A Review on Image Enhancement of Satellite and CCTV

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Abstract: Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission is often corrupted with noise. The received image needs processing before it can be used in applications. Image denoising involves the manipulation of the image data to produce a visually high quality image. This thesis reviews the existing denoising algorithms, such as filtering approach, wavelet based approach, and multifractal approach, and performs their comparative study. Different noise models including additive and multiplicative types are used. They include Gaussian noise, salt and pepper noise, speckle noise and Brownian noise. Selection of the denoising algorithm is application dependent.

Keywords: PCA, LCA, ICA, Image-denoising

1. Introduction:

The performance of image-denoising algorithms using wavelet transforms can be improved significantly by taking into account the statistical dependencies among wavelet coefficients as demonstrated by several algorithms presented in the literature. The performance can also be improved using simple models by estimating model parameters in a local neighborhood. Some recent research has addressed the development of statistical models of wavelet coefficients of natural images and application of these models to image denoising [5]. Recently, highly effective yet simple schemes mostly based on soft thresholding have been developed [1]. In [10], the wavelet coefficients are modeled with a Gaussian a priori density, and locally adaptive estimation is done for coefficient variances. Also, prior knowledge is taken into account to estimate coefficient variances more accurately. In [1], the interscale dependencies are used to improve the performance. In [2], the simple soft-thresholding idea is used for each of the wavelet subbands, and the threshold value is estimated to minimize the mean-square error. The models that exploit the dependency between coefficients give better results compared to the ones using an independence assumption [5]. However, some of these models are complicated and result in high computational cost. In [12], a bivariate probability density function (pdf) is proposed to model the statistical dependence between a coefficient and its parent, and the corresponding bivariate shrinkage function is obtained. This new rule maintains the simplicity, efficiency, and intuition of soft thresholding. An explicit multivariate shrinkage function for wavelet denoising is also presented in [16]. In this letter, the local adaptive estimation of necessary parameters for the bivariate shrinkage function will be described. Also, the performance of this system will be demonstrated on both the orthogonal wavelet transform.

A very large portion of digital image processing is devoted to image restoration. This includes research in algorithm development and routine goal oriented image processing. Image restoration is the removal or reduction of degradations that are incurred while the image is being obtained [3]. Degradation comes from blurring as well as noise due to electronic and photometric sources. Blurring is a form of bandwidth reduction of the image caused by the imperfect image formation process such as relative motion between the camera and the original scene or by an optical system that is out of focus [4]. When aerial photographs are produced for remote sensing purposes, blurs are introduced by atmospheric turbulence, aberrations in the optical system and relative motion between camera and ground. In addition to these blurring effects, the recorded image is corrupted by noises too. A noise is introduced in the transmission medium due to a noisy channel, errors during the measurement process and during quantization of the data for digital storage. Each element in the imaging chain such as lenses, film, digitizer, etc. contribute to the degradation. Image denoising is often used in the field of photography or publishing where an image was somehow degraded but needs to be improved before it can be printed. For this type of application we need to know something about the degradation process in order to develop a model for it. When we have a model for the degradation process, the inverse process can be applied to the image to restore it back to the original form. This type of image restoration is often used in space exploration to help eliminate artifacts generated by mechanical jitter in a spacecraft or to compensate for distortion in the optical system of a telescope. Image denoising finds applications in fields such as astronomy where the resolution limitations are severe, in medical imaging where the physical requirements for high quality imaging are needed for analyzing images of unique events, and in forensic science where potentially useful photographic evidence is sometimes of extremely bad quality [4].

2. Related Work:

David L. Donoho & Iain M. Johnstone (1995) [20], they attempt to recover a function of unknown smoothness from noisy sampled data. They introduce a procedure, SureShrink, that suppresses noise by thresholding the empirical wavelet coefficients. The thresholding is adaptive: A threshold level is assigned to each dyadic resolution level by the principle of minimizing the Stein unbiased estimate of risk (Sure) for threshold estimates. The computational effort of the overall procedure is order $N \cdot \log(N)$ as a function of the sample size N. SureShrink is smoothness adaptive: If the unknown function contains jumps, then the reconstruction (essentially) does also; if the unknown function has a smooth piece, then the reconstruction is (essentially) as smooth as the mother wavelet will allow. The procedure is in a sense optimally smoothness adaptive: It is near minimax simultaneously over a whole interval of the Besov scale; the size of this interval depends on the choice of mother wavelet. We know from a previous work by the authors that traditional smoothing methods—kernels, splines, and orthogonal series estimates—even with optimal choices of the smoothing parameter, would be unable to perform in a near-minimax way over many spaces in the Besov scale. Examples of SureShrink are given. The advantages of the method are particularly evident when the underlying function has jump discontinuities on a smooth background.

