Optimal Bilateral Filtering of CT Images

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Overview

- Introduction
- Proposed Optimization
- Experimental Results
- Conclusions

Introduction

- Bilateral filtering – very popular algorithm; smooths homogenous areas; preserves edges; non-iterative approach; fast execution; does not filter photon-limited images, adding hallo artifacts [1, 2];
- Exemplary applications in medical imaging:
  - Low dose CT noises – removed by iterative bilateral filtering with neural network (JBFnet) - 112 tunable parameters per image block; PSRN ~46.8 dB, SSIM ~ 0.9770 [3];
  - CT images in dentistry - bilateral filter + wavelet transform; more computationally demanding [4]; another solution - biltareal filter + Bayes shrinkage rule; also computationally demanding [5];
  - Ischemic posterior fossa CT images – bilateral filter leads to PSNR 32.95 dB, SSIM – 0.9749 [6].

Introduction

- Exemplary applications in medical imaging:
  - CT images of general type – bilateral filter shows 25% less efficiency than the selective mean filter [7];
  - An attempt for better preservation on the smaller details in CT images with bilateral filter – SNR 24.4 [8];
  - Low-dose CT image filtering – 3-dimensional cross-directional bilateral filter [9] – better than model-based reconstruction (28.5% increase in resolution);
  - Another study on the bilateral filter, applied over CT images – PSNR of ~32 dB.
- Often the bilateral filter is used without additional tuning of its parameters or as a combination with other methods for specific tasks.
- The main aim of the current work is to propose a general optimization procedure for the bilateral filter in its original form [1], when applied over CT images with Additive White Gaussian Noise (AWGN).

Proposed Optimization

- Principle of operation of the bilateral filter
- $I_f(i_o, j_0) =$
$$c \sum_{i=1}^{P'} \sum_{j=1}^{Q'} I_n(i,j) w(i,j,i_o,j_0,I_n(i_o,j_0),I_n(i,j)), \qquad (1)$$
- $w(i,j,i_o,j_0,I_n(i_o,j_0),I_n(i,j)) =$
$$e^{\left(\frac{-0.5d([i_0,j_0],[i,j])^2}{\sigma_d^2}\right)} e^{\left(\frac{-0.5d(I_n(i_0,j_0),I_n(i,j))^2}{\sigma_r^2}\right)}, \qquad (2)$$
- $I_f(i_0, j_0) =$
$$= \frac{1}{2\pi\sigma_d^2} \sum_{i=-P'/2}^{P'/2} \sum_{j=-Q'/2}^{Q'/2} I_n(i_0,j_0)\, e^{-\frac{(i_0-i)^2+(j_0-j)^2}{2\sigma_d^2}}. \qquad (3)$$
- $I_f(i_0, j_0) = \frac{1}{P'Q'} \sum_{i=-P'/2}^{P'/2} \sum_{j=-Q'/2}^{Q'/2} I_n(i,j). \quad (4)$
- In (3) and (4), (i_0, j_0) falls within the center of the area $<P',Q'>$.

