Generalized Signal-Dependent Noise Model and Parameter Estimation for Natural Images

Thanh Hai Thai, Florent Retraint and, Rémi Cogranne∗∗

ICD - LM2S - University of Technology of Troyes - UMR STMR CNRS
12, rue Marie Curie - CS 42060 - 10004 Troyes cedex - France

© 2013 Elsevier B.V. All rights reserved. Accepted version provided for non-commercial research and education use.
This article appeared in a journal published by Elsevier. The attached copy is furnished to the author for internal non-commercial research and education use, including for instruction at the authors institution and sharing with colleagues. Other uses, including reproduction and distribution, or selling or licensing copies, or posting to personal, institutional or third party websites are prohibited.

Abstract

The goal of this paper is to propose a generalized signal-dependent noise model that is more appropriate to describe a natural image acquired by a digital camera than the conventional Additive White Gaussian Noise model widely used in image processing. This non-linear noise model takes into account effects in the image acquisition pipeline of a digital camera. In this paper, an algorithm for estimation of noise model parameters from a single image is designed. Then the proposed noise model is applied with the Local Linear Minimum Mean Square Error filter to design an efficient image denoising method.

Keywords: Signal-Dependent Noise Model, Noise Measurement, Noise Parameter Estimation, Denoising.

1. Introduction

Noise has been studied for decades in computer vision, image processing and statistical signal processing because of its impact in various applications such as image denoising, image segmentation or edge detection. To improve performance in those applications, it is important to identify noise characteristics. Noise models proposed in the literature can be roughly divided into two groups: signal-independent and signal-dependent. A typical model for the group of signal-independent noise is the Additive White Gaussian Noise (AWGN) that is widely used in image processing. However, this signal-independent AWGN model is not relevant due to the dominant contribution of the Poisson noise corrupting a natural image acquired by imaging device [1, 2]. While signal-independent noise models assume the stationarity of noise in the whole natural image, regardless original pixel intensity, signal-dependent noise models take into account the proportional dependence of noise variance on the original pixel intensity. Signal-dependent noise models include Poisson noise or film-grain noise [3], Poisson-Gaussian noise [4, 5], heteroscedastic noise model [2, 6], and non-linear noise model [7, 8]. The signal-dependent noise model gives the noise variance as a function of pixel’s expectation. This function can be linear [4, 5, 2, 6] or non-linear [7, 8]. To identify noise characteristics or attenuate noise impact in many image processing applications, it is desirable to design an algorithm that estimates noise model parameters accurately.

Estimation of noise model parameters can be performed from a single image or multiple images. From a practical point of view, this paper mainly focuses on noise parameter estimation from a single image. Several methods have been proposed in the literature for estimation of signal-dependent noise parameters [2, 6, 7, 8]. They rely on similar basic steps but differ in details. The common methodology starts from obtaining local estimates of noise variance and image content, then performing the curve fitting to the scatter-plot based on the prior knowledge of noise model. The existing methods involve two main diffi-
RAW image can be modeled by considering noise sources that corrupt the image during its acquisition process [1, 2, 6]. Typically, the RAW image model consists of a Poissonian part that addresses the photon shot noise and dark current and a Gaussian part for the remaining stationary disturbances, e.g. read-out noise. For the sake of simplification, the Gaussian approximation of the Poisson distribution can be exploited because of a large number of incident photons, which leads the heteroscedastic noise model [6, 2]

\[ x_i \sim N(\mu_i, \sigma^2_i), \]

(1)

where \( x_i \) denotes a RAW pixel, \( i \in \{1, \ldots, N\} \) and \( N \) is the number of pixels. By convention, \( \mu_i \) and \( \sigma^2_i \) denote expectation and variance of a random variable \( X \) respectively. The index of color channel is omitted for simplicity. This model gives pixel’s variance \( \sigma^2_i \) as a linear function of pixel’s expectation \( \mu_i \). As discussed in [6, 2], the heteroscedastic noise model characterizes a RAW image more accurately than the conventional AWGN model widely used in image processing. The heteroscedastic noise model in a natural RAW image is illustrated in Figure 1.

