Noise Reduction with Edge Preservation by Multiscale Analysis of Medical X-Ray Image Sequences

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Abstract. Real-time visualization of digital X-ray image sequences requires the reduction of severe noise while preserving diagnostic details. We introduce a noise reduction method for X-ray image sequences using products of Laplacian pyramid coefficients. The method features SNR improvement comparable to the Wiener filter, however, being superior in the preservation of fine structures and generating a more stable image impression in sequences.

1 Introduction

In medical diagnosis digital X-ray image sequences have important applications, e.g. in angiography. In order to keep radiation exposure of medical staff and patients as low as possible, very low radiation doses are used, resulting in severe noise that must be reduced with image processing methods in real-time. At the same time, diagnostic details must be preserved, thus, an efficient reduction of strong noise while preserving fine image structures is required.

Originating from MR imaging, the multiscale products noise reduction technique by Bao and Zhang [1, 2] is known. Current methods to process X-ray image sequences contain a multiscale decomposition as well, which, among other things, is used to enhance image contrast [3]. However, a decomposition in form of the Laplacian pyramid [4] is used while the method of Bao and Zhang is based on non-decimating wavelets. Moreover, Bao and Zhang apply their method to MRI data that has properties significantly different from digital X-ray image sequences.

In this context we identified the task, staring from the method of Bao and Zhang, to develop a noise reduction method for X-ray image sequences based on multiscale products of the Laplacian pyramid. By utilizing the Laplacian pyramid already available in the image processing pipeline no additional cost in time or memory demands is required to generate the decomposition. Additionally, the resulting adaptive non-linear spatial filter is to be extended by temporal filtering, as in our experience pure spatial filtering leads to an unbalanced and unstable image impression in sequences [5].

2 State-of-the-Art

Known related methods perform a thresholding of high-frequency components. They feature poor separation of structure and noise and therefore tend to blur edges in the filtered images.

Whereas Bao and Zhang exploit that structure and noise evolve differently across the scales due to their negative and positive Lipschitz regularities, respectively [6, 7]. Structure is represented by significant signal across the scales while noise amplitudes decrease rapid toward low frequencies. Hence, it is possible to separate structure and noise e.g. by multiplying coefficients of different scales and thresholding of coefficient products of adjacent scales.

Multiscale coefficient product methods known to us are based on non-decimating wavelets [1, 2]. Therefore, they do not treat the difficulty of adapting data sizes of different levels for the multiplication and do not regard the specific properties of the Laplacian pyramid levels. Whereas algorithms based on the Laplacian pyramid merely perform a simple thresholding of the single levels, but do not combine the coefficients of different levels [8].

3 Methods

The Gaussian-Laplacian pyramid is a decomposition of an image in frequency bands. Noise and fine structures are situated predominantly in the lower levels L_0 and L_1 of the Laplacian pyramid, which contain the high frequencies, while coarse structures are located in the upper pyramid layers.

Adjacent Laplacian levels are combined to products $L_0 \odot L_1$ and $L_1 \odot L_2$ and the corresponding coefficients of the pyramid layers L_0 and L_1 are classified into *signal* and *noise* by thresholding the products. In this context, $L_k \odot L_{k+1}$ denotes the multiplication by components, $A \otimes B$, of two layers transformed to the same size by an operation still to define. In the subsequent image reconstruction from the pyramid, the components representing noise are weighted significantly lower than coefficients representing signal, whereby noise is reduced in the reconstructed image.

Apart from the value of the threshold applied to the coefficient product, the degree of filtering is in particular depending on the minimum and maximum coefficient weights in the reconstruction. By attenuating coefficients classified as noise instead of setting these to zero, even fine structures that have wrongly been classified as noise are partially preserved. In the same way, the noise superposed on structures is smoothed by slightly reducing coefficients classified as representing signal.

The primal difficulty when developing the method was intense impulse noise remaining in the filtered image (fig. 1), which we were able to reduce significantly by several modifications to the method. Apart from introducing linear weighting with a minimum and maximum weight, this was achieved above all by forming products in the adjacent level $k + 1$

$$L_k \odot L_{k+1} = REDUCE(L_k) \otimes L_{k+1} \tag{1}$$

Fig. 1. Original image detail (left), remaining impulse noise in the unmodified method (middle), processed with the proposed method (right).

and interpolating the resulting weights W_{k+1} to the size of the pyramid level k, i.e. the level that is to be weighted,

$$W_{k+1,1} = EXPAND(\ W_{k+1}\ ) = EXPAND(\ f(L_k \odot L_{k+1})\ ) \qquad (2)$$

with the *EXPAND* and *REDUCE* operations according to [4] and a weight function f. The modified Laplace levels $\tilde{L}_k$ used for reconstruction are given by:

$$\tilde{L}_k = W_{k+1,1} \otimes L_k \qquad (3)$$

As noise in low-dose X-ray images is inherent signal-dependent, a signal-dependent threshold determination has been implemented, leading to further significant improvement of the noise reduction. The threshold is determined against a noise estimation based on a noise model developed specifically for the X-ray image sequences used.

