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Automated Filter Parameter Selection using Measures of Noiseness

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ABSTRACT: *Despite the vast body of literature on image denoising, relatively little work has been done in the area of automatically choosing the filter parameters that yield optimal filter performance. The choice of these parameters is crucial for the performance of any filter. In the literature, some independence-based criteria have been proposed, which measure the degree of independence between the denoised image and the residual image (defined as the difference between the noisy image and the denoised one). We contribute to these criteria and point out an important deficiency inherent in all of them. We also propose a new criterion which quantifies the inherent 'noiseness' of the residual image without referring to the denoised image, starting with the assumption of an additive and i.i.d. noise model, with a loose lower bound on the noise variance. Several empirical results are demonstrated on two well-known algorithms: NL-means and total variation, on a database of 13 images at six different noise levels, and for three types of noise distributions.*

1. Problem Definition & Motivation

- Research on image filtering has been extensive: PDEs (Perona and Malik, TPAMI '90), spatially varying regressions (Milanfar et al, TIP '07) and convolutions (Subakan and Vemuri, ICCV '07), learning based methods like KSVD etc (Elad et al, CVPR '06) etc.
- All filtering methods require tuning of critical parameters, especially the smoothing parameter.
- Existing methods select parameters that minimize MSE (mean-squared error) between denoised and true (clean) image.
- **Our aim: Propose a criterion for automated filter parameter selection that does not require knowledge of true image, and uses minimal assumptions.**

2. Independence-based Measures

- Let noisy image = I, denoised image = D, residual image = R = I-D.
- Independence-based measures assume that for optimal filtering, residual is independent of the denoised image.
- Example: **Correlation Coeffcient** (Weickert, '98 + Mrazek et al, IJCV '01)

$$CC(R,D) = \frac{Cov(R,D)}{\sqrt{\text{var}(R)\cdot\text{var}(D)}}$$

- For PDEs, local minimum of CC is seen to be very close to optimal filter parameter value given by MSE (Mrazek et al, IJCV '01).
- But CC ignores higher order statistics.
- We propose: **Mutual information (MI)** between R and D

$$MI(R,D) = H(R) + H(D) - H(R,D)$$
$$H(X) = \text{entropy of } X$$

- Takes **higher order statistics** into account, produces better results than CC.
- But CC and MI (and all independence-based measures) give false global minima for **extreme oversmoothing** (denoised image is a constant signal) and **extreme undersmoothing** (residual image has value zero at each pixel).

