

Spectral Estimation Filters for Noise Reduction in X-ray Fluoroscopy Imaging

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SPECTRAL ESTIMATION FILTERS FOR NOISE REDUCTION IN X-RAY FLUOROSCOPY IMAGING

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ABSTRACT

In clinical x-ray fluoroscopy, moving images are acquired at very low x-ray dose so that only 10–500 x-ray quanta contribute to each pixel. The resulting Poisson statistic causes the images to be strongly affected by quantum *noise*, which, in the observed images, is spatially correlated and signal-dependent. In this contribution, we develop a spatial frequency domain method for intraframe quantum noise reduction, which takes the nonwhite noise power spectrum into account. Each image is subjected to a block DFT or DCT. The magnitude of each observed spectral coefficient is compared to the expected noise variance for it, which is derived from a suitable quantum noise model. Depending on this comparison, each coefficient is more or less attenuated, leaving the phase unchanged. Finally, the image is backtransformed and re-assembled. Using this method, noise power reductions of 60% are possible.

1. INTRODUCTION

In clinical procedures like gastro-intestinal examinations, catheterization or balloon angioplasty, x-ray fluoroscopy is used as an imaging technique to monitor and provide visual guidance for the diagnostic examination or therapeutical intervention. The resulting moving images are viewed immediately on a CRT monitor while the clinical procedure is carried out. Patient and medical staff are hence exposed to radiation during prolonged periods of time. To keep these exposures to a minimum, very low x-ray dose rates are used for the imaging process, which, however, result in considerable degradations of image quality through x-ray quantum noise.

Quantum noise originates inherently from low dose x-ray beams, where only between 10–500 x-ray quanta per pixel are available for image acquisition. If the frame rate is sufficiently high, temporal filters can be employed to reduce quantum noise [1, 2, 3]. Their efficiency, however, diminishes with decreasing frame rates often used in pulsed fluoroscopy [4], and high erratic local motion. In order to complement temporal filtering in general, and to provide an alternative to temporal filtration for the mentioned cases, we therefore concentrate here on intra-frame noise reduction algorithms.

Spatial processing of individual images has to exploit structural differences between noise-free images and noise. Whereas modelling of noise can be guided by knowledge of the underlying physical processes, appropriate modelling of noise-free medical images is difficult if not impossible. The often used Markov random field models, for example, do not capture sufficient medical detail if kept mathematically tractable. It is therefore desirable to keep the assumptions on the image as weak as possible. We hence rely here on a noise model as starting point and assume those input observations as containing image signal (in addition to noise) that cannot be explained well by noise only.

As quantum noise can be described as a Poisson random process, its power is signal dependent [5, 6]. The originally white noise process is filtered by the imaging system's transfer function, resulting in a lowpass shaped, non-white noise power spectrum (NPS) [6]. A relatively high proportion of the overall noise power is hence contributed from low spatial frequencies. Standard spatial window-based filters, like lowpass convolution kernels, nonstationary Wiener approaches [7], or order statistic-based filters [8, 9, 10], however, tend to attenuate high spatial frequency components only. This has the twofold shortcoming that, firstly, the full noise reduction potential is not exploited. Secondly, the spectral composition of quantum noise is shifted even more towards low spatial frequencies by these filters, which is often visually unpleasing despite a reduction of the overall noise power. Additionally, order statistic-based filters tend to generate patches or streaks of constant intensity [10, p. 1897], [11], which add to the unnatural appearance of such processed images.

To avoid such artifacts without sacrificing noise reduction performance, and in particular to be able to tailor our filters to spatially coloured noise, we follow here the concept of so-called spectral magnitude estimation [12, 13], where noise attenuation is carried out in the spectral domain. Based on a decomposition of the input images into overlapping blocks which are then subjected to a standard block transform (Discrete Fourier Transform (DFT) or Discrete Cosine Transform (DCT)), the central idea is to compare each transform coefficient to its counterpart from the NPS [14]. Each coefficient is then attenuated depending on how likely it is that it contains only noise.

