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Locally Adaptive Probabilistic Wavelet Shrinkage Algorithms And Application To Colour Image Denoising

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Abstract:

The core of our approach is estimation of the probability that a given coefficient contains a significant noise-free component, which we call "signal of interest". We develop three novel wavelet domain denoising methods for subband-adaptive, spatially adaptive and multivalued image denoising. In this respect we analyze cases where the probability of signal presence is (i) fixed per sub band, (ii) conditioned on a local spatial context and (iii) conditioned on information from multiple image bands. All the probabilities are estimated assuming generalized Laplacian prior for noise-free subband data and additive white Gaussian noise. The results demonstrate that the new subband-adaptive shrinkage function outperforms in terms of mean squared error Bayesian thresholding approaches. Spatially adaptive version of the proposed method yields better results than the existing spatially adaptive ones of similar and of higher complexity. The performance on color and on multispectral images is superior with respect to recent multiband wavelet thresholding.

***Keywords**:Image denoising, wavelets, generalized likelihood ratio, color, multispectral images*

Introduction

In image denoising, where a trade-off between noise suppression and the preservation of actual image discontinuities must be made, solutions are sought which can "detect" important image details and accordingly adapt the degree of noise smoothing. In the wavelet transform domain [1], noise reduction results from shrinking the noisy coefficient magnitudes: ideally, the wavelet coefficients that contain primarily noise should be reduced to negligible values while ones containing a "significant" noise-free component should be reduced less. A common shrinkage approach is thresholding [2-7], where the coefficients with magnitudes below a certain threshold are treated as "non significant" and are set to zero, while the remaining, "significant" ones are kept unmodified (hard-thresholding) or reduced in magnitude (soft-thresholding). The main novelties and contributions of this project are: (1) A novel sub band-adaptive shrinkage function, which shrinks each coefficient according to probability that it presents a signal of interest. We show that for natural images this estimator outperforms in terms of MSE any classical soft-thresholding rule with a uniform threshold per sub band. (2) We develop a spatially adaptive version of the proposed method. The results demonstrate that the new method outperforms spatially adaptive thresholding with context modeling as well as MMSE approaches that employ much more complex HMTs and related methods based on MRFs. (3) We extend the proposed method for multivalued data. The results on color and on Multispectral images demonstrate a significant improvement with respect to recent multiband Wavelet thresholding approaches.

Subband Adaptive Bayesian Wavelet Shrinkage

We assume the input image is contaminated with additive white Gaussian noise of zero mean and variance σ2. An orthogonal wavelet transformation [3,4] of the noisy input yieldsan equivalent additive white noise model in each wavelet subband1

$y_i = \beta_i + \varepsilon_i, \quad i = 1, \ldots, n,$

Where β_i are noise-free wavelet coefficients, _i are independent identically distributed (i.i.d.) Normal random variables $\varepsilon_i \sim N(0, \sigma^2)$ and n is the number of coefficients in a subband. A widely used generalized Laplacian (also called generalized Gaussian) prior for the noise-free sub band data [14] is

$f(\beta) = \lambda\nu/2\Gamma(1/\nu)\exp(-\lambda|\beta|^\nu),$

∞

Where $\Gamma(x) = \int_0 t^{x-1}e^{-t}dt$ is theGammafunction, $\lambda > 0$ is the scale parameter and ν is the shape parameter, which is for natural images typically $\nu \in [0, 1]$.Let us define a "signal of interest" as a noise-free coefficient component that exceeds a specific threshold T and formulate the following two hypotheses: H0: "signal of interest is absent" and H1: "signal of interest is present" (in a given **coefficient) precisely as:**

H0: $|\beta| \leq T$ and H1 : $|\beta| > T$

We consider a simple estimator where each wavelet coefficient is multiplied with the probability that it contains a signal of interest, given its observed value

$\beta = P(H1|y)\, y = [\mu\eta/(1 + \mu\eta)]\, y,$

Where $\mu = P(H1)/P(H0)$ and $\eta = f(y|H1)/f(y|H0)$ and the product $\mu\eta$ is called generalized likelihood **ratio [5]. In the remainder, we call the above shrinkage rule ProbShrink[12]. The ProbShrink rule outperforms BayesShrink on all tested images. Since BayesShrink [9]is soft-thresholding with the MSE optimum threshold, we can deduce that ProbShrink (at least on the tested images) outperforms soft thresholding with any threshold that is constant per sub band. We believe that this is an important argument in favor of the new shrinkage rule, especially because it is of similar complexity to Bayesian thresholding.**

Spatially Adaptive Ayesian Shrinkage

we adapt the estimator to the local spatial context in the image using a local spatial activity indicator (LSAI) zl for each spatial position l as follows:

$\beta l\,\hat{} = P(H1|yl, zl)yl = [\eta l\xi l\mu/\{1 + \eta l\xi l\mu\}]yl,$ (11)

Where $\eta l = f(yl|H1)/f(yl|H0)$,

$\xi l = f(zl|H1)/f(zl|H0)$ and $\mu = P(H1)/P(H0)$.

The characteristic parts of the method are illustrated in Fig. 1, where the generalized likelihoodratio denotes the product $\eta l\xi l\mu$. **The proposed method has a nice heuristic explanation: each coefficient is** shrunk according to how probable it is that it presents useful information, based on its value (via ηl), based on a measurement from the local surrounding (via ξl) and based on the **global statistical** properties of the coefficients in a given subband (via μ).