Proposed Optimization

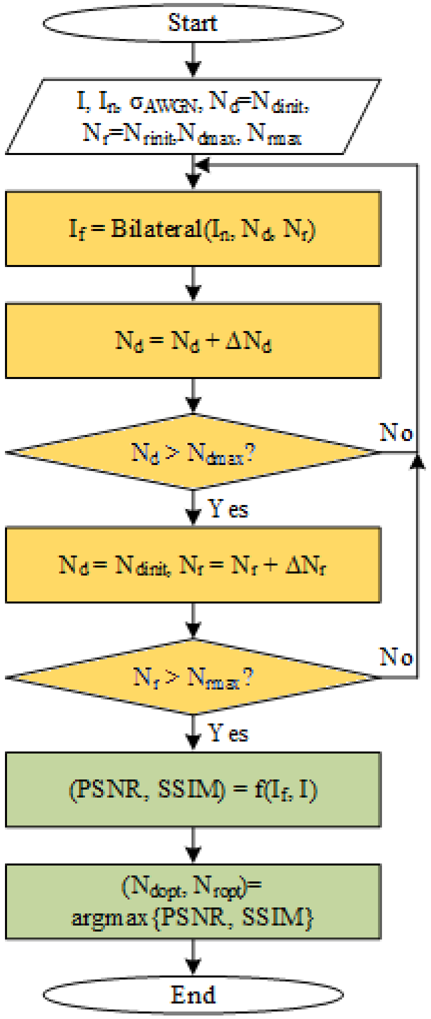

Fig. 1. Proposed optimization procedure

Experimental Results

- **Experimental setup:**
  - Testing environment: Intel Xeon E5-1620 CPU 4 cores, 3.6 GHz, 64 GB RAM, 2 TB 7200 rpm HDD. Software GNU Octave v. 6.1.0 over 64-bit MS Windows 10 Professional. Test images - 103 from DeepLesion dataset [12]; 512x512 pixels, 16 bpp. Noised with AWGN at 3 levels - $\sigma^2 = 0.001$, 0.01 and 0.1.
- Measured parameters:
  - *At* $\sigma^2 = 0.001$ – tried ranges $N_d \in [1, 10]$ and $N_r \in [2570, 25700]$

Experimental Results

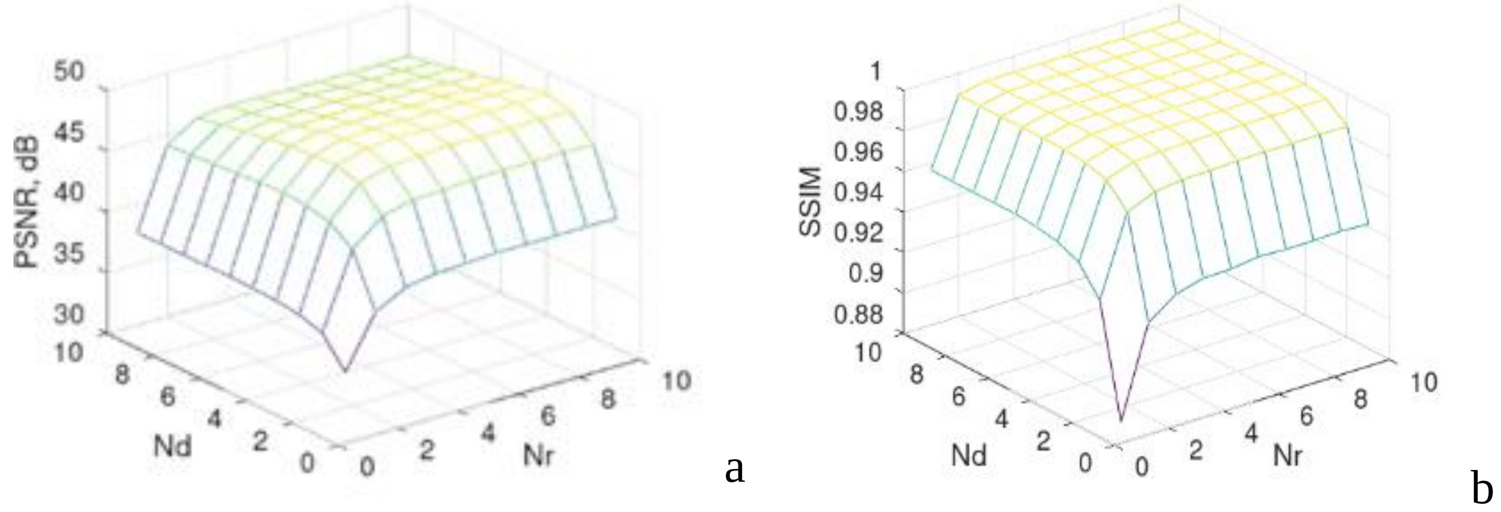

Fig. 2. Finding the optimal N_d and N_r for $\sigma^2 = 0.001$

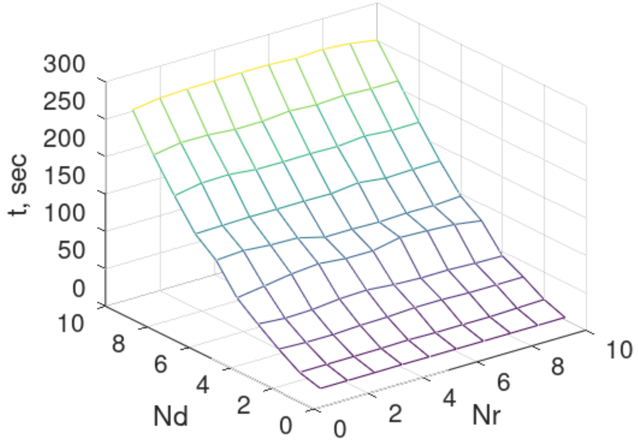

Fig. 3. Filtering times at various N_d and N_r for $\sigma^2 = 0.001$

Experimental Results

The optimal set of parameters are as follows:

- at $\sigma^2 = 0.001$ – $N_d = 5$, $N_r = 12\,850$;
- at $\sigma^2 = 0.01$ – $N_d = 10$, $N_r = 25700$;
- at $\sigma^2 = 0.1$ – $N_d = 8$, $N_r = 25700$.