In order to study noise statistics in a TIFF image, it is necessary to consider the effects of post-acquisition operations. In this paper, the demosaicing and white-balancing operations are assumed to be linear [10, 12]. Therefore, a short calculation shows that the white-balanced pixel still follows the Gaussian distribution and the relation between its expectation and variance remains linear

\[ y_i \sim N(\mu_i + \eta_i, \sigma^2_i), \]

(2)

where \( y_i \) denotes the white-balanced pixel and the parameters \((\tilde{a}, \tilde{b})\) differ from the parameters \((a, b)\) due to effects of demosaicing and white-balancing. The white-balanced pixel \( y_i \) can be equivalently rewritten as

\[ y_i = \mu_i + \eta_i \quad \text{with} \quad \eta_i \sim N(0, \tilde{a}\mu_i + \tilde{b}), \]

(3)

where \( \eta_i \) represents the zero-mean signal-dependent noise after white-balancing. Meanwhile, the gamma correction is defined

\[ y_i = \mu_i + \eta_i + \gamma_i \quad \text{with} \quad \gamma_i \sim N(0, \tilde{a}\mu_i + \tilde{b}), \]

where \( \gamma_i \) represents the gamma correction-induced noise.
as the following element-wise power-law expression
\[ z_i = y_i^\gamma = \left(\mu_i + \eta_i\right)^\gamma = \mu_i^{\frac{1}{\gamma}} \left(1 + \frac{\eta_i}{\mu_i}\right)^\gamma, \]
where \( \gamma \) is the correction factor (typically, \( \gamma = 2.2 \)) and \( z_i \) denotes the gamma-corrected pixel. The first order of Taylor’s series expansion of \((1 + x)^\gamma\) at \( x = 0 \) leads to
\[ z_i = \mu_i^\gamma + \frac{1}{\gamma} \mu_i^{\gamma-1} \eta_i + o\left(\frac{\eta_i}{\mu_i}\right) \approx \mu_i + \mu_i^{1-\gamma} \eta_i, \]
where \( \mu_i = \mu_i^\gamma \) is the expected value of the gamma-corrected pixel \( \tilde{z}_i \). Taking expectation and variance on the both sides of the equation (5), it follows that
\[ \sigma_i^2 = \frac{1}{\gamma} \mu_i^{2-2\gamma} \sigma_i^2 + \frac{1}{\gamma} \mu_i^{2-2\gamma} (\tilde{\eta}_i^\gamma + b). \]
Finally, the gamma-corrected image undergoes the quantization \( Q_\Delta \) with step \( \Delta \) in the image acquisition pipeline. Under mild assumptions [13], the quantization noise can be modeled as an additive noise that is uniformly distributed and uncorrelated with the input signal. Taking into account the variance of the quantization noise, the generalized noise model of a natural image is derived as
\[ \sigma_i^2 \triangleq f(\mu_i; \tilde{a}, \tilde{b}, \gamma) = \frac{1}{\gamma} \mu_i^{2-2\gamma} (\tilde{\eta}_i^\gamma + b) + \Delta^2 \frac{12}{}, \]
where, to simplify the notations, \( z_i \) is referred to as the final output pixel. For the sake of simplification, it is assumed that the quantization step is unitary, i.e. \( \Delta = 1 \). Since this generalized noise model accounts for heteroscedasticity of noise, it is more appropriate to characterize than existing non-linear models used in [8, 7]. The generalized noise model (7) is illustrated in Figure 2.

3. Estimation of Noise Model Parameters from a Single Image

The generalized noise model (7) is non-linear, which causes a difficulty of estimating the noise model parameters. When the gamma factor \( \gamma \) is known in advance, an obvious approach is to invert the gamma correction for obtaining again the heteroscedastic relation (3), and then to perform the Weighted Least Squares (WLS) estimation as proposed in [6]. Unfortunately, this approach leads to many problems in practice [14]. Firstly, the value of \( \gamma \) can not be known in practice. One method is proposed in [15] to estimate \( \gamma \) blindly without calibration information or knowledge of imaging device. However the stability of this method on a large real image database is still questioned. Secondly, even when the value of \( \gamma \) is exactly known, the effect of the quantization \( Q_\Delta \) makes the inversion of the gamma correction ill-conditioned. Finally, this non-linear inversion would introduce artefacts into the signal, which prevents from obtaining a subsequent good estimation of parameters. Therefore, the goal of this section is to develop an algorithm that works directly on the non-linear generalized noise model (7) for estimating the noise model parameters.

