J IT College of Engineering Nagpur, RTMNU University, India

ABSTRACT

Now a days ,wavelet-based image denoising method ,which extends a recently emerged “geometrical” Bayesian framework. The new scheme combines three criteria of sparsity, clustering,and persistence which are united in a Bayesian network. We address the image denoising difficulty ,where zero-mean white and Gaussian additive noise is to be uninvolved from a given image . We employ the belief propagation (BP) algorithm which estimates a coefficient based on every one the coefficient of a picture as the maximum-a-posterior (MAP) estimator to derive the denoised wavelet coefficients. We show that if the network is spanning tree, the standard BP algorithm can perform MAP estimation efficiently. Our research consequences show that in condition of the peak-Signal- to-noise-ratio and perceptual quality. The planned approach out performs state-of -the-art algorithm on a several images, particularly in the textured regions with various amount of white Gaussian noise.

Keywords : Bayesian Network, Image Denoising, Wavelet Transform, Bayesian Restoration

I. INTRODUCTION

In daily life digital image plays an important role. In Many applications such as satellite Television, GIS System etc. Further more noise can be introduced by transmission error & compression. It is necessary to apply as efficient denoising technique to compensate for such a data corruption, but it still remains a challenge for researcher because noise removal introduces artefacts and causes blurring of images. Thus here our focus is on noise removal technique for natural images. Bayesian network are probably the most popular type of graphical model. The construction of Bayesian network involves prior knowledge of the probability relationships between the variables of interest. In Bayesian restoration method, the image manifold is encoded in the form of prior knowledge that express the probabilities that combination of Pixel intensities can be experiential in an image. In some recent results in statistical modeling of natural images that attempt to explain statistical analysis of images which are invariance of image statistics to scaling of images, and non-Gaussian behavior of image statistics. They also discussed some recent advances in statistical modeling of natural images which are unable to capture the variety and complexity of real world images but we are still quite far from a full probability model[2].They implement a Wiener filter motivated by the statistical analysis of the performance bounds of patch-based methods is proposed. The filters parameters are estimated from geometrically as well as photometrically similar patches[3]. The construction of a Bayesian network involves prior knowledge of the probability relationships between the variables of interest. Learning approaches are widely used to construct Bayesian network that best represent the joint probabilities of training data .In practice, an optimization process based on a heuristic search technique is used to find the best structure over the space of all possible networks. However the approach is computationally intractable because it must explore several combination of dependant variables to derive an optimal Bayesian network. The difficulty is resolved in this paper by representing the data in wavelet domains and restricting the space of possible networks by using certain techniques, such as the “maximal weighted spanning tree". Three wavelet properties, Sparsity, cluster and motion can be oppressed to reduce the computational complexity of learning a Bayesian network [4]-[5]. Author describe a method for removing noise from digital imges, based on a statistical model of coefficients of an over complete multiscale oriented basis. Two basic assumptions are commonly made in order to reduce dimensionally. The first is that the probability structure may be defined locally. Second is an assumption of spatial homogeneity. Last assumption is problematic for image modeling where the complexity of local structure is not well described by Gaussian densities [10]. They presents a new wavelet-based image denoising method, which extends a recently emerged "Geometrical" Bayesian framework. The new method combines three criteria for distinguishing supposedly useful coefficients from noise: coefficients magnitudes, their evolution across scales and spatial clustering of large coefficients near image edges. These three criteria are combined in a Bayesian framework. Instead of using earlier heuristic model such a ratios we determine empirically their realistic conditional probability density given pure noise & given noisy edges.[15]. They propose a novel image denoising strategy based on an enhanced sparse representation in transform domain. The enhancement of the sparsity is achieved by grouping similar 2-D image fragments (e.g., blocks) into 3-D data arrays which we call "groups". Collaborative filtering is a special procedure developed to deal with these 3-D groups using the three successive steps: 3-D transformation of a group, shrinkage of the transform spectrum, and inverse 3-D transformation. The approach can be adopted to various noise models by modifying the calculations of co-efficient variance in the basic & Wiener parts of the algorithm in addition the developed method can be modified for denoising 1-D signals & video for image restoration as well for other problems that can benefits highly sparse signals representations.[18].