2. THE QUANTUM NOISE MODEL

In x-ray fluoroscopy, quantum noise is by far dominating so that other noise sources can be neglected (*quantum-limited* imaging). Two aspects of quantum noise will be taken into account:

- Being Poisson-distributed [5], the quantum noise power is signal dependent.
- As quantum noise originates from the x-ray beam before images are picked up by the x-ray detector, it is filtered by the transfer function of the imaging system.

The basic idea for our noise model is to separate these two aspects.

Quantum noise as it originates from the x-ray beam is white and Poisson distributed, with its variance equal to the mean number of x-ray quanta absorbed per frame within pixel area. After image detection, usually by an image-intensifier/TV camera chain, the video signal may experience an intended nonlinear gain curve (white compression) before being displayed. Hence, the relation between noise power and signal intensity is characterized by an approximately linear rise over low and medium intensities caused by the Possionian noise nature, and a drop-off towards high intensities caused by white compression (Fig. 1).



Figure 1: Noise variance versus intensity for original and processed images. The original image is shown in Fig. 4, and the DFT-processed one in Fig. 5. The DCTprocessed picture is not shown, but looks similar to the DFT-based result.

Let us now consider an image region of approximately constant signal intensity I. The quantum noise process in these regions exhibits a lowpass-shaped NPS due to filtering by the system transfer function. Regarding the system transfer function as signal independent and linearizing the white compression curve around the operating point corresponding to I, we can separate the NPS into a scale factor which determines the overall noise power $\sigma^2(I)$, and a reference NPS model $p_d(\omega)$ determining the NPS shape, the noise power of which integrates to unity (*scale/shape* separability). The NPS is thus given by

$$P_d(\omega) = \sigma^2(I) \cdot p_d(\omega) \quad , \tag{1}$$

where ω denotes spatial frequency. For discrete transforms like DFT or DCT, $p_d(\omega)$ can be estimated by wellknown periodogram techniques. Up to a scaling factor, (1) then represents the noise variance estimate for each coefficient. Both the $\sigma^2(I)$ and the shape $p_d(\omega)$ are assumed to be known for the image acquisition parameters and system in use.

3. SPECTRAL MAGNITUDE ESTIMATION

Two approaches will be derived, one motivated by the Wiener filter and one based on minimum mean square error (MMSE) estimation. The block diagram for both algorithms is depicted in Fig. 2: First, the image is decomposed into overlapping blocks. Each block is subjected to the DFT or DCT, where in case of the DFT windowing prior to the transform prevents leakage. The magnitude of each spectral coefficient is compared to the corresponding noise standard deviation, which is stored in the box marked "noise model" in the form of $\sigma(I)$ and $\sqrt{p_d(\omega)}$ (cf. eq. (1)). Each coefficient is attenuated according to this comparison, leaving the phase unchanged. Back-transform and re-assembly produce the noise-reduced final image.



Figure 2: Basic structure of the algorithms.

3.1 Generalized Wiener filter-based estimation

The observed noisy signal g(n) is modelled to consist of the undistorted signal f(n) and additive noise d(n). Unlike for d(n), the statistical properties of f(n) are usually unknown and non-stationary. However, we can assume the spectral content of the undistorted signal to be constant over sufficiently small blocks. The block transform coefficients of the (in case of the DFT windowed) observation, undistorted signal, and noise are denoted $G^w(\omega)$, $F^w(\omega)$ and $D^w(\omega)$, respectively. A generalized Wiener filter produces an estimate $\hat{F}^w(\omega)$ by

$$\hat{F}^{w}(\omega) = G^{w}(\omega) \cdot \left(\frac{E(|F^{w}(\omega)|^{2})}{E(|F^{w}(\omega)|^{2}) + \alpha \cdot E(|D^{w}(\omega)|^{2})}\right)^{\beta}.$$
(2)



Figure 3: Attenuation functions (a) for power subtraction (3), (b) Wiener filter-based estimation (4), and (c) MMSE filter (5) as a function of the square root r of the a posteriori SNR, all for $\alpha = 1$, and (c) $\lambda = 1.5$.