The average PSNR, SSIM and filtering times t for the bilateral, Gaussian and average filter are given in Table I.

Table I. Average Filtering Efficiency Parameters

σ^2	Filter	PSNR, dB	SSIM	t, sec
0.001	Bilateral	51.25	0.9965	67.2880
	Gaussian	30.00	0.7927	0.0055
	Average	39.50	0.9296	0.0082
0.01	Bilateral	42.66	0.9860	257.6300
	Gaussian	20.00	0.2836	0.0057
	Average	29.52	0.5777	0.0082
0.1	Bilateral	19.28	0.2519	162.3100
	Gaussian	11.18	0.0485	0.0074
	Average	20.44	0.1493	0.0081

Experimental Results

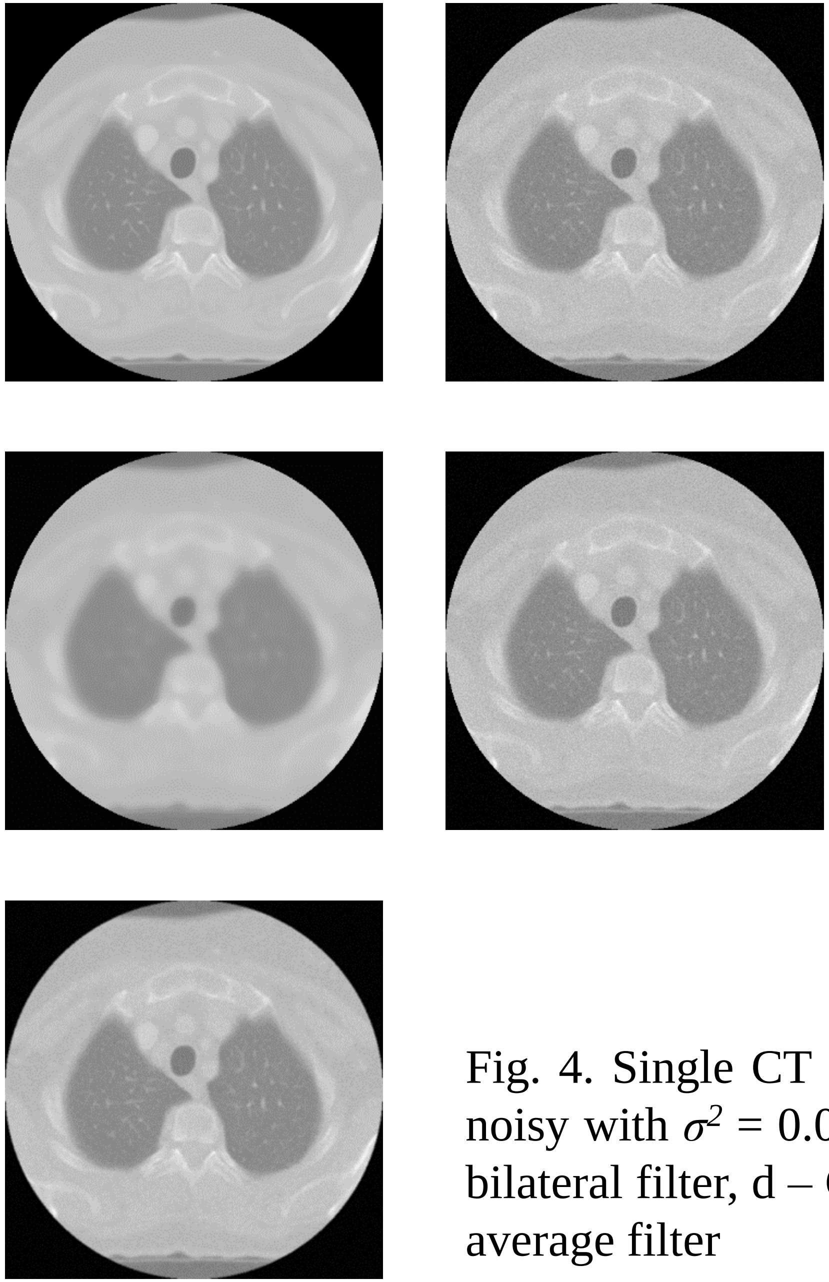

Fig. 4. Single CT slice: a – original, b – noisy with $\sigma^2 = 0.001$, and filtered by c – bilateral filter, d – Gaussian filter, and e – average filter