II. METHODS AND MATERIAL

1 RELATED WORK

A survey of different digital image processing techniques used in enhancing the quality and information content in ovary ultrasound image is presented. It can also remove the noise and retain the image details better. In this paper new threshold estimation technique has been presented along with the standard thresh holding and filtering techniques [1]. Because image spaces are high dimensional, one often isolates the manifolds by decomposing images into their components and by fitting probabilistic models on it[6]-[7]. During the last decades,,multi resolution image representation ,like wavelets ,have received attention for this purpose, due to their sparseness which manifests in highly non Gaussian statistics for wavelet coefficients.[8].

They describe the mathematical properties of such decompositions and introduce the wavelet transform. They review the classical multi resolution pyramidal transforms developed in computer vision and show how they relate to the decomposition of an image into a wavelet orthonormal basis[9]. In our construction, we use image patches to take into account complex spatial interactions in images. In contrast to exemplar-based approaches for image modeling . An unsupervised method that uses no collection of image patches and no computational intensive training algorithms. Our adaptive smoothing works in the joint spatial-range domain as the nonlocal means filter but have a more powerful adaptation to the local structure of the data since the size of windows and control parameters are estimated from local image statistics [11]. We create the presentation of the proposed denoising algorithm by first introducing how sparsity and redundancy are brought to exploit. We do that via the beginning of the Sparse land reproduction Once this is set, we will talk about how local management on image patches turns into a global prior in a Bayesian rebuilding framework. The second part of the paper attempts to further validate recent claims that lossy compression can be used for denoising. The Bayes Shrink threshold can aid in the parameter selection of a coder designed with the intention of denoising, and thus achieving concurrent denoising and looseness. Specifically, the zero-zone in the quantization step of compression is analogous to the threshold value in the thresholding function. The left behind coder design parameters are selected based on a criterion derived from Rissanen's minimum description length (MDL) theory [12]. Experiments show that this compression method does indeed remove noise extensively, especially for great noise power. although it introduces quantization noise and should be used only if bit rate were an additional concern to denoising. In meticulous, the transform-domain denoising methods normally assume that the true signal can be well approximated by a linear combination of few basis elements. That is, the signal is sparsely represent in the transform domain. thus, by preserving the few high-magnitude transform coefficients that convey typically the accurate-signal energy and discarding the rest which are mainly due to noise, the correct signal can be successfully estimated. The sparsity of the representation depends on both the transform and the true-signal's properties. The multi resolution transforms can achieve first-class sparsity for spatially localized fine points, for instance edges and singularities. When this prior-learning plan is combined with sparsity and redundancy, it is the glossary to be used that we target as the learned set of parameters [13].

2 IMAGE DENOISING TECHNIQUES.

The noise in the image is the random variation of brightness. Noise removal is necessary to obtain the better quality of image. The properties of an excellent image denoising model are that it will eliminate noise while preserving edges. Many filtering technique are used to remove the noise from the image, mainly linear and non-linear .One large advantage of linear noise model is the speed. But a reverse draw of the linear models is that they are not able to preserve edges in a excellent way. Non linear models on the other hand can handle edges in a much better way than linear models can. This filter is very good at preserving edges, but smoothly unstable regions in the input image are transformed into piecewise constant regions in the output image. This can be done for example by solving a 4th order PDEd instead of the 2nd order PDE from the TV-filter. Result show that the 4th order filter produces greatly better results in smooth regions and removing preserves edges in a very excellent way. Image denoising algorithms may be the oldest in image processing. Various methods in spite of implementation share the similar basic plan noise reduction through image blurring.

A) Patch –Based Image denoising

A novel adaptive and patch-based approach is proposed for image denoising and representation. The method is based on a point wise selection of small image patches of fixed size in the variable neighborhood of each pixel. Our involvement is to associate with each pixel the weighted sum of data points within an adaptive neighborhood, in a manner that it balances the exactness of approximation and the stochastic error, at each spatial location. This method is general and can be applied under the assumption that there exist repetitive patterns in a local neighborhood of a point. By introducing spatial adaptively, we expand the work earlier described by Buades et al. which can be measured as an addition of bilateral filtering to image patches. Finally, we recommend a nearly parameter-free algorithm for image denoising. The scheme is applied to both artificially despoiled (white Gaussian noise) and real images and the performance is extremely close to, and in some cases yet surpasses, that of the already published denoising schemes. A novel adaptive and exemplar-based approach is proposed for image restoration and representation. The method is based on a point wise selection of small image patches of fixed size in the variable neighborhood of each pixel. The core idea is to associate with each pixel the weighted sum of data points within an adaptive neighborhood. This method is general and can be applied under the assumption that the image is a locally and fairly stationary process. In this paper, we spotlight on the problem of the adaptive neighborhood selection in a manner that it balances the accuracy of approximation and the stochastic error, at each spatial location. Thus, the new proposed point wise estimator mechanically adapts to the degree of underlying smoothness which is unidentified with minimal a priori assumptions on the function to be recovered [14].