This section presents an algorithm for estimation of noise model parameters from a single image. The proposed algorithm consists of three fundamental steps: homogeneous block detection, level-set segmentation, and Maximum Likelihood (ML) estimation of parameters. The first two steps aim at detecting homogeneous blocks and partition the image into non-overlapping level sets (or segments) in which the pixels are assumed to be independent and identically distributed. Thus local expectations and local variances in each segment can be calculated, allowing to estimate the noise model parameters simultaneously.

3.1. Homogeneous Block Detection and Level-Set Segmentation

Let \( Z \) be a two-dimensional matrix representing a natural image. Firstly, an estimation of image structure is performed using a denoising filter \( D: Z^{app} = D(Z) \) where \( Z^{app} \) denotes the approximate image structure. The residual image \( Z^{res} \), which is the difference between the noisy image \( Z \) and the denoised image \( Z^{app} \), is further used to estimate local noise variances. Since it is desirable that the proposed algorithm can be further applied on JPEG images, and JPEG compression works separately on each \( 8 \times 8 \) block, it is proposed to decompose the image \( Z \) (accordingly \( Z^{app} \) and \( Z^{res} \)) into 64 vectors of pixels \( z_L = (z_{L,1,\ldots, z_{L,64}}) \), where \( L \in \{1, \ldots, 64\} \) denotes the location index in the \( 8 \times 8 \) grid and \( N_B \) is the number of blocks. Therefore, the vector \( z_L \) contains all the pixels at the same location of the \( 8 \times 8 \) grid and the pixels \( (z_{1, B, \ldots, z_{64, B}}) \) are in the same block \( B \).

In order to identify if a \( 8 \times 8 \) block is homogeneous or contains an edge or discontinuity, it is proposed to calculate the standard deviation of each block and compare it with a threshold \( \tau \). The median of absolute deviations (MAD), which is considered as a robust estimator of standard deviation [16], is employed to calculate the standard deviation of the block. Therefore, the standard deviation of block \( B \) is calculated in the DCT domain as follows
\[ \hat{s}_B = 1.4826 \cdot \text{MAD}\left(DCT(z_{app, L, B}, \ldots, z_{app, L, 64})\right). \]

Here, the denoised image \( Z^{app} \) is employed instead of the noisy image \( Z \) because the noise may severely contaminate the calculation of standard deviation. Moreover, only 63 AC coefficients are used in (8). The DC coefficient is excluded. The block \( B \) is selected if the standard deviation \( \hat{s}_B \) is smaller than the threshold \( \tau \). Hence the set of homogeneous blocks is defined by
\[ S = \{1 \leq B \leq N_B : \hat{s}_B \leq \tau\}. \]

After detecting homogeneous blocks, it is proposed to use only a sub-image \( z_L \), for partitioning into \( K \) non-overlapping segments by dividing the dynamic range. Each segment \( S_k \), \( k \in \{1, \ldots, K\} \) is defined by
\[ S_k = \{z_{L,B} : z_{app, L, B} \in \left[u_k - \frac{\Delta_k}{2}, u_k + \frac{\Delta_k}{2}\right], B \in S\}. \]

The number of segments \( K \) is set to the number of quantization levels, e.g. \( K = 2^8 \) and \( \Delta_k = 1 \). If the value of \( K \) is larger than...
the number of quantization levels, the result is finer, i.e. the pixels in each level can be more probably identically distributed, but the number of pixels is smaller, which could lead to a case that there is not enough data for the subsequent parameter estimation. The situation is opposite when the value of $K$ is smaller than the number of quantization levels. For the sake of clarity, the pixel in each segment $S_k$ is now denoted $z_{k,i}$, $i \in \{1, \ldots, n_k\}$ where $n_k$ is the number of pixels in segment $S_k$. Analogously, $z_{k,\text{pop}}$ and $z_{k,\text{res}}$ denote respectively its denoised value and residual value.