M. K. Mihcak et. al. (1996) [19], they introduce a simple spatially adaptive statistical model for wavelet image coefficients and apply it to image denoising. their model was inspired by a recent wavelet image compression algorithm, the Estimation Quantization coder. They model wavelet image coefficients as zeromean Gaussian random variables with high local correlation. We assume a marginal prior distribution on wavelet coefficients variances and estimate them using an approximate Maximum A Posteriori Probability rule. Then they apply an approximate Minimum Mean Squared Error estimation procedure to restore the noisy wavelet image coefficients. Despite the simplicity of our method, both in its concept and implementation, our denoising results are among the best reported in the literature.
In this work, they confined ourselves to square–shaped neighborhoods with fixed size, for simplicity. In general, it would be desirable to automatically select both the size and the shape of the neighborhood region. But clearly, this would introduce additional difficulties. The selection of the window size suggests a trade-off which has been discussed in detail. The flexibility of our proposed method lends itself to the usage of different shaped neighborhoods for each coefficient. This could be implemented by using edge- and shape-adapted windows. Such an adaptation is likely to further improve denoising performance.

The method of wavelet thresholding for removing noise, or denoising, has been researched by **S. Grace Chang et. al. (2000) [18],** extensively due to its effectiveness and simplicity. Much of the literature has focused on developing the best uniform threshold or best basis selection. However, not much has been done to make the threshold values adaptive to the spatially changing statistics of images. Such adaptivity can improve the wavelet thresholding performance because it allows additional local information of the image (such as the identification of smooth or edge regions) to be incorporated into the algorithm. This work proposes a spatially adaptive wavelet thresholding method based on context modeling, a common technique used in image compression to adapt the coder to changing image characteristics. Each wavelet coefficient is modeled as a random variable of a generalized Gaussian distribution with an unknown parameter. Context modeling is used to estimate the
parameter for each coefficient, which is then used to adapt the thresholding strategy. This spatially adaptive thresholding is extended to the overcomplete wavelet expansion, which yields better results than the orthogonal transform. Experimental results show that spatially adaptive wavelet thresholding yields significantly superior image quality and lower MSE than the best uniform thresholding with the original image assumed known.
They have proposed a simple and effective spatially and scale-wise adaptive method for denoising via wavelet thresholding in an overcomplete expansion. The adaptivity is based on context-modeling which enables a pixel-wise estimation of the signal variance and thus of the best threshold. The issue of spatially adapting the threshold values has not been addressed in the literature. As we have shown in this work, adapting the threshold values to local signal energy allows us to keep much of the edge and texture details, while eliminating most of the noise in smooth regions, something that may be hard to achieve with a uniform threshold. The results show substantial improvement over the optimal uniform thresholding both in visual quality and mean squared error.

I. Prudyus et. al. (2001) [14], their work advocated a statistical approach to image denoising based on a maximum a posteriori (MAP) estimation in the wavelet domain. In this framework, a new class of independent identically distributed stochastic image priors is considered to obtain a simple and tractable solution in a closed analytical form. The proposed prior model is considered in the form of a student distribution. The experimental results demonstrate the high fidelity of this model for approximation of the sub-band distributions of wavelet coefficients. The obtained solution is presented in the form of well-studied shrinkage functions.

This work proposed by **L. Kaur et. al. (2002) [7],** an adaptive threshold estimation method for image denoising in the wavelet domain based on the generalized Guassian distribution (GGD) modeling of subband coefficients. The proposed method called NormalShrink is computationally more efficient and adaptive because the parameters required for estimating the threshold depend on subband data. The threshold is computed by $\beta\sigma^2/\sigma y$ where σ and y σ are the standard deviation of the noise and the subband data of noisy image respectively. β is the scale parameter, which depends upon the subband size and number of decompositions. Experimental results on several test images are compared with various denoising techniques like Wiener Filtering, BayesShrink and SureShrink. To benchmark against the best possible performance of a threshold estimate, the comparison also include Oracleshrink. Experimental
results show that the proposed threshold removes noise significantly and remains within 4% of OracleShrink and outperforms SureShrink, BayesShrink and Wiener filtering most of the time.
In this work, a simple and subband adaptive threshold is proposed to address the issue of image recovery from its noisy counterpart. It is based on the generalized Guassian distribution modeling of subband coefficients. The image denoising algorithm uses soft thresholding to provide smoothness and better edge preservation at the same time. Experiments are conducted to assess the performance of NormalShrink in comparison with the OracleShrink, SureShrink, BayesShrink, OracleThresh and Wiener. The results show that
NormalShrink removes noise significantly and remains within 4% of OracleShrink and outperforms SureShrink, BayesShrink and Wiener filtering most of the time. Moreover NormalShrink is 4% faster than BayesShrink. It is further suggested that the proposed threshold may be extended to the compression framework, which may further improve the denoising performance.