For $\alpha = \beta = 1$, this is the Wiener filter, whereas $\alpha = 1$, $\beta = 0.5$ yields the power spectrum equalizing filter. The drawback of (2) is that $E(|F^w(\omega)|^2)$ is unknown. Assuming that $\hat{F}^w(\omega)$ were already available, this quantity could be estimated by $\hat{E}(|F^w(\omega)|^2) = |\hat{F}^w(\omega)|^2$. Inserting this estimate into (2), and observing that (2) does not affect the (DFT) phase, the resulting expression can straightforwardly be solved for $\beta = 0.5$ and $\beta = 1$ to yield $\hat{F}^w(\omega)$.

For $\beta = 0.5$, we obtain the *power spectrum subtraction* or *correlation subtraction* formula

$$\hat{F}^{w}(\omega) = G^{w}(\omega)\sqrt{1 - \alpha/r^{2}(\omega)} \quad , \tag{3}$$

and for $\beta = 1$ the Wiener estimate

$$\hat{F}^w(\omega) = \frac{1}{2} G^w(\omega) \cdot \left(1 + \sqrt{1 - 4\alpha/r^2(\omega)}\right) \quad , \qquad (4)$$

where $r^2(\omega) = |G^w(\omega)|^2 / E(|D^w(\omega)|^2)$ is the a posteriori SNR, which compares the *instantaneous* power of an observed coefficient with the *expected* noise power for that coefficient derived from the noise model (1). Eqs. (3) and (4) can be regarded as attenuation functions for the observed coefficients $G^w(\omega)$. The dependency of the attenuation factor on $r(\omega)$ is depicted in Fig. 3¹.

3.2 Minimum mean square error (MMSE) estimation

The alternative estimation algorithm described in this section is based on the conditional mean $\hat{F}^w(\omega) = E(F^w(\omega)|G^w(\omega))$, and explicitly exploits the well-known energy compaction properties of both the DFT and the DCT. Assuming for each block that the undistorted image signal appears in only a few coefficients, each observed coefficient represents either noise only (null hypothesis H_0), or signal and

noise (alternative hypothesis H_1). Splitting up $E(F^w(\omega)|G^w(\omega))$ according to these hypotheses, we clearly have $E(F^w(\omega)|G^w(\omega), H_0) = 0$. Furthermore, based on the single observation $G^w(\omega)$ corrupted by zero-mean noise, and without further prior knowledge, we have $E(F^w(\omega)|G^w(\omega), H_1) = G^w(\omega)$. Modelling the coefficients under both hypotheses as Gaussian distributed (central limit theorem), with known noise variance under H_0 , and unknown but much higher variance in case signal is present (H_1) , the following attenuation function can be derived (cf. [15]):

$$\hat{F}^{w}(\omega) = E\left[F^{w}(\omega)|G^{w}(\omega)\right] = \frac{G^{w}(\omega)}{1 + \lambda \exp\left(-r^{2}(\omega)/\alpha\right)} .$$
(5)

The parameter λ depends on signal and noise variances and on the a priori probability of the observed coefficient to contain signal, but is regarded here as a free parameter controlling the trade-off between noise reduction and signal preservation. Eq. (5) is also shown in Fig. 3 as an attenuation function for $G^w(\omega)$. Note that, unlike (3) and (4), this function is free from steep slopes and bends. This behaviour can be shown to help avoid certain artifacts which may appear in processed images when using (3) or (4). All subsequent results are therefore based on (5) with $\lambda = 1.5$.

4. RESULTS

An original frame from a fluoroscopy sequence is given in Fig. 4. Fig. 5 shows the corresponding processing result obtained by employing the FFT in connection with a blocksize of 64×64 pixel and an overlap of 16 pixel. The FFT window was a modified separable 2D Hanning window, whose cosine-shaped drop-off was restricted to a 16 pixel wide border region. To allow better visual examination, only the central region of each image is depicted in both Fig. 4 and Fig. 5.

DCT based processing results are hardly distinguishable from those obtained using DFT. Quantitative evaluation also shows similar performance (see Fig. 1). Since the DCT exhibits only negligible leakage, windowing before taking the transform is omitted. Block overlap is then only necessary to avoid the block raster from becoming visible, what can be ensured by overlaps as low as two pixel, reducing the computational load by about 40%. The corresponding window operation is now performed within the image reconstruction box in Fig. 2.

