Wavelet Denoising of Multiple-Frame OCT Data Enhanced by a Correlation Analysis

M.A. Mayer[1,2], M. Wagner[1], J. Hornegger[1,2], R.P. Tornow[3]

[1]Pattern Recognition Lab, Department of Computer Science, [2]Erlangen Graduate School of Advanced Optical Technologies (SAOT), [3] Department of Ophthalmology
Friedrich-Alexander University Erlangen-Nuremberg, Erlangen, Germany
markus.mayer@informatik.uni-erlangen.de

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Friedrich-Alexander-Universität Erlangen-Nürnberg

Purpose

Speckle noise suppression on OCT images is currently performed by averaging multiple frames. In contrast to this common approach we propose a novel wavelet merging method that uses the structural properties of the actual image content to better differentiate between speckle and relevant tissue information.

Data

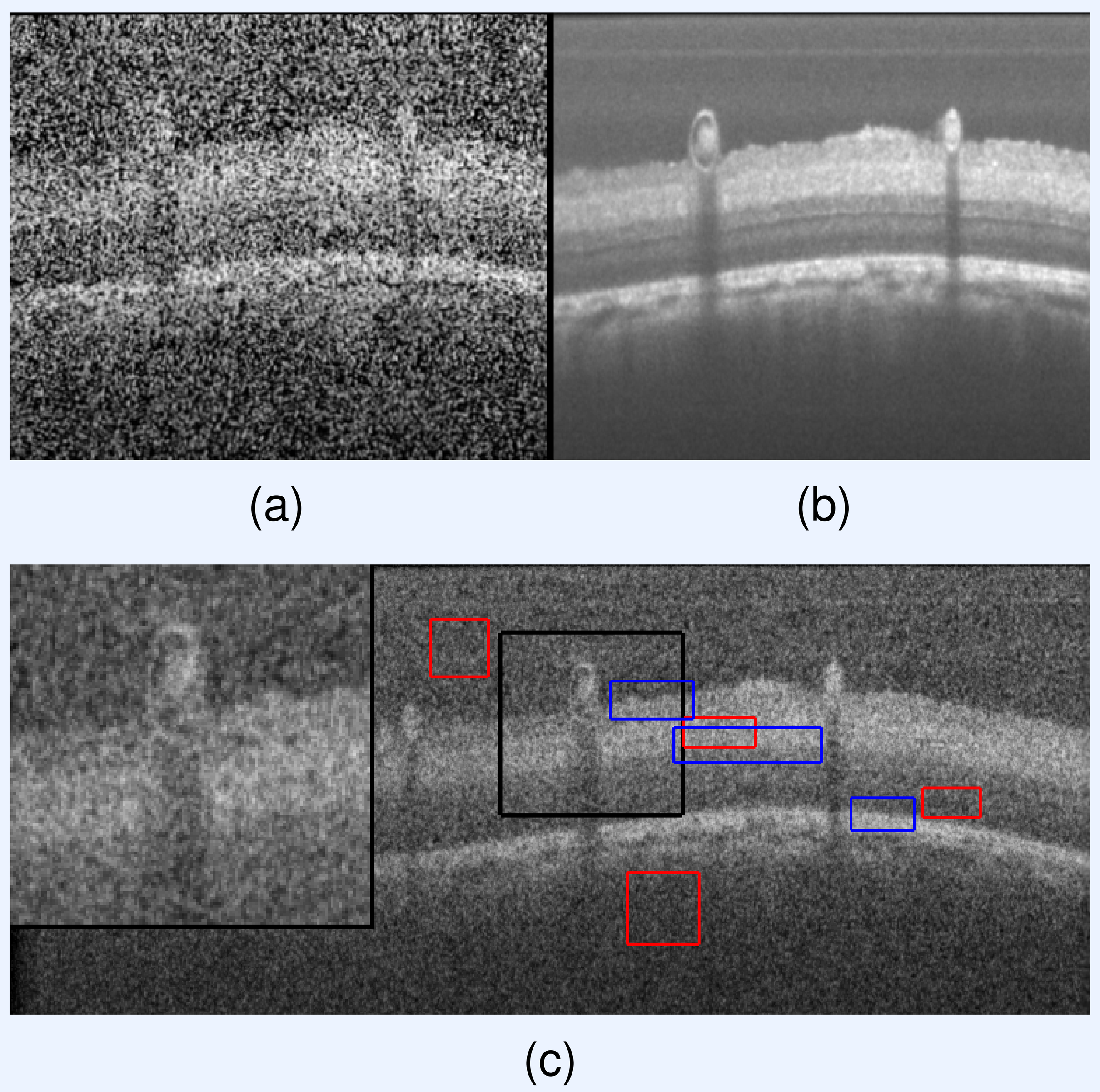

Figure 1: Example images from the dataset. (a) Crop out of one single frame. (b) Crop out of goldstandard image generated by averaging 355 frames. (c) Average of 8 frames. For a better visual inspection, an area (marked with a black square) is magnified. Red rectangles: Regions of interest (ROIs) used for the signal-to-noise ratio gain evaluation. Blue rectangles: edges used for the sharpness reduction evaluation.