Levent S¸endur and Ivan W. Selesnick, (2002) [8], according to them the performance of image-denoising algorithms using wavelet transforms can be improved significantly by taking into account the statistical dependencies among wavelet coefficients as demonstrated by several algorithms presented in the literature. In two earlier works by the authors, a simple bivariate shrinkage rule is

described using a coefficient and its parent. The performance can also be improved using simple models by estimating model parameters in a local neighborhood. This letter presents a locally adaptive denoising algorithm using the bivariate shrinkage function. The algorithm is illustrated using both the orthogonal and dual tree complex wavelet transforms. Some comparisons with the best available results will be given in order to illustrate the effectiveness of the proposed algorithm.
This letter presents an effective and low-complexity image denoising algorithm using the joint statistics of the wavelet coefficients of natural images. We presented our result for both orthogonal and dual-tree CWTs and compared it with the other published results in order to illustrate the effectiveness of the proposed algorithm. The comparison suggests the new denoising results are competitive with the best wavelet-based results reported in the literature.

Recently, the dual-tree complex wavelet transform has been proposed by **Alin Achim et. al. (2005) [15],** as a novel analysis tool featuring near shift-invariance and improved directional selectivity compared to the standard wavelet transform. Within this framework, we describe a novel technique for removing noise from digital images. We design a bivariate maximum a posteriori estimator, which relies on the family of isotropic -stable distributions. Using this relatively new statistical model we are able to better capture the heavy-tailed nature of the data as well as the interscale dependencies of wavelet coefficients. We test our algorithm for the Cauchy case, in comparison with several recently published methods. The simulation results show that our proposed technique achieves state-of-the-art performance in terms of root mean squared error.
They proposed an effective wavelet-domain MAP processor that makes use of bivariate -stable distributions to account for the interscale dependencies of natural image subbands. We tested our algorithm for the Cauchy case and we compared it with several other results reported in the recent literature. We conclude that our proposed method achieves state-of-the-art performance, being competitive with the best wavelet-based denoising systems. We are currently exploring several ways to extend the work presented in this letter. An interesting direction is the further improvement of the statistical image model, by considering the case of general bivariate -stable distributions. The implementation of the method employing isotropic stable densities, with $0< \alpha \leq 2$ in general, is straightforward, provided that we are equipped with an efficient program for computing bivariate S α S densities. Instead, considering general -stable densities would be a much more challenging task, presupposing accurate estimation of the spectral measure from noisy observations. Finally, capturing intrascale dependencies of wavelet coefficients by means of -stable Markov random fields promises to significantly improve the overall performance of a denoising scheme.

Aleksandra Pizurica and Wilfried Philips (2006) [9], they develop three novel wavelet domain denoising methods for subband-adaptive, spatially-adaptive and multivalued image denoising. The core of our approach is the estimation of the probability that a given coefficient contains a significant noise-free component, which we call "signal of interest." In this respect, we analyze cases where the probability of signal presence is 1) fixed per subband, 2) conditioned on a local spatial context, and 3) conditioned on information from multiple image bands. All the probabilities are estimated assuming a generalized Laplacian prior for noise-free subband data and additive white Gaussian noise. The results demonstrate that the new subband-adaptive shrinkage function outperforms Bayesian thresholding approaches in terms of mean-squared error. The spatially adaptive version of the proposed method yields better results than the existing spatially adaptive ones of similar and higher complexity. The performance on color and on multispectral images is superior with respect to recent multiband wavelet thresholding.
They developed a new wavelet domain denoising method based on the probability that a given coefficient represents a significant noise-free component, which we call "signal of interest." First, we developed a novel sub band adaptive wavelet shrinkage function. Experiments on natural images yielded a better MSE performance than Bayesian soft-thresholding with the MSE optimum threshold. The proposed spatially adaptive denoising method yields superior results as compared to some much more complex recent approaches based on HMT and MRF models. These results motivate strongly a further development of the presented concept. Also, improvements are expected by implementing the proposed method with a transform of a better orientation selectivity, like complex wavelets, steerable pyramids, or curvelets. We also demonstrated that the proposed method can be easily extended to deal with multivalued images simply by defining the local spatial activity indicator as a function of the coefficients from multiple image bands. Our initial experiments on color and on multispectral Landsat images already showed a significant improvement over MBT.