5. CONCLUSION

The strength of the non-linear spectral domain noise reduction techniques described in this paper is that they can be tailored specifically to the known properties of quantum noise, while only very weak assumptions concerning the unknown signal are required. To capture the spatial correlation and signal dependence properties of quantum noise, we have first derived a model for quantum noise power spectra which is based on the assumption of scale/shape separability. Both the signal

¹In both equations, it is possible that the expression under the square root becomes negative, in which case the root is set to zero.



Figure 4: Central 256×256 -pixel region of an original 512×512 -pixel image from a fluoroscopy image sequence, depicting a patient's vertebrae and a catheter.

dependent overall noise power (scale) and the distribution of the noise power over spatial frequency (shape) can be obtained off-line from phantom measurements.

It might appear as a shortcoming of the discussed algorithms that processing is based on an unnatural block structure. In the context of quantum noise reduction, however, blockwise processing has the significant advantage that inevitable "decision" errors, like mistaking noise for signal, are dispersed over entire blocks as sinelike gratings. The occasional appearance of these gratings can easily be concealed by retaining a low wide band noise floor. The visually much more unpleasing patchlike artifacts of spatial domain filters are thus completely avoided. The block raster itself is prevented from becoming visible through the use of overlapping blocks. The computational overhead can be kept to a minimum when the DCT is employed, which allows for very small overlaps.

REFERENCES

- C. L. Chan, A. K. Katsaggelos, A. V. Sahakian, "Image sequence filtering in quantum-limited noise with applications in low-dose fluoroscopy," *IEEE Trans. Med. Im.* 12(3):610–620, 1993.
- [2] A. Singh, "Enhancement of x-ray fluoroscopy images," *Image Processing* (SPIE Vol. 1898), 304–310, 1993.
- [3] J. C. Brailean et al., "Noise reduction for dynamic image sequences: A review," *Proc. IEEE* 83(9):1272–1291, 1995.
- [4] R. Aufrichtig et al., "Perceptual comparison of pulsed and continuous fluoroscopy," *Med. Phys.* 21(2):245-256, 1994.
- [5] A. L. Evans, The Evaluation of Medical Images. Bristol: Adam Hilger Ltd, 1981.



Figure 5: Processing result for Fig. 4 (MMSE attenuation, $\alpha = 3$, $\lambda = 1.5$).

- [6] G. Spekowius et al., "Simulation of the imaging performance of x-ray image intensifier/ TV camera chains," *Med. Imag. 1995* (SPIE Vol. 2432), 12–23, 1995.
- [7] D. T. Kuan et al., "Adaptive noise smoothing filter for images with signal-dependent noise," *IEEE Trans. Pat. Anal. Mach. Intel.* 7(2):165–177, 1985.
- [8] A. Nieminen, P. Heinonen, Y. Neuvo, "A new class of detail-preserving filters for image processing," *IEEE Trans. Pat. Anal. Mach. Intel.* 9(1):74–90, 1987.
- [9] Y. S. Fong, C. A. Pomalaza-Ráez, X. H. Wang, "Comparison study of nonlinear filters in image processing applications," *Opt. Eng.* 28(7):749–760, 1989.
- [10] I. Pitas, A. N. Venetsanopoulos, "Order statistics in digital image processing," *Proc. IEEE* 80(12):1892– 1921, 1992.
- [11] A. C. Bovik, "Streaking in median filtered images," *IEEE Trans. Acoust. Speech Sig. Proc.*, 35:493–503, 1987.
- [12] P. Vary, "Noise suppression by spectral magnitude estimation – mechanism and limits," *Signal Proc.* 8(4):387–400, 1986.
- [13] J. S. Lim, A. V. Oppenheim, "Enhancement and bandwidth compression of noisy speech," *Proc. IEEE* 67(12):1586–1604, 1979.
- [14] J. S. Lim, "Image restoration by short space spectral subtraction," *IEEE Trans. Acoust. Speech Sig. Proc.* 28(2):191–197, 1980.
- [15] Y. Ephraim, D. Malah, "Speech enhancement using a minimum mean-square error short-time spectral amplitude estimator," *IEEE Trans. Acoust. Speech Sig. Proc.* 32(6):1109–1121, 1984.