B) Image Denoising by Sparse 3D Transform-Domain collaborative filtering

Image denoising strategy based on an enhanced sparse representation in transform domain. The improvement of the sparsity is achieved by grouping similar 2D image fragments (e.g. blocks) into 3D data arrays which we call "groups". Collaborative filtering is a special procedure developed to deal with these 3D groups. We appreciate it using the three successive steps: 3D transformation of a group, reduction of the transform band, and inverse 3D transformation. The result is a 3D approximate that consists of the together filtered grouped image blocks. By attenuating the noise, the simultaneous filtering reveals even the finest details shared by grouped blocks and at the same time it preserves the essential unique features of each character block. The filtered blocks are returned to their original locations. since these blocks are overlapping, for each pixel we obtain several different estimates which need to be combined. Aggregation is a particular averaging process which is exploited to take advantage of this redundancy. A important improvement is obtained by a specially developed collaborative Wiener filtering. An algorithm based on this description denoising approach and its efficient implementation is presented in full detail; an extension to color-image denoising is also developed. The experimental results display that this computationally scalable algorithm achieves state-of-the-art denoising performance in terms of both peak signal-to-noise ratio and subjective visual quality [18].

C) Adaptive Wavelet Thresholding for Image restoration (denoising)

An adaptive, data-driven threshold for image denoising via wavelet soft-thresholding. The threshold is derivative in a Bayesian framework, and the previous used on the wavelet coefficients is the generalized Gaussian distribution (GGD) widely used in image processing applications. The anticipated threshold is simple and closed-form, and it is adaptive to each sub band because it depends on data-driven estimates of the parameters. Investigational results show that the proposed method, called BayesShrink, is usually within 5% of the MSE of the best soft-thresholding benchmark with the image assumed known. It also outperforms Donohue and Johnston's Sure Shrink most of the time. The subsequent part of the paper attempt to further validate recent claims that lossy compression can be used for denoising. The BayesShrink threshold can serve in the parameter selection of a coder designed with the intention of denoising, and thus achieving instantaneous denoising and compression. particularly, the zero-zone in the quantization step of compression is analogous to the threshold value in the thresholding function. The residual coder design parameters are chosen based on a criterion derived from Rissanen's minimum description length (MDL) principle. Experiments show that this compression scheme does indeed remove noise considerably, especially for huge noise power. However, it introduces quantization noise and should be used only if bitrates were an additional concern to denoising. is often corrupted by noise in its acquisition or transmission. The goal of denoising is to eliminate the noise while retaining as much as possible the important signal features. Conventionally, this is achieved by linear processing such as Wiener filtering. A vast literature has emerged freshly on signal denoising using nonlinear techniques, in the location of additive white Gaussian noise [17].

Figure 1: shows the wavelet based Adaptive Wavelet Thresh holding for Image Denoising [17].

D. Image denoising using mixtures of projected Gaussian scale mixtures

A new statistical model for image restoration in which neighborhoods of wavelet sub bands are modeled by a discrete mixture of linear projected Gaussian Scale Mixtures . In each projection, a lower dimensional approximation of the local neighborhood is obtained, thus modeling the strongest correlations in that neighborhood. The model is a generalization of the just developed Mixture of GSM (MGSM) model that offers a significant improvement both in PSNR and visually compared to the current state-of-the-art wavelet techniques. Though the computation cost is very high this hampers its use for practical purposes. We present a quick EM algorithm that takes advantage of the projection bases to speed up the algorithm. The results explain that, when foretelling on a fixed data-independent basis, even computational advantages with a imperfect loss of PSNR can be obtained with respect to the BLS-GSM denoising method, although data-dependent bases of Principle Components offer a higher denoising presentation, both visually and in PSNR compared to the current wavelet-based state-of-the-art denoising methods. The Mixtures of Projected Gaussian Scale Mixtures (MPGSM) as a means to further improve upon the recently proposed MGSM model. The new model is a generalization of the existing SVGSM, OAGSM and MGSM techniques and allows for a lot of flexibility with regard to the neighborhood size, spatial adaptation and even when modeling dependencies between different wavelet sub bands. We developed a fast EM algorithm for the model training, based on the winner-take all‖ approach, taking benefit of the Principal Component bases. We discussed how this technique can also be used to speed up the denoising itself. We discussed how data independent projection bases can be constructed to allow flexible neighborhood structures, offering computational savings compared to the GSM-BLS method which can be useful for real-time denoising applications. Finally we showed the PSNR improvement of the complete MPGSMBLS method compared to recent wavelet-domain state-of the- art methods [19].