Discussion

- During the optimization procedure, it is observed that the variation of PSNR and SSIM within the whole range of applicable N_d and N_r is not negligible. For $\sigma^2 = 0.001$, the average PSNR is 45.09 dB with a deviation (as absolute difference) of 13.81 dB (Fig. 2.a). SSIM in the same time deviates around 0.9822 within an interval of 0.1124 (Fig. 2.b). Filtering time changes almost linearly with the increase of N_d from 3.31 sec up to 259.64 sec, regardless of the change of N_r (Fig. 3). A bit different is the distribution of PSNR for $\sigma^2 = 0.01$ – its average value is 31.90 dB with an absolute deviation of 21.14 dB, and SSIM varies around 0.7571 with 0.6830, that is there is more smooth increase for both these parameters over both the N_d and N_r parameters. Global maximum in filtration efficiency is achieved for the very end of the tested interval. The change of filtration time is again close to linear, covering virtually the same range as that for $\sigma^2 = 0.001$. When σ^2 is 0.1, PSNR falls to an average value of 14.32 dB and it varies with 8.36 dB, depending more on N_r (almost linearly over its whole range) and very slightly on N_d, just at the beginning of its interval change, after which a saturation zone is formed. Similar is the distribution of SSIM on (N_d, N_r) with total variation of 0.2072 and an average of just 0.1091 due to the extremely strong deteriorations in the image in this instance. Filtering time stays within the same boundaries for this case as well.

Discussion

- With the exception of the slightly higher PSNR, obtained by the average filter for $\sigma^2 = 0.1$, a difference of 1.16 dB with that of the bilateral filter, in all other cases both the PSNR and SSIM for the latter are highest (Table I). On a second place is the average filter (with PSNR drop of around 12 dB for $\sigma^2 = 0.001$ and 0.01, and increasing difference in SSIM up to 0.4803 for $\sigma^2 = 0.01$), followed by the Gaussian filter with an average difference of around 9 dB for the PSNR and SSIM offset varying between 0.1 and 0.3. These numerical observations are supported by the visual inspection of filtered images (Fig. 4). The average filter has an effect over homogenous areas of the image of clearing out most of the noise disturbances (Fig. 4.e), which is also true for the bilateral filter (fig. 4.c). The observable difference is the better preservation of the edges of objects in the second case. The Gaussian filter, on the other hand, preserves most of the smaller details from the objects in the image, but significant amount of noise deteriorations could still be seen (Fig. 4.d).

Discussion

- Processing time is about 4 orders of a magnitude higher for the bilateral filter than that of the Gaussian and average filter (Table I). The spread of the bilateral filter N_d, which varies with the change of σ^2 from one to another optimal configuration, affects its filtering time in direct proportion (linearly). At $\sigma^2 = 0.001$ it takes 256.68 µs/px (microseconds per pixel) on average for the bilateral filter to accomplish it tasks. In the same time the processing times for the Gaussian filter and the average filter are 0.02 µs/px and 0.03 µs/px, respectively. Increasing σ^2 to 0.01 leads to increase of t up to 982.78 µs/px for the bilateral filter, while the filtering times of the Gaussian and average filters stay almost unchanged – again approximately equal to 0.02 µs/px and 0.03 µs/px, respectively. And in the third case of $\sigma^2 = 0.1$, there is slight increase of t for the Gaussian filter up to 0.03 µs/px – a result mainly due to a light shift of the CPU load during computation, rather than the actual number of arithmetic operations performed, and the same t for the average filter – 0.03 µs/px as in the previous two cases. At that same noise level with a variance, equal to 0.1, the bilateral filter needs 619.16 µs/px – an intermediate value in comparison to the first two test scenarios.

Conclusions

- In this paper an optimization procedure for finding proper values of the spread and intensity range parameters of the bilateral filter is proposed, depending on the level of AWGN noise present in the input images, aiming the highest possible PSNR and SSIM of the output images. Objective quality parameters depend on both the spread and intensity range, which dependency becomes stronger with the increase of the variance of the present noise. Applying the optimization procedure over a slice of a CT image and filtering subsequently all slices provides an efficient way of getting the highest quality for the whole set. This approach is considered applicable also for other types of images, such as Magnetic Resonance Images, multispectral and hyperspectral images and others. Future work would reveal its applicability not only for different kind of images, but also advancing further the optimization for different kind of noises, using suitable adapted forms of the filter, considering also the work of other authors.

Thanks for your attention!