### 3.2. Maximum Likelihood Estimation

Consequently, local expectation and local variance in each segment are given by

$$
\hat{\mu}_k = \frac{1}{n_k} \sum_{i=1}^{n_k} z_{k,i} \quad \text{(11)}
$$

$$
\hat{\sigma}_k^2 = \frac{1}{n_k - 1} \sum_{i=1}^{n_k} (z_{k,i} - \hat{\mu}_k)^2 \quad \text{with} \quad \hat{\sigma}_k^\text{res} = \frac{1}{n_k} \sum_{i=1}^{n_k} z_{k,\text{res}}. \quad \text{(12)}
$$

Because the local expectation $\hat{\mu}_k$ is calculated as the average of all denoised value in each segment, it is assumed that its variance is negligible when the number of pixels is large, i.e. the local expectation $\hat{\mu}_k$ is close to the true value $\mu_k$; $\hat{\mu}_k \cong \mu_k$. Meanwhile, the variance of $\hat{\sigma}_k^2$ is much more crucial and needs to be treated carefully. In virtue of Lindeberg Central Limit Theorem (CLT) [17, theorem 11.2.5], for a very large number of pixels $n_k$, the local variance $\hat{\sigma}_k^2$ follows the Gaussian distribution

$$
\hat{\sigma}_k^2 \sim \mathcal{N}(\sigma_k^2, d_k \sigma_k^4) \quad \text{with} \quad d_k = \frac{2}{n_k}. \quad \text{(13)}
$$

where $\sigma_k^2 = f(\mu_k; \bar{a}, \bar{b}, \bar{g})$ is the true variance with respect to $\mu_k$. The Figure 2 illustrates the scatter-plot of couples $[\hat{\mu}_k, \hat{\sigma}_k^2]_{k=1}^K$ and the generalized noise model (7) in natural images in JPEG format acquired by Nikon D70 and Nikon D200 cameras [9].

The ML approach is used to fit the global parametric model $\sigma_k^2 = f(\mu_k; \bar{a}, \bar{b}, \bar{g})$ to the scatter-plot of couples $[\hat{\mu}_k, \hat{\sigma}_k^2]_{k=1}^K$. The log-likelihood function of $K$ segments is given by

$$
\mathcal{L} = -\frac{1}{2} \sum_{k=1}^{K} \left[ \log(2\pi d_k f(\mu_k; \bar{a}, \bar{b}, \bar{g})) + \frac{\hat{\sigma}_k^2 - f(\hat{\mu}_k; \bar{a}, \bar{b}, \bar{g})}{d_k \hat{\sigma}_k^4} \right]. \quad \text{(14)}
$$

Here, because the true value $\mu_k$ is unknown in practice, $\mu_k$ is replaced by $\hat{\mu}_k$ in the log-likelihood function $\mathcal{L}$. The ML estimates of $(\bar{a}, \bar{b}, \bar{g})$ are obtained by maximizing the log-likelihood function $\mathcal{L}$

$$
(\hat{\bar{a}}, \hat{\bar{b}}, \hat{\bar{g}}) = \arg \max_{(\bar{a}, \bar{b}, \bar{g})} \mathcal{L}(\bar{a}, \bar{b}, \bar{g}). \quad \text{(15)}
$$

Because there is no closed form for ML estimates, the problem (15) is proposed to be solved numerically by using the Nelder-Mead method [18].

### 4. Numerical Results

It can be noted that the accuracy of the homogeneous block detection and segmentation depends on the performance of the denoising filter $D$. We have conducted some denoising methods such as Gaussian filter, Wiener filter, wavelet-based filter [19] and Block-Matching and 3D (BM3D) filter [20]. The usual denoising methods as Gaussian filter and Wiener filter provide very poor results. The results provided by the wavelet-based filter and BM3D filter are equivalent but the BM3D filter takes much processing time. The wavelet-based denoising filter is employed in this paper because of its relative accuracy and computational efficiency.

The proposed algorithm for estimation of noise model parameters requires an appropriate threshold $\tau$ such that we have sufficient statistics for estimation process. In this paper, the threshold $\tau$ is defined as the median of absolute deviations of all residual pixels $z_{i,\text{res}}^\text{res}$

$$
\tau = 1.4826 \cdot \text{MAD}(z_{i,\text{res}}^\text{res}), \quad \text{(16)}
$$

This threshold is simple and efficient for rejecting blocks with strong edges. Besides, the sub-image used segmentation and parameter estimation corresponds to the location (4, 4) of the 8×8 grid since compression error is higher for pixels near block boundaries, especially high at block corners [21].