This work introduced by **Florian Luisier et. al. (2007) [13],** a new approach to orthonormal wavelet image denoising. Instead of postulating a statistical model for the wavelet coefficients, we directly parametrize the denoising process as a sum of elementary nonlinear processes with unknown weights. We then minimize an estimate of the mean square error between the clean image and the denoised one. The key point is that we have at our disposal a very accurate, statistically unbiased, MSE estimate—Stein's unbiased risk estimate—that depends on the noisy image alone, not on the clean one. Like the MSE, this estimate is quadratic in the unknown weights, and its minimization amounts to solving a linear system of equations. The existence of this a priori estimate makes it unnecessary to devise a specific statistical model for the wavelet coefficients. Instead, and contrary to the custom in the literature, these coefficients are not considered random anymore. We describe an interscale orthonormal wavelet thresholding algorithm based on this new approach and show its near-optimal performance—both regarding quality and CPU requirement—by comparing it with the results of three state-of-the-art nonredundant denoising algorithms on a large set of test images. An interesting fallout of this study is the development of a new, group-delay-based, parent–child prediction in a wavelet dyadic tree.
They have presented a new approach to orthonormal wavelet image denoising that does not need any prior statistical modelization of the wavelet coefficients. This approach is made possible thanks to the existence of an efficient estimate of the MSE between noisy and clean image—the SURE—that is based on the noisy data alone. Its minimization over a set of denoising processes automatically provides a near-optimal solution in the sense of the a posteriori MSE. For efficiency reasons, we have chosen this set to be a linear span of basic nonlinear mappings. Using this approach, we have designed an image denoising algorithm that takes into account interscale dependencies, but discards intrascale correlations. In order to compensate for features misalignment, we have developed a rigorous procedure based on the relative group delay between the scaling and wavelet filters— group delay compensation. The

information brought by this new interscale predictor is used to classify smoothly between high- and low-SNR wavelet coefficients. The comparison of the denoising results obtained with our algorithm, and with the best state-of-the-art nonredundant techniques (that integrate both inter- and intrascale dependencies), demonstrate the efficiency of our SURE-based approach which gave the best output PSNRs for most of the images. The visual quality of our denoised images is moreover characterized by fewer artifacts than the other methods. We are currently working on an efficient integration of the intrascale correlations within the SURE-based approach. Our goal is to show that the consideration of inter- and intrascale dependencies brings denoising gains that rival the quality of the best redundant techniques such as BLS-GSM.

This work presentd by **Hossein Rabbani (2009)** [17] a new image denoising algorithm based on the modeling of coefficients in each subband of steerable pyramid employing a Laplacian probability density function (pdf) with local variance. This pdf is able to model the heavy-tailed nature of steerable pyramid coefficients and the empirically observed correlation between the coefficient amplitudes. Within this framework, we describe a novel method for image denoising based on designing both maximum a posteriori (MAP) and minimum mean squared error (MMSE) estimators, which relies on the zero-mean Laplacian random variables with high local correlation. Despite the simplicity of our spatially adaptive denoising method, both in its concern and implementation, our denoising results achieves better performance than several published methods such as Bayes least squared Gaussian scale mixture (BLS-GSM) technique that is a state-of-the-art denoising technique.

A new method based on the curvelet transform is proposed by **Qiang Guo et. al. (2010)**, [11] for image denoising. This method exploits a multivariate generalized spherically contoured exponential (GSCE) probability density function to model neighboring curvelet coefficients. Based on the multivariate probability model, which takes account of the dependency between the estimated curvelet coefficients and their neighbors, a multivariate shrinkage function for image denoising is derived by maximum a posteriori (MAP) estimator. Experimental results show that the proposed method obtains better performance than the existing curvelet-based image denoising method.

