LAST Filter for Artifact-Free Noise Reduction of Fluoroscopic Sequences in Real-Time

Marc Hensel[1], Thomas Pralow[2] and Rolf-Rainer Grigat[1]

[1]Vision Systems, TU Hamburg-Harburg, 21079 Hamburg
[2]General X-Ray, Philips Medical Systems, 22335 Hamburg
Email: marc.hensel@tu-harburg.de

Abstract. We present a spatio-temporal filter for real-time noise reduction of strongly corrupted X-ray image sequences. It possesses efficient noise reduction while, at the same time, preventing typical artifacts of state-of-the-art methods. Decisive for these features are, in particular, innovative motion detection as well as noise-adaptive filter parametrization. Motion detection based on twofold signed binarization proved to be a powerful method for pixelwise separation of motion and strong noise. Drawbacks of threshold determination by Euler curve analysis as applied previously were eliminated by integration of signal-dependent noise estimation.

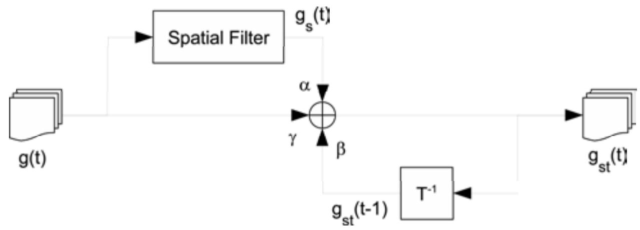
1 Introduction

Real-time noise reduction, enhancement, and visualization of X-ray image sequences is the basis of several established clinical applications. For instance, in angiography, medical instruments are navigated and the distribution processes of contrast agents are observed. As medical staff and patients are exposed over a long period, very low X-ray doses are applied in these examinations. Consequently, images exhibit severe noise.

The advance of digital technologies and powerful computers enables us to apply image processing methods of increasing complexity. State-of-the-art in real-time noise reduction is spatio-temporal filtering. Temporal filtering is well suited for noise reduction of static image regions. Motion, however, generates perturbing artifacts. Hence, moving structures should be detected and temporal filtering reduced at these structures. Motion detection is complicated significantly by severe signal-dependent noise in the image data at hand.

In last year's BVM workshop our groups have presented motion detection based on independent binarization of positive and negative values in temporal difference images [1]. In this paper we report on the development status of the enhanced noise reduction method, which we named – for lack of better ideas – *LAST* (*Local Adaptive Spatio-Temporal*) *filter*. Following a brief description of the filter, we focus on advances in motion detection and filter parametrization. In particular, we replaced blockwise processing based on Euler curves by a pixelwise motion probability that is motivated by an appropriate noise model.

Fig. 1. Temporal recursive filter structure ($\alpha + \beta + \gamma = 1$)



2 State-of-the-Art

Typically, temporal recursive filters [2] are applied for real-time noise reduction of X-ray image sequences exhibiting severe noise [3, 4]. In static image regions, temporal filtering significantly improves image quality and preserves fine structures far better than spatial filters of comparable complexity. However, motion generates distracting artifacts (motion shadows).

Motion artifacts can be prevented by detecting motion and reducing the strength of temporal filtering in favor of spatial filtering at these locations. As motion generates strong signal in temporal difference images, motion detection is commonly based on the current and the last filtered image [5]. However, pixel-based motion detection without consideration of the neighborhood yields artifacts as frayed edges or salt-and-pepper noise in very noisy images.

Aufrichtig and Wilson [4] assume motion artifacts in non-cardiac angiography to be caused predominantly by long, thin objects like catheters or guide-wires rather than organic structures. They use templates of small line segments to identify these objects and control spatio-temporal filtering. However, at least in angiography, large vessels brought out by contrast agents and, in general, bone structures are likely to produce artifacts as well.

Recently, we have presented a method to detect strong noise and motion by independent binarization and postprocessing of positive and negative gray value differences [1]. For binarization, images are divided into blocks and a threshold for each block is determined in a noise-adaptive way by Euler curve analysis. Problems are, in particular, blocking artifacts and the complexity of Euler curve generation and analysis.