#### 4.1. Parameter Estimation on Synthetic Images

The reference images from TID2008 database [22] are chosen to evaluate the accuracy of the proposed approach. The parameters $(\bar{a}, \bar{b}, \bar{g})$ are used to generate synthetics images according to the generalized noise model (7). Those parameters are estimated from natural JPEG images that are acquired by Nikon D70 and Nikon D200 cameras (see Figure 2). The synthetic images are then compressed with different quality factors.
signal-dependent noise, where 

imaged scenes, different camera models. As expected, the estimated parameters of different camera devices, different camera settings and different environmental conditions is chosen for this experiment. All images of the database are acquired with the highest available JPEG quality setting and maximum available resolution. Figure 3 shows the database [9] that covers different camera models. It can be noted that the estimated parameters of the same camera model are close to each other. Furthermore, it is desirable to compare estimated gamma provided by the proposed algorithm with the algorithm proposed by Farid [15].

4.2. Parameter Estimation on Natural Images

To highlight the relevance of the proposed approach, experiments are then conducted on a large image database. The Dresden database [9] that covers different camera devices, different imaged scenes, different camera settings and different environmental conditions is chosen for this experiment. All images of the database are acquired with the highest available JPEG quality setting and maximum available resolution. Figure 3 shows estimated parameters \((\hat{a}, \hat{b})\) over 1000 JPEG images of different camera models. As expected, the estimated parameters of the same camera model are close to each other. Furthermore, it is desirable to compare estimated gamma provided by the proposed algorithm with the algorithm proposed by Farid [15]. Figure 4 shows estimated gamma of the two algorithms on the JPEG images taken from Nikon D200 camera model. It can be noted that the variability of gamma estimated by the proposed algorithm is considerably smaller than Farid’s, thus the amount of gamma can be estimated more efficiently.

4.3. Application to Image Denoising

To highlight the usefulness of the generalized noise model (7), it is proposed to combine it with the LLMMSE filter [3] to design an efficient image denoising method. The LLMMSE filter is based on the non-stationary mean, non-stationary variance image model. From (5), the pixel \(z\) can be decomposed as

\[
z = \mu + \frac{1}{\gamma} u^{1-\gamma} \eta_u,
\]

where \(u\) denotes the original pixel and \(\eta_u\) is the zero-mean signal-dependent noise, \(\sigma^2_{\eta_u} = \hat{a} \mu_u + \hat{b}\). The index of pixel is omitted for the sake of clarity. The original pixel \(u\) involves non-stationary mean and non-stationary variance. The non-stationary mean describes the gross structure of an image and the non-stationary variance characterizes edge information of the image [3]. In the decomposition (17), the quantization noise is assumed to be negligible. As explained in [3], the LLMMSE filter for any signal-dependent noise model is formulated as

\[
\hat{u} = \left(1 - \frac{\sigma^2_{\eta_u}}{\sigma^2_z}\right) \mu_u + \frac{\sigma^2_{\eta_u}}{\sigma^2_z} z,
\]

where \(\mu_u\) and \(\sigma^2_{\eta_u}\) are respectively local mean and local variance of the pixel \(z\), \(\mu_u\) and \(\sigma^2_{\eta_u}\) are respectively local mean and local variance of the original pixel \(u\). Since the noise \(\eta_u\) is zero-mean, it follows from (17) that \(\mu_u = \mu_u\). The LLMMSE filter (18) is the weighted sum of original signal mean \(\mu_u\) and the noisy observation \(z\) where the weight is determined as the ratio of the original signal variance and noise variance. A simple technique to obtain local statistics \(\mu_u\) and \(\sigma^2_{\eta_u}\) is to calculate over a sliding window of size \((2r + 1) \times (2c + 1)\)

\[
\mu_u(m,n) = \frac{1}{(2r + 1)(2c + 1)} \sum_{i=-r}^{r} \sum_{j=-c}^{c} z(i,j), \quad (19)
\]

\[
\sigma^2_{\eta_u}(m,n) = \frac{1}{(2r + 1)(2c + 1)} \sum_{i=-r}^{r} \sum_{j=-c}^{c} (z(i,j) - \mu_u(m,n))^2. \quad (20)
\]