3. Conclusion:

In this work several journal articles are reviewed for observing the various techniques utilized for the field of image denoising. It has been analyzed that noise estimation is mostly performed by Laplacian probability density, maximum a posteriori (MAP) estimation or Bayesian probability etc related detection methods. Some of the literatures also used wavelet transform for detecting noisy components for achieving enhanced performance. It has been found that these literatures lacks the application of feature extraction approach like PCA, LCA, ICA etc. Recently all the prediction and pattern recognition methods are utilizing these approach very frequently and getting assured results. So we incorporated an advanced method of denoising images using PCA in hybrid with wavelet filtering can help out to get high quality of results in image denoising.

References:

[1] Z. Cai, T. H. Cheng, C. Lu, and K. R. Subramanian, “Efficient waveletbased image denoising algorithm,” Electron. Lett., vol. 37, no. 11, pp. 683–685, May 2001.
[2] S. Chang, B. Yu, and M. Vetterli, “Adaptive wavelet thresholding for image denoising and compression,” IEEE Trans. Image Processing, vol. 9, pp. 1532–1546, Sept. 2000.
[3] Castleman Kenneth R, Digital Image Processing, Prentice Hall, New Jersey, 1979.
[4] Reginald L. Lagendijk, Jan Biemond, Iterative Identification and Restoration of Images, Kulwer Academic, Boston, 1991.
[5] M. S. Crouse, R. D. Nowak, and R. G. Baraniuk, “Wavelet-based signal processing using hidden Markov models,” IEEE Trans. Signal Processing, vol. 46, pp. 886–902, Apr. 1998.
[6] D. L. Donoho and I. M. Johnstone, “Ideal spatial adaptation by wavelet shrinkage,” Biometrika, vol. 81, no. 3, pp. 425–455, 1994.
[7] L. Kaur, S. Gupta, and R. C. Chauhan, “Image denoising using wavelet thresholding,” Proc. Int. Conf. Computer Vision, Graphics and Image Process., pp. 1-4, 2002.
[8] L. Sendur and I. W. Selesnick, “Bivariate shrinkage with local variance estimation,” IEEE Signal Process. Lett., vol. 9, pp. 438-441, 2002.
[9] 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 Process., vol. 15, pp. 654-665, 2006.
[10] M. K. Mihcak, I.Kozintsev, K. Ramchandran, and P. Moulin, “Low-complexity image denoising based on statistical modeling of wavelet coefficients,” IEEE Signal Processing Lett., vol. 6, pp. 300–303, Dec. 1999.
[11] Q. Guo and S. Yu, “Image denoising using a multivariate shrinkage function in the curvelet domain,” IEICE Electron. Express, vol. 7, pp. 126-131, 2010.
[12] L. Sendur and I. W. Selesnick, “A bivariate shrinkage function for wavelet based denoising,” in IEEE ICASSP, 2002.
[13] F. Luisier, T. Blu, and M. Unser, “A new SURE approach to image denoising: Interscale orthonormal wavelet thresholding,” IEEE Trans. Image Process., vol. 16, pp. 593-606, 2007.
[14] I. Prudyus, S. Voloshynovskiy, and A. Synyavskyy, “Wavelet-based MAP image denoising using provably better class of stochastic i.i.d. image models,” Proc. Int. Conf. Telecommun., Modern Satellite, Cable and Broadcasting Service, pp. 583-586, 2001.
[15] A. Achim and E. E. Kuruoglu, “Image denoising using bivariate α-stable distributions in the complex wavelet domain,” IEEE Signal Process. Lett., vol. 12, pp. 17-20, 2005.
[16] T. Cai and B.W. Silverman, “Incorporating information on neighboring coefficients into wavelet estimation,” Sankhya, vol. 63, pp. 127–148, 2001.
[17] H. Rabbani, “Image denoising in steerable pyramid domain based on a local Laplace prior,” Pattern Recognition, vol. 42, pp. 2181-2193, 2009.

[18] S. G. Chang, B. Yu, and M. Vetterli, "Spatially adaptive wavelet thresholding with context modeling for image denoising," IEEE Trans. Image Process., vol. 9, pp. 1522-1531, 2000.
[19] M. K. Mihcak, I. Kozintsev, K. Ramchandran, and P. Moulin, "Low-complexity image denoising based on statistical modeling of wavelet coefficients," IEEE Signal Process. Lett., vol. 6, pp. 300-303, 1999.
[20] D. L. Donoho and I. M. Johnstone, "Adapting to unknown smoothness via wavelet shrinkage," J. Amer. Statist. Assoc., vol. 90, pp. 1200-1224, 1995.