3. Proposed Criteria

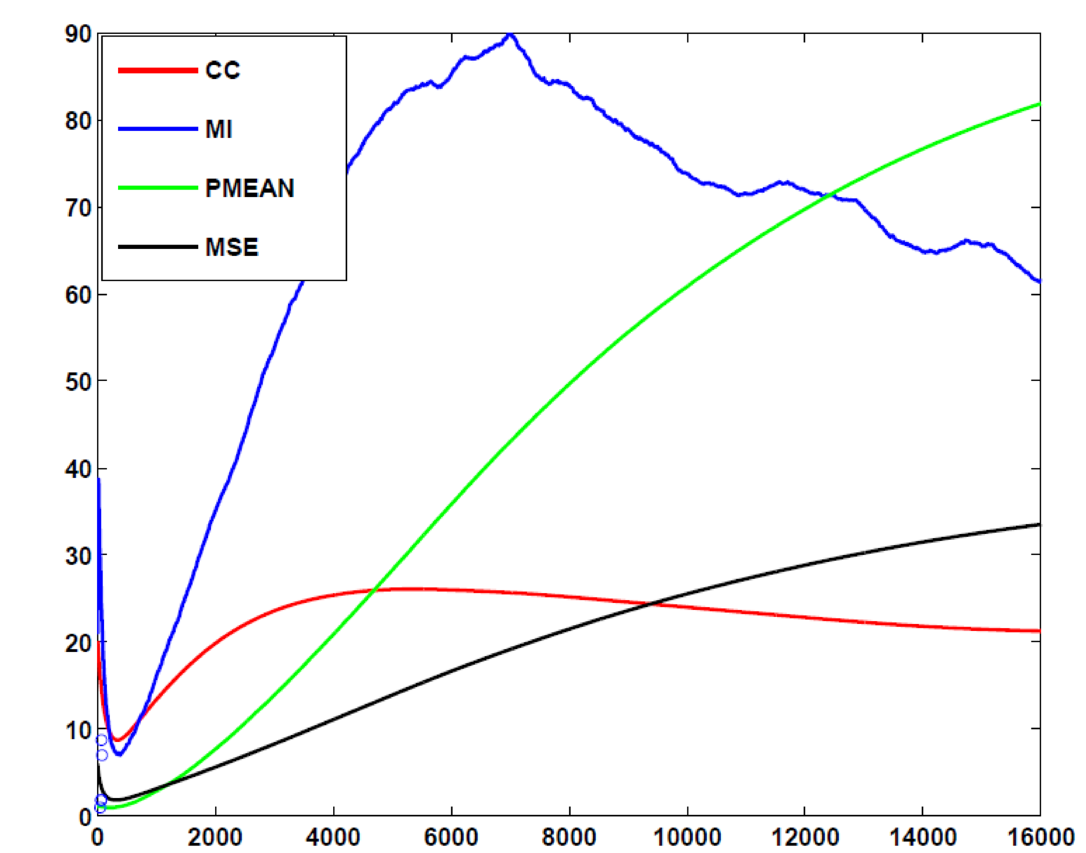
- Assume noise is i.i.d. and signal independent.
- For ideal filtering, residual should obey characteristics of noise, i.e. it should be identically distributed.
- To check this, perform two-sample KS test between non-overlapping patch pairs from residual image:

$$\text{K}_{ij} = \sup_x |\text{F}_i(x) - \text{F}_j(x)|$$
$$\text{F}_i(\cdot) = \textit{empirical CDF from } i^{th} \textit{ patch}$$
$$\text{P}_{ij} = \Pr(\text{K} \leq \text{K}_{ij}) \; \textit{(called p-value)}$$
$$\textit{where } \text{K} = \textit{test statistic}$$
$$\text{Km} = \textit{mean } \text{K}_{ij}, \; \text{Pm} = \textit{mean } \text{P}_{ij}.$$

- The lower the values of *Km* (or *Pm*), the "noisier" the residual (and hence more optimal the filtering).

4. Advantages of Proposed Criteria

- Just like independence-based measures, **do not require knowledge of noise distribution or noise variance** (unlike some contemporary methods: example by Gilboa, TIP '06).
- Unlike independence-based measures, **no false minima under extreme oversmoothing**.
- Prone to false minima under extreme undersmoothing, but this can be overcome by imposing very loose **lower bound** on noise variance.
- Better experimental results than MI/CC (see next section).



Plots of CC, MI, Pmean and MSE on an image treated with 16000 iterations of total variation denoising.

4. Experiments

NL Means:

- A state of the art algorithm proposed by Buades et al , CVPR '05.

$$J(x) = \frac{\sum_{y \in N(x)} w_x(y) I(y)}{\sum_{y \in N(x)} w_x(y)} \text{ where}$$
$$N(x) = \text{neighborhood around } x$$

$$w_x(y) = \exp\left(-\frac{\|q(x)-q(y)\|^2}{\sigma}\right)$$
$$\text{where } q(x) = \text{patch around pixel } x.$$

- Critical filter parameter is sigma.
- Experiments run on Lansel's benchmark database (13 images of size 256 x 256) on 6 noise levels (from 0.0001 to 0.05), and 3 different noise distributions (Gaussian, negative exponential, bounded uniform).