Therefore, it remains to calculate the variance \(\sigma^2_{\eta_u}\). From (17), the variance \(\sigma^2_{\eta_u}\) can be given by

\[
\sigma^2_{\eta_u} = \sigma^2_u + \frac{1}{\gamma} \mathbb{E}[u^{2-2\gamma}] \mu^2_u. \quad (21)
\]

By using the Taylor series expansion of \(u^{2-2\gamma}\) around \(\mu_u\), the expression of \(\mathbb{E}[u^{2-2\gamma}]\) can be simplified as

\[
\mathbb{E}[u^{2-2\gamma}] = \mu_u^{2-2\gamma} + (1 - \gamma)(1 - 2\gamma)\mu_u^{2-2\gamma}\sigma^2_u. \quad (22)
\]
Combining (21) and (22), the expression of the variance $\sigma_u^2$ is derived as
\[
\sigma_u^2 = \frac{\sigma_z^2 - \frac{1}{\gamma \mu} \gamma^2 \sigma_w^2}{1 + \frac{1}{\gamma (1 - \gamma) (1 - 2\gamma) \mu \sigma_w^2}}.
\] (23)

The LLMMSE filter (18) follows immediately.

To evaluate the denoising performance of the extended LLMMSE filter, experiments are conducted on the synthetic non-compressed images generated from TID2008 database. The parameters ($\hat{a}, \hat{b}, \gamma$) are estimated on each synthetic image. Estimated parameters are then used in the extended LLMMSE filter. Table 2 shows the averaged Peak Signal-to-Noise Ratio (PSNR) of the extended LLMMSE filter compared with other denoising methods, e.g. some classical methods such as Wiener filter and wavelet-based filter [19], and some state-of-the-art methods such as BM3D filter [20] and Shape-Adaptive DCT (SA-DCT) filter [23]. It can be noted that the extended LLMMSE filter outperforms the Wiener, wavelet-based, BM3D, and is rather equivalent to the SA-DCT filter. This can be justified due to the fact that the SA-DCT is designed for signal-dependent noise whilst the others do not consider the non-stationarity of noise. Different denoising filters are illustrated in Figure 5.

**Remark 1.** One of the main contributions of the paper is to propose the generalized noise model that has not been provided yet in the literature. This work is accomplished by studying
the main steps of the image processing pipeline inside a digital camera. The relevance of the proposed model is highlighted by applying on a real image database. However, this approach involves a limitation, namely that the demosaicing and white balancing are not completely modeled. The proposed approach assumes that those operations are linear, which simplifies the statistical study and results in a more exploitable model, say the generalized noise model. It must be noted that the demosaicing always involves a convolution operation, which requires us to consider multivariate distribution. The resulting model could be more relevant but inexplicable in practice. Overall, the generalized noise model can be seen as a trade-off between the reality in image acquisition and the exploitability in practice.

5. Conclusion

This paper proposes a novel generalized signal-dependent noise model that is more relevant to characterize a natural image acquired by a digital camera. An algorithm for estimating noise model parameters accurately from a single image is also designed. The proposed algorithm can work on JPEG images with moderate-to-high quality factors. Another strength of the proposed algorithm is the ability to estimate the gamma factor more efficiently. Moreover, the LLMMSE filter is extended by combining with the proposed generalized noise model. The proposed noise model could be useful in many applications. A first step is to exploit the parameters of the generalized noise model as camera fingerprint for camera model identification, as proposed in [24].

References

Figure 5: Illustration of different denoising filters for $\tilde{a} = 1$, $\tilde{b} = 10$, $\gamma = 0.85$.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$-0.0012$</td>
<td>0.11</td>
<td>0.8</td>
<td>30.06</td>
<td>41.33</td>
<td>42.85</td>
<td>49.75</td>
<td>50.97</td>
</tr>
<tr>
<td>$-0.0025$</td>
<td>0.20</td>
<td>0.85</td>
<td>30.05</td>
<td>40.37</td>
<td>42.56</td>
<td>47.73</td>
<td>48.61</td>
</tr>
<tr>
<td>1</td>
<td>10</td>
<td>0.85</td>
<td>24.88</td>
<td>26.13</td>
<td>26.32</td>
<td>27.08</td>
<td>29.14</td>
</tr>
</tbody>
</table>

Table 2: PSNR of different denoising filters