E. Non-Adaptive thresh holding for image denoising

Visu Shrink is non-adaptive universal threshold which depends only on number of data points. It has asymptotic equivalence suggesting best performance in terms of MSE when the number of pixels reaches infinity. Visu shrink is known to yield overlay smoothed images because it’s threshold choice can be unwarrantedly large due to it’s dependence on the number of pixels in the image[12].

III. RESULTS AND DISCUSSION

THE OVERVIEW OF OUR METHOD

Bayesian Network Image Denosing

From the perspective of the Bayesian approach, the denoising problem is basically a prior probability modeling and estimation task. In this paper, we suggest an approach that exploits a hidden Bayesian system, constructed from wavelet coefficients, to model the previous probability of the original image. Then, we use the belief propagation (BP) method, which estimates a coefficient based on all the coefficients of an image, as the maximum-a-posterior (MAP) estimator to develop the denoised wavelet coefficients. We explain that if the network is a spanning tree, the standard BP algorithm can execute MAP estimation competently. Our experiment results demonstrate that, in conditions of the peak-signal-to-noise-ratio and perceptual quality, the projected approach outperforms state-of-the-art algorithms on various images, particularly in the textured regions, with various amounts of white Gaussian noise [20].

In this paper we present constructive data adaptive procedure that drives hidden graph structure from the wavelet coefficients and then graph is used to model the prior probability of original image for denoising purpose.

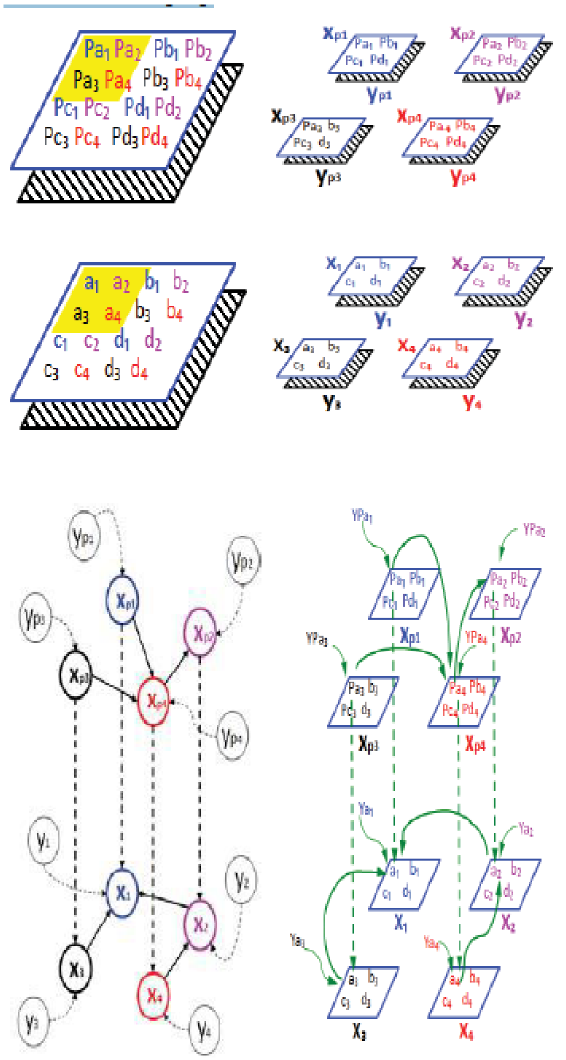

Figure 2: Bayesian Network Image Denoising [20].

IV. CONCLUSION

Bayesian image denoising using prior models for spatial clustering. A new MRF prior model was introduced to preserve image details better. A joint significance measure, which combines coefficients magnitudes and their evolution through scales, was introduced. For the resulting, joint conditional model a simple practical realization was proposed and motivated via simulations. We have described a novel adaptive denoising algorithm where patch-based weights and variable window sizes are jointly used. An advantage of the method is that internal parameters can be easily chosen and are relatively stable. The algorithm is able to denoise both piecewise-smooth and textured natural images since they contain enough redundancy. Actually, the performance of our algorithm is very close, and in some cases still surpasses, to that of the previously published denoising methods. Also we

just mention that the algorithm can be easily parallelized since at iteration, each pixel is processed independently. However, some problems may occur when the texture sample contains too many Texel's making hard to find close matches for the locality context window.