3 Methods

The filter is composed of a recursive spatio-temporal filter structure (Fig. 1) and a control unit determining local filter parameters. Latter includes a shutter, noise estimation, motion detection (twofold signed binarization and binary post-processing) and automatic parametrization. The shutter determines the region of X-ray (ROX). Outside this region no motion is expected. Thus, maximal temporal filtering is applied. The integrated noise estimator is subject to a further paper presented by our groups [6].

Main features of the proposed motion detection and filter control are:

1. *Twofold Signed Binarization*: Independent binarization of positive and negative temporal gray value differences generates two binary images.
2. *Postprocessing*: By means of morphological operations, both binary images are divided into two masks representing motion and strong noise, each. Positive and negative motion masks are combined to one binary image. The proceeding for the noise masks is analogous.
3. *Local adaptive control* of spatial and temporal filter strengths via motion and noise masks as well as a motion probability based on local noise estimation.

3.1 Twofold Signed Binarization and Postprocessing

By independent binarization of positive *and* negative gray value differences, motion forms connected objects in the binary images while strong noise above the threshold does not form objects of significant size. Consequently, motion and noise can be separated into binary motion and noise masks b_{motion} and b_{noise} with $b_{motion} \cap b_{noise} = \emptyset$ by simple morphological operations [1].

For each pixel, thresholds are determined based on an estimation of the local signal-dependent additive noise [6]. For this purpose, gray value differences $g_{\Delta}(\mathbf{x}, t) = g(\mathbf{x}, t) - g_{st}(\mathbf{x}, t-1)$ of the current (g) and the last spatio-temporal filtered (g_{st}) image are normed to the signal-dependent standard deviation $\sigma_{\eta_e}(\mathbf{x}, t)$ of the estimated noise η_e:

$$q(\mathbf{x}, t) = \frac{|g_{\Delta}(\mathbf{x}, t)|}{\sigma_{\eta_e}(\mathbf{x}, t)} \tag{1}$$

Absolute differences above three times the estimated noise level ($q > 3$) are interpreted as being caused by structure, i.e. motion. Further, by applying a sigmoid function, the normed differences are mapped to a continuous motion probability:

$$\mathrm{prob}(q) = c_1 + \frac{c_2}{1 + \exp\left(\frac{c_3 - q}{c_4}\right)} \tag{2}$$

Extremely noisy pixels wrongly classified as motion are not problematic as these are detected and collected in the noise mask in postprocessing.

3.2 Control

The overall goal of filter parametrization is to maximize the temporal filter strength, i.e. parameter β, while, at the same time, preventing motion artifacts. Pixels identified as representing motion are predominantly filtered spatially, noise pixels are mainly filtered temporally. The spatio-temporal weighting $w(\,\cdot\,)$ of the remainder is carried out on basis of the calculated motion probability:

$$\beta(\mathbf{x}, t) = \begin{cases} \beta_{motion} & : b_{motion}(\mathbf{x}, t) = 1 \\ \beta_{noise} & : b_{noise}(\mathbf{x}, t) = 1 \\ w\big(\, \mathrm{prob}(q(\mathbf{x}, t))\, \big) & : \text{else} \end{cases} \tag{3}$$

Table 1. Coefficients a_1 and a_2 for correlated $\alpha\beta\gamma$-filtering

Filter	a_2	a_1
Binomial 3×3	0.6406	1.5
Binomial 5×5	0.7935	1.7188
Binomial 7×7	0.8556	1.8047

The remaining parameters α and $\gamma = 1 - (\alpha + \beta)$ are optimized in such way to maximize noise reduction performance for given β. For observed medical X-ray images g, the true signal s being corrupted by additive zero-mean uncorrelated Gaussian noise η with signal-dependent variance, i.e. $g = s + \eta(s)$, is a valid assumption [6]. The signal is modeled to be approximately homogeneous in a small neighborhood. Furthermore, in practice, the spatial filter is a (linear) binomial filter h of small size (3×3 to 7×7 pixels).