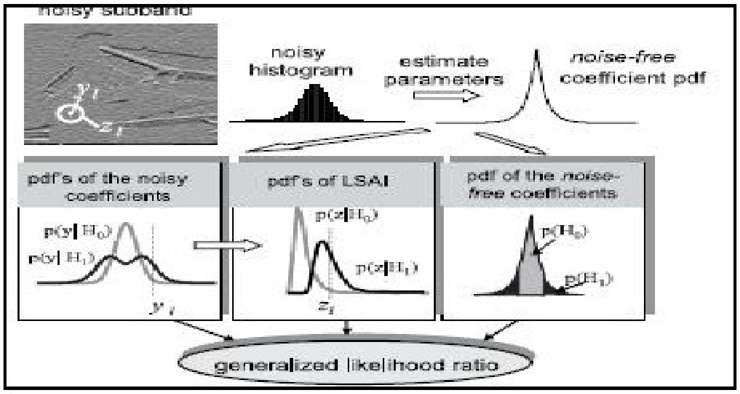

Figure1: An Illustration Of The Proposed Denoising Method, Where Pdf Denotes The Probability Density Function And Where Lsai Denotes The Local Spatial Activity Indicator

We do not need any binary masks here, nor empirical density estimation or fitting procedures. All the required probabilities and probability density functions are now expressed analytically, starting from the generalized Laplacian prior. We define LSAI as the locally averaged magnitude of the coefficients in a relatively small square window δ (l) of a fixed size N, within the same subband:

$z_l = 1/N \sum \omega k$

$K \in \delta(l)$

Where ω_l denotes the coefficient magnitude $\omega l = |y_l|$. For practical reasons, we simplify the statistical characterization of z_l considerably assuming that all the coefficients within the small window are equally distributed and conditionally independent (given H_0 or H_1). The resulting spatially adaptive estimator yields a significant improvement with respect

to the sub band-adaptive estimator

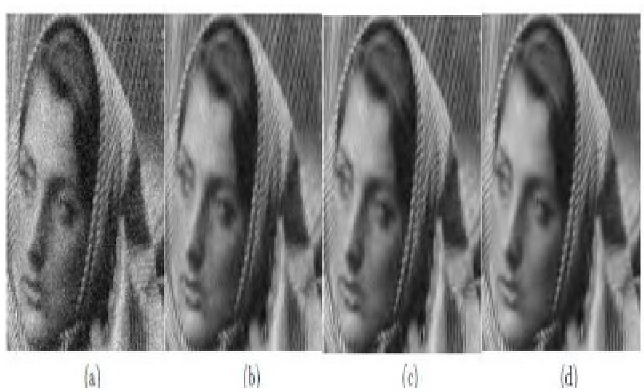

Figure2: Visual Performance Of Different Versions Of The Proposed Probshrink Method

Noisy *Barbara* image, $\sigma = 20$, PSNR=22.09dB.

Subband adaptive shrinkage in the orthogonal transform, PSNR=27.54dB.

Spatially adaptive shrinkage in the orthogonal transform PSNR=28.4dB.

Spatially adaptive shrinkage in the non-decimated transform PSNR=29.53dB.

Extensions To Multivalued Data

The proposed denoising approach leads to efficient low-complexity noise filters for *multivalue* data like color images, multispectral and hyper spectral data or multimodal magnetic resonance images. In all these cases different image bands are correlated: an image discontinuity from one band is likely to occur in at least some of the remaining bands. The simplest approach to extend our method for multivalued images is to include the interband correlation in the definition of the local spatial activity indicator. Let $\omega^i_{l,s}$ denote the noisy coefficient magnitude in the image band i, wavelet sub band s and spatial position l. A possible multiband extension of the LSAI is:

$$Z^b_{l,s} = 1/NB \sum_{i=1}^{B} \sum_{k \in \delta(l)} \omega^i_{k,s}$$

Where B is the number of image bands. With this definition of the LSAI the probability of signal presence is conditioned on the spatial context as well as on information from other image bands. Based on experiments with standard color and with high-resolution multispectral *Land sat* images, we found that best results are obtained when the neighborhood $\delta(l)$ is reduced to a single pixel, i.e., when LSAI includes only the coefficients at the same spatial position from different image bands:

$$Z^b_{l,s} = 1/B \sum_{i=1}^{B} \omega^i_{l,s}$$

Its conditional densities are estimated by convolving the corresponding densities of the coefficient magnitudes.

Experimental Results

In the proposed method, the parameters λ and ν of the generalized Laplacian prior for noise-**free data are estimated from the noisy histogram in each subband, like in [7, 14]. The results in this project were** obtained assuming that the noise standard deviation σ was known (as it is usual for **reporting the results**

in case of artificially added noise). In practice the noise standard deviation is usually not known in advance, but its reliable estimate can be obtained as the median absolute deviation of the coefficients in the highest frequency subband divided by 0.6745.

Figure3: Parts Of The Noise-Free, Noisy (Σ=25, PSNR=20.17db) And The Denoised (PSNR=30.73db) Image.

Conclusion

We developed a new wavelet domain denoising method based on probability that a given coefficient represents a significant noise-free component, which we call "signal of interest". First we developed a novel subband-adaptive wavelet shrinkage function, which on natural images yields 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 further development of the presented concept. 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 multiband wavelet thresholding.

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