355 linear B-scans were acquired from a pig's eye ex vivo with a Spectralis HRA+OCT, Heidelberg Engineering. Correlated noise was avoided by slightly moving the eye every 13 frames. All images are rigidly registered and averaged to form a noise suppressed gold standard.

Method

Each of the recorded single B-Scans is decomposed by a **wavelet analysis**, resulting in approximation coefficients A_i^l and detail coefficients $W_{i,d}^l$ (l: Decomposition level, i: Frame number, d: Detail coefficient direction).

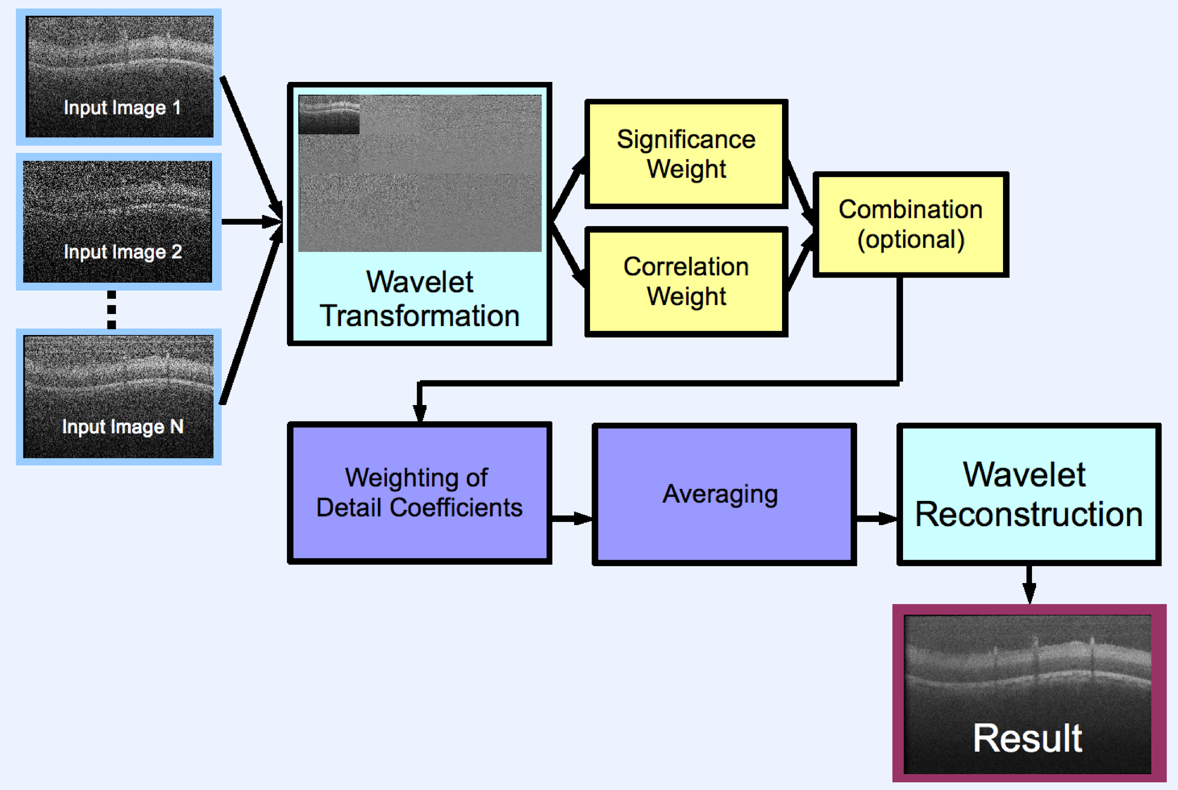

Figure 2: Algorithm overview.

Two different wavelet weighting factors are proposed:

The **significance weight** [1] provides a local noise estimation on the detail coefficients.
The mean squared distances $\sigma_{L,i}$ of the detail coefficients of one image to the other are computed:

$$\sigma_{L,i,D}^{(l)}{}^2(x) = \frac{1}{m-1}\sum_{j=0 \wedge j\neq i}^{m-1}\left(W_{i,D}^{(l)}(x) - W_{j,D}^{(l)}(x)\right)^2 \quad (1)$$

The significance weight G_{sig} for each detail coefficient is then calculated by

$$G_{sig,i,D}^{(l)}(x) = \begin{cases} 1, & \left|W_{i,D}^{(l)}(x)\right| \geq k\sigma_{L,i,D}^{(l)}(x) \\ \frac{W_{i,D}^{(l)}(x)}{k\sigma_{L,i,D}^{(l)}}, & else. \end{cases} \quad (2)$$

Parameter k controls the amount of noise reduction.