Assume the neighborhood of a pixel to be corrupted with noise of standard deviation σ_0. Then the spatio-temporal filtered image exhibits noise of strength

$$\sigma_{st}(t) = \sqrt{\beta^{2t} + (\beta^{2t} - 1)\left[\frac{a_2}{\beta - 1}\alpha^2 + a_1\alpha + (\beta - 1)\right]} \cdot \sigma_0 \qquad (4)$$

with:

$$a_1 = 2(1 - h_{0,0}) \qquad (5)$$

$$a_2 = \sum_{i=-K}^{K} \sum_{j=-K}^{K} \left[1 - \delta(i)\delta(j)\right] h_{i,j}^2 + (1 - h_{0,0})^2 \qquad (6)$$

For static regions ($t \to \infty$) and constant $\beta < 1$, the optimum parameters are given by

$$\alpha = \frac{a_1}{2a_2}(1 - \beta) \qquad (7)$$

and $\gamma = 1 - (\alpha + \beta)$. Table 1 shows parameters a_1 and a_2 for typical filters used.

4 Results

Diverse clinical sequences as well as a X-ray image sequence showing a dynamic test object were used in the evaluation. For quantification in terms of signal-to-noise-ratio (SNR), only the ROX was evaluated as the clinical irrelevant shuttered regions falsified the results by approximately 5 to 10 dB.

State-of-the-art filtering without noise estimation or motion detection generated perceivable motion artifacts even for low temporal filter portions of about 5% ($\beta = 0.05$). At the same time, static image regions were hardly denoised with these parameter settings. Contrarily, even for strong noise reduction settings no temporal or spatial artifacts were observed when applying the presented

Fig. 2. Original image detail (left), motion artifacts due to temporal averaging at dark structures (middle), processed with proposed method (right)

method. Due to strong temporal filtering of broadly static image regions, clearly improved image quality and good temporal stability was notable in large image regions (Fig. 2). Objective evaluation of frames exhibiting about 18.5 dB SNR resulted in SNR improvement (SNRI) of about 9.1 dB.

5 Discussion

The presented method exhibits efficient noise reduction while, at the same time, preventing artifacts. Motion artifacts, typical for temporal averaging, are prevented by motion detection based on processing positive and negative instead of absolute gray value differences. Artifacts due to blockwise binarization were eliminated by integration of a motion probability based on signal-dependent noise estimation. By this, improved adaptation of the method to signal-dependent noise has been achieved and the former discrete filter parametrization could be replaced by a continuous parametrization.

References

1. Hensel M, Wiesner G, Kuhrmann B, et al. Motion Detection for Adaptive Spatio-Temporal Filtering of Medical X-Ray Image Sequences. In: Procs BVM; 2005. p. 68–72.
2. Lagendijk RL, van Roosmalen PMB, Biemond J, et al. Video Enhancement and Restoration. In: Bovik A, editor. Handbook of Image and Video Processing. 2nd ed. Elsevier Academic Press; 2005. p. 275–294.
3. Sanchez-Marin FJ, Srinivas Y, Jabri KN, Wilson DL. Quantitative Image Quality Analysis of a Nonlinear Spatio-Temporal Filter. IEEE Trans Image Proc 2001;10(2):288–295.
4. Aufrichtig R, Wilson DL. X-Ray Fluoroscopy Spatio-Temporal Filtering with Object Detection. IEEE Trans Med Imaging 1995;14(4):733–746.
5. Konrad J. Motion Detection and Estimation. In: Bovik A, editor. Handbook of Image and Video Processing. 2nd ed. Elsevier Academic Press; 2005. p. 253–274.
6. Hensel M, Lundt B, Pralow T, Grigat RR. Robust and Fast Estimation of Signal-Dependent Noise in Medical X-Ray Image Sequences. In: Procs BVM; 2006.