

Abstract

We propose here a new pointwise wavelet thresholding function that incorporates inter-scale dependencies. This non-linear function depends on a set of four linear parameters per subband which are set by minimizing Stein's unbiased MSE estimate (SURE). Our approach assumes additive Gaussian white noise.

In order for the inter-scale dependencies to be faithfully taken into account, we also develop a rigorous feature alignment processing, that is adapted to arbitrary wavelet filters (e.g. non-symmetric filters).

Finally, we demonstrate the efficiency of our denoising approach in simulations over a wide range of noise levels for a representative set of standard images.

Noisy signal model

- In the image domain:** $\mathbf{g} = \mathbf{f} + \mathbf{w}$, $w_n \sim \mathcal{N}(0, \sigma^2)$
 - \mathbf{f} : unknown noise-free image
 - \mathbf{g} : observed noisy image
 - \mathbf{w} : additive Gaussian white noise
 - σ^2 : noise variance (assumed to be known)
- After an orthonormal wavelet transform (OWT):** $\mathbf{y} = \mathbf{x} + \mathbf{b}$, $b_n \sim \mathcal{N}(0, \sigma^2)$
 - \mathbf{x} : noise-free wavelet coefficients
 - \mathbf{y} : noisy wavelet coefficients
 - \mathbf{b} : wavelet coefficients of the additive Gaussian white noise
- Consequence:** mean square error (MSE) preservation \Rightarrow independent processing of the wavelet subbands

SURE-based wavelet thresholding

- New linearly parameterized thresholding function which integrates the parent Y :**

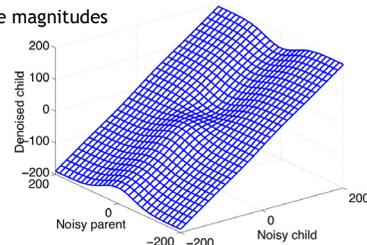
- Required properties:

- Differentiable
- Anti-symmetric
- Linear for extreme magnitudes

$$\theta_0(y; \mathbf{u}) = (u_1 + u_2 e^{-\frac{y^2}{12\sigma^2}})y$$

$$\theta(y, Y; \mathbf{u}, \mathbf{v}) = e^{-\frac{y^2}{12\sigma^2}} \theta_0(y; \mathbf{u}) + (1 - e^{-\frac{y^2}{12\sigma^2}}) \theta_0(y; \mathbf{v})$$

Low-SNR coefficients High-SNR coefficients



- SURE-based parameters optimization:**

- Stein's unbiased MSE estimate (SURE):

Theorem: Given noisy $y_n = x_n + b_n$, with original unknown x_n and noise $b_n \sim \mathcal{N}(0, \sigma^2)$, the following random variable:

$$\varepsilon = \frac{1}{N} \sum_{n=1}^N \left(\theta^2(y_n, Y_n; \mathbf{u}, \mathbf{v}) - 2y_n \theta(y_n, Y_n; \mathbf{u}, \mathbf{v}) + 2\sigma^2 \frac{\partial \theta}{\partial y_n}(y_n, Y_n; \mathbf{u}, \mathbf{v}) + y_n^2 - N\sigma^2 \right)$$

is an unbiased estimate of the MSE, i.e. $\mathcal{E}\{\varepsilon\} = \mathcal{E}\left\{ \frac{1}{N} \sum_{n=1}^N \left| \theta(y_n, Y_n; \mathbf{u}, \mathbf{v}) - x_n \right|^2 \right\} = \mathcal{E}\{\text{MSE}\}$

- Thanks to the linear parameterization and the quadratic form of ε in (\mathbf{u}, \mathbf{v}) :

SURE minimization \Leftrightarrow resolution of a **linear system of equations**

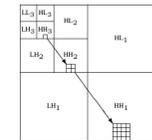
Aim: given $\theta(y, Y; \mathbf{p}) = \sum_{k=1}^4 p_k f_k(y, Y)$, find the parameters $\mathbf{p} = \begin{bmatrix} \mathbf{u} \\ \mathbf{v} \end{bmatrix}$ which will minimize the MSE estimate ε :

$$\frac{\partial \varepsilon}{\partial p_k} = 0, \forall k \in [1; 4] \Leftrightarrow \mathbf{p} = \mathbf{M}^{-1} \mathbf{c}$$