The field image processing has been growing speedily. The day to day emerging technology require more and more revolution and evolution in the image processing field. The work proposed in this paper also portrays a small contribution in this regard. This work can be further enhanced to the other types as well.

V. REFERENCES

[1]. Alka Vishwa,Vishkha Goyal –An Improved Threshold Estimation Technique for Ultrasound Image Denoising,ISSN ,Vol.3,Issue7,July 2013.

[2]. A. Srivastava, A. B. Lee, E.P. Simoncelli, and S-C. Zhu, OnAdvances in Statistical Modeling of Natural Images, Journal of Mathematical Imaging and Vision, vol. 18, pp. 17–33, 2003.

[3]. P.chatterjee and p.Milanfar- Patch based Near –optimal Image Denoising,IEEE Trans.Vol.21,no.4 April 2012.

[4]. J. Ho and W.-L. Hwang, Wavelet Bayesian Network Image Denoising, IEEE Trans. Image Process., vol. 22, no. 4, Apr. 2013.

[5]. D. M. Chickering, D. Heckerman, and C. Meek, A Bayesian approach to learning Bayesian networks with local structure, in Proc. 13th Conf. Uncertainty Artif. Intell., 1997, pp. 80–89.

[6]. B. Goossens, A. Pizurica, and W. Philips, Image denoising using mixtures of projected Gaussian scale mixtures, IEEE Trans. Image Process., vol. 18, no. 8, pp. 1689–1702, Aug. 2009

[7]. A.Srivastav ,A.B.Lee ,and S. C. Zhu-On Advances in Statistical Modelling of Natural Images,Journal of Mathematical Imaging ,2003.

[8]. S. Mallat, Multifrequency channel decomposition of images and wavelet models, IEEE Trans.

Acoust., Speech, Signal Proc., vol. 37, no. 12, pp. 2091–2110, Dec. 1989.

[9]. D. J. Field, Relations between the statistics of natural images and the response properties of cortical cells, J. Opt. Soc. Am. A, vol. 4, no. 12, pp. 2379–2394, 1987.

[10]. J. Portilla, V. Strela, M. Wainwright, and E. Simoncelli, Image denoising using Gaussian Scale Mixtures in the Wavelet Domain, IEEE Trans. Image Processing, vol. 12, no. 11, pp. 1338–1351, Nov. 2003.

[11]. J. Mairal, F. Bach, J. Ponce, and G. Sapiro, Non-local sparse models for image restoration, in Proc. IEEE Int. Conf. Comput. Vis., Kyoto, Japan, 2009, pp. 2272–2279.

[12]. G. Chang, B. Yu, and M. Baraniuk, Spatially adaptive wavelet thresholding with context modeling for image denoising, IEEE Trans. Image Process., vol. 9, no. 9, pp. 1522–1531, Sep. 2000.

[13]. M. Elad and M. Aharon, Image denoising via sparse and redundant representations over learned dictionaries, IEEE Trans. Image Process., vol. 15, no. 12, pp. 3736–3745, Dec. 2006

[14]. 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.

[15]. A. Pizurica, W. Philips, I. Lemahieu, and M. Acheroy, A joint inter- and intrascale statistical model for Bayesian wavelet based image denoising, IEEE Trans. Image Process., vol. 11, no. 5, pp. 545–557, May 2002.

[16]. M. Elad and M. Aharon, Image denoising via sparse and redundant representations over learned dictionaries, IEEE Trans. Image Process., vol. 15, no. 12, pp. 3736–3745, Dec. 2006.

[17]. G. Chang, B. Yu, and M. Baraniuk, Spatially adaptive wavelet thresholding with context modeling for image denoising, IEEE Trans. Image Process., vol. 9, no. 9, pp. 1522–1531, Sep. 2000.

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

[19]. B. Goossens, A. Pizurica, and W. Philips, Image denoising using mixtures of projected Gaussian scale mixtures, IEEE Trans. Image Process., vol. 18, no. 8, pp. 1689–1702, Aug. 2009.

[20]. J. Ho and W.-L. Hwang, Wavelet Bayesian Network Image Denoising, IEEE Trans. Image Process., vol. 22, no. 4, Apr. 2013.