Validation Methods:

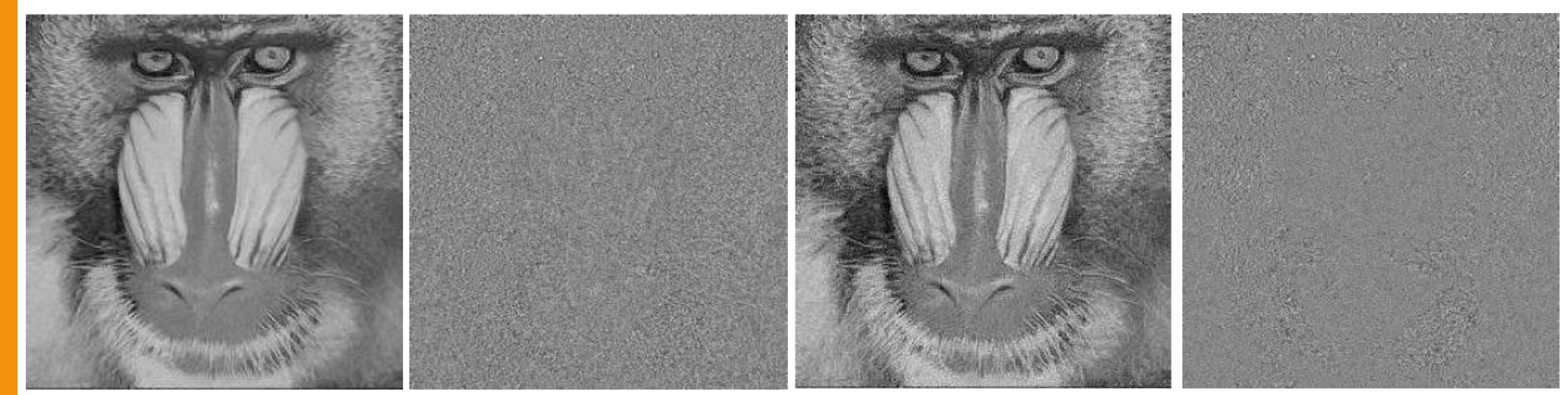
- Sigma parameter varied from 1 to 6400.
- For each sigma, following criteria are computed: CC, MI, Km, Pm. Optimal sigma for each criterion recorded.
- Computed optimal sigma values compared with those that optimized full-reference quality measures like L1 error between true and denoised image, Structured similarity index (SSIM)
- Assumed lower bound on noise variance: 10^(-8).

Table 3. (NLMeans)Gauss. noise $\sigma_n^2 = 0.001$.

-	Δ_{L1}	$d\sigma_{L1}$	Δ_{SSIM}	$d\sigma_{SSIM}$
h	0.041	9.231	0.004	16.154
P	**0.024**	**5.385**	0.005	16.923
K	0.035	7.692	**0.004**	14.615
CC	0.151	16.154	0.004	**12.308**
MI	0.126	19.231	0.008	18.462
η_1	0.126	19.231	0.008	18.462
η_2	0.157	26.923	0.013	29.231
Local MI	0.191	20.308	0.003	10.308
h_n	0.218	22.308	0.001	6.154
P_n	0.041	10	0.002	12.308
K_n	0.100	15.385	0.001	6.923
Min	3.069	-	0.879	-
Max	9.601	-	0.976	-

Table 4. (NLMeans)Gauss. noise $\sigma_n^2 = 0.005$.

-	Δ_{L1}	$d\sigma_{L1}$	Δ_{SSIM}	$d\sigma_{SSIM}$
h	**0.206**	**33.846**	**0.003**	**24.615**
P	0.207	33.846	0.003	24.615
K	0.488	43	0.005	33.769
CC	2.253	92.308	0.034	55.385
MI	2.677	79.538	0.054	67.231
η_1	2.720	81.077	0.054	68.769
η_2	2.119	105.231	0.053	105.231
Local MI	3.889	107.846	0.069	74
h_n	1.337	38	0.032	38
P_n	1.335	33.538	0.033	36.615
K_n	1.336	33.538	0.034	42.769
Min	4.838	-	0.791	-
Max	10.695	-	0.955	-



Denoised image and residual, using sigma as per optimal Pm (first and second from left), and as per optimal MI (third and fourth from left).