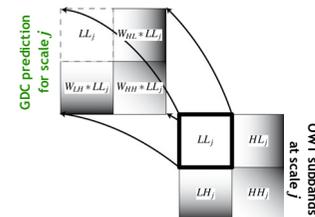
where: $m_{k,l} = \frac{1}{N} \sum_{n=1}^N f_k(y_n, Y_n) f_l(y_n, Y_n)$ and $c_k = \frac{1}{N} \sum_{n=1}^N (y_n f_k(y_n, Y_n) - \sigma^2 f'_k(y_n, Y_n))$

Inter-scale dependencies in the OWT

- Paradigm:** a coefficient at the current scale (child) depends on the coefficient at the next coarser scale (parent).
- Usual approach:** expansion of the parent subband by a factor of 2.
 - Limits:**
 - features misalignment
 - only the adjacent scale is taken into account
- New approach:** construction of an inter-scale predictor Y out of the lowpass subband of the current scale



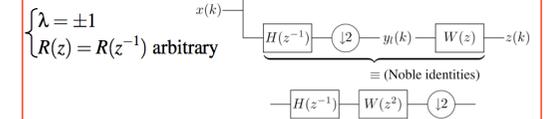
- Group delay compensation (GDC) with filter $W(z)$



Theorem: In order for the output of a dyadic filterbank to be aligned, it is necessary and sufficient that:

$$W(z^2) = G(z^{-1})G(-z^{-1})(1 + \lambda z^{-2})R(z^2)$$

where:



Required properties for W :

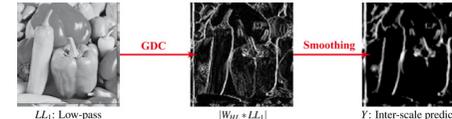
- Energy preservation
- Highpass behavior
- Shortest possible impulse response

Simple solution for symmetric filters:

$$W(z) = 1 - z$$

- Homogenization by 2D-smoothing of the magnitude

Overview of the whole procedure which leads to the inter-scale predictor Y :

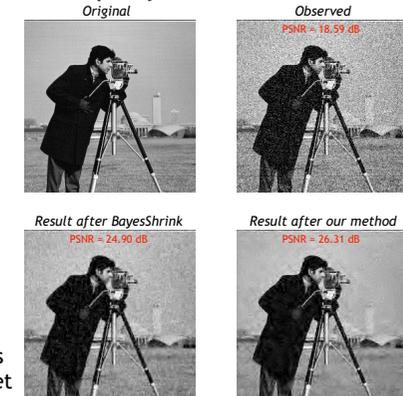


Results and conclusions

- PSNR comparison after 5 iterations of an OWT (sym8):**

σ	5	10	20	30	50	100	5	10	20	30	50	100
Input PSNR	34.15	28.13	22.11	18.59	14.15	8.13	34.15	28.13	22.11	18.59	14.15	8.13
Method	Poppers 256 x 256						House 256 x 256					
BayesShrink	35.83	31.49	27.85	25.73	23.17	20.73	36.91	32.92	29.42	27.66	25.49	22.87
BiShrink 7 x 7	36.61	32.55	28.66	26.51	23.89	20.80	37.54	33.60	30.16	28.20	25.83	22.84
BL-S-GSM 3 x 3	36.80	32.86	29.07	26.97	24.40	20.88	38.01	34.26	30.79	28.72	26.15	22.97
Our method	37.17	33.18	29.33	27.13	24.43	21.32	37.88	34.29	30.93	28.98	26.58	23.51
Method	Lens 512 x 512						Goldhill 512 x 512					
BayesShrink	37.01	33.44	30.24	28.54	26.50	23.91	35.93	31.94	28.69	27.13	25.41	23.32
BiShrink 7 x 7	37.56	34.23	31.00	29.15	26.87	23.91	36.17	32.27	29.07	27.44	25.57	23.26
BL-S-GSM 3 x 3	37.84	34.59	31.32	29.41	27.07	24.06	36.37	32.61	29.41	27.73	25.73	23.30
Our method	37.96	34.55	31.34	29.51	27.29	24.47	36.53	32.69	29.52	27.89	26.06	23.82

- Visual quality:**



- Computation time:**

- 0.6s for 256x256 images!
 - 2.7s for 512x512 images!
- 4 times faster than the best state-of-the-art with OWT!

- Conclusions:**

- New approach to image denoising with OWT without prior statistical modelization of the noise-free wavelet coefficients
- Fast, robust and competitive SURE-based inter-scale wavelet thresholding algorithm