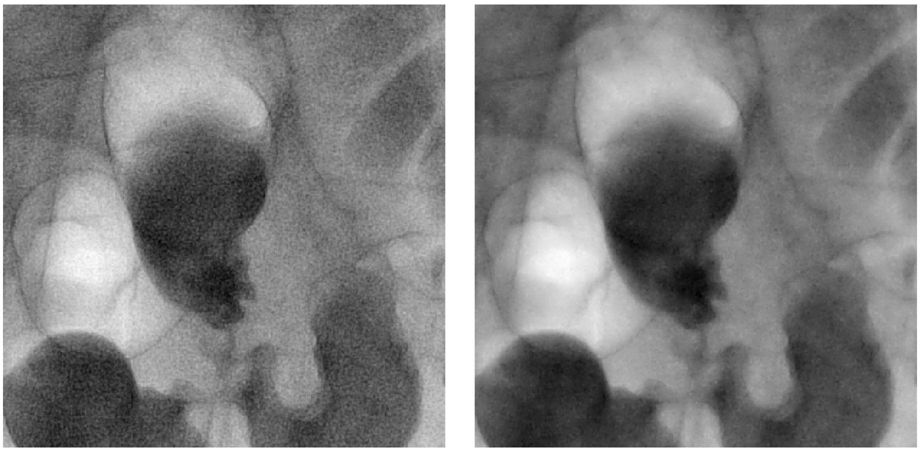
Even without temporal filtering the method generates a comparatively steady image impression. This was further improved considerably by the controllable weighted averaging of temporal neighboring pixels, i.e. pixels at same locations (x, y), of the reconstructed images. To prevent artifacts, temporal filtering is applied in image regions without significant motion, only.

4 Results

The presented method has been compared to Wiener and binomial filters up to 9×9 pixel. For these methods, clinical X-ray sequences as well as an artificial sequence have been evaluated objectively and subjectively. The signal-to-noise ratio (SNR) was 20.3–32.8 dB in the clinical sequences and 14.58 dB in the sequence created artificially and superposed with Poisson-distributed noise. To begin with, the results for the artificial sequence are presented as the undisturbed signal is known and no noise estimation is required in this case.

While fine structures were considerably degraded and the SNR was improved only by approximately 5.03 dB in binomial filtering, the SNR improvement when applying Wiener filtering and the presented method was on a comparable high

Fig. 2. Original image detail (left), processed with the proposed method (right).



level of 11.12 dB and 11.90 dB (without temporal filtering) or 12.66 dB (with temporal filtering), respectively. However, the presented method features a much higher stability of 22.6% (without temporal filtering) and 40.3% (with temporal filtering) compared to 1.3% in Wiener filtering. Alike, applied to clinical sequences, the presented method and Wiener filtering led to a comparable SNR improvement in the range 4.2–10.8 dB, depending on the sequence analyzed.

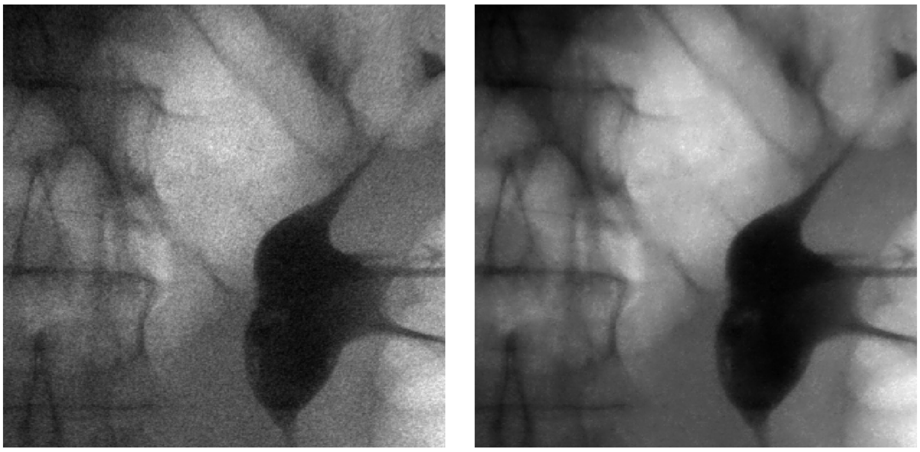
The subjective evaluation yielded excellent results for the presented method (fig. 2 and 3) as well as Wiener filtering. In both methods, areas are considerably smoothed and even though notable noise remains at edges, these are well preserved. However, the presented method features somewhat superior smoothing while simultaneously preserving structures. Moreover, a far more balanced and stable image impression is generated when viewing sequences instead of single images. This was to be expected regarding the high stability of the method.

5 Discussion

The method of Bao and Zhang based on wavelet decomposition and MRI data has been adapted for Laplacian pyramids and harnessed for X-ray image sequence applications. The presented method can be integrated in techniques already based on Laplacian pyramids with low additional complexity. Hence, the important constraint of real-time processing remains fulfilled and real-time noise reduction with preservation of important diagnostic details has been achieved.

The direct adaptation of the method led to artifacts that we were able to reduce significantly. The separation of signal and noise by coefficient products can now be used for noise reduction of X-ray images exhibiting severe noise. Due to the already high temporal stability a simple temporal filter can be applied, further improving the stable image impression in sequences. Significant gray value differences between temporal adjacent pixels are with high probability due to motion. Therefore, complex motion detection can be omitted.

Fig. 3. Original image detail (left), processed with the proposed method (right).



The evaluation of various X-ray image sequences showed a SNR improvement comparable to Wiener filtering. However, even without temporal filtering the multiscale approach leads to a far more stable image impression in sequences. In general, advances in noise reduction bear the prospect of reducing radiation doses while keeping the image quality constant.

References

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