The **correlation weight** provides information wether an edge is present in the current frame or not.
For each decomposition level l it is calculated on the approximation coefficients of the layer above $(l-1)$ where $l = 0$ is the original image. For each approximation coefficient the median of the correlation to each other image within a small neighborhood is calculated:

$$G_{corr,i}^{(l)}(x) = \text{med}_{i\neq j}\left(\frac{1}{2}\text{Corr}(F_i^{(l-1)}(x), F_j^{(l-1)}(x)) + 1\right)^p \quad (3)$$

where $F_i^{(l-1)}(x)$ is the vector of all approximation coefficients in a neighborhood (5×5) around position x in decomposition layer $l-1$ of frame i. Corr is Pearsons correlation coefficient. p is a parameter that controls the amount of noise reduction applied. Each detail coefficient is calculated from four neighboring approximation coefficients in the decomposition level above. The final weight $G_{corr,i,D}^{(l)}(x)$ is averaged from these.

A **combination** of the two weights can be achieved by estimating the parameter p in G_{corr} by the significance weights:

$$G_{comb} = G_{corr}, \quad with \quad p = p_1(1 - G_{sig})^2 + 1 \quad (4)$$

with smoothing parameter p_1
The weights $G_{i,D}^{(l)}$ are used for denoising by **scaling the detail coefficients** of each image.

$$W_D^{(l)}(x) = \frac{1}{m}\sum_{i=0}^{m-1} G_{i,D}^{(l)}(x) W_{i,D}^{(l)}(x) \quad (5)$$

In a **final step** the modified wavelet transformations of the single frames are averaged. An inverse wavelet transform is performed to yield the denoised image.

Results

The signal-to-noise (SNR) ratio gain compared to the mean image (SNRG) is measured in selected regions of interest (see Figure 1). The noise is estimated on each image by subtracting the gold standard image, which is assumed to be nearly noise free. The sharpness reduction (SR) at selected borders is computed using Full-Width-Half-Maximum (see Figure 1). The evaluation is performed for each parameter set and method on 10 sets of 8 randomly selected frames. The results are averaged over these sets.

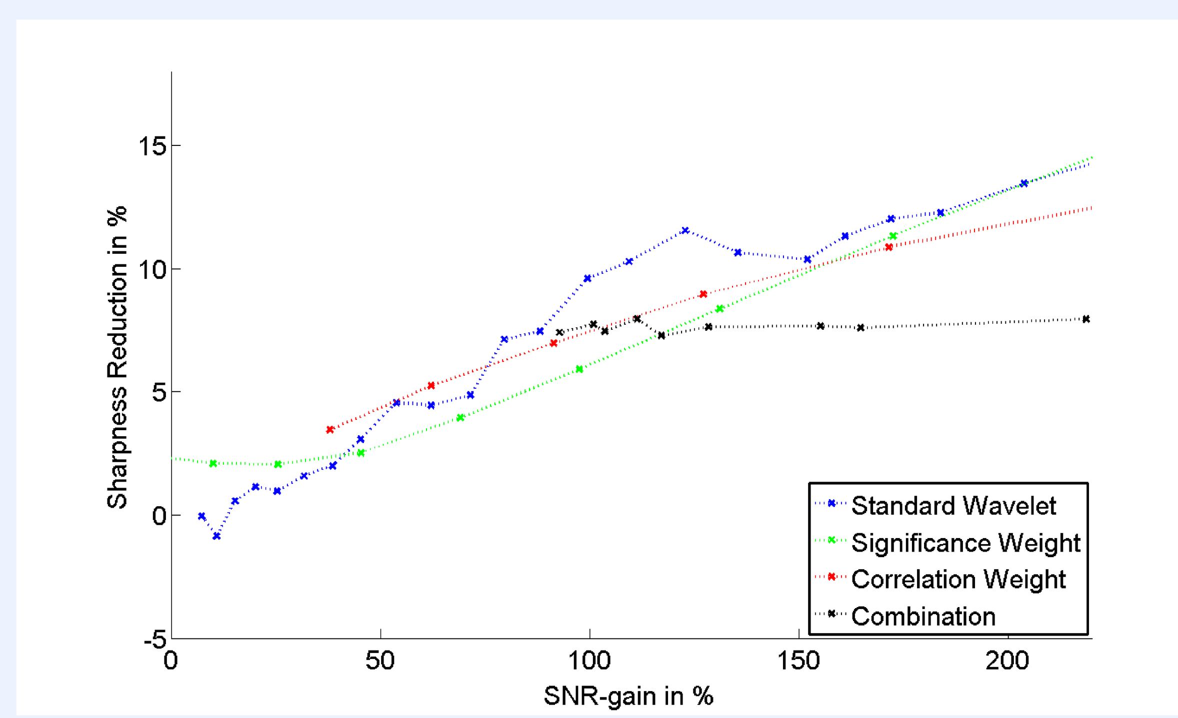

Figure 3: Quantitative evaluation of the denoising algorithm. Sharpness reduction plotted against signal-to-noise ratio gain for varying algorithms and noise reduction parameters. Standard wavelet denoising is compared to multiple frame wavelet denoising with using only significance weights, only correlation weights and both.

The SNRG achieved by standard averaging of more frames is 55% for 20 frames and 111% for 35 frames. We achieve an SNRG of 111% with a SR of 8.0% by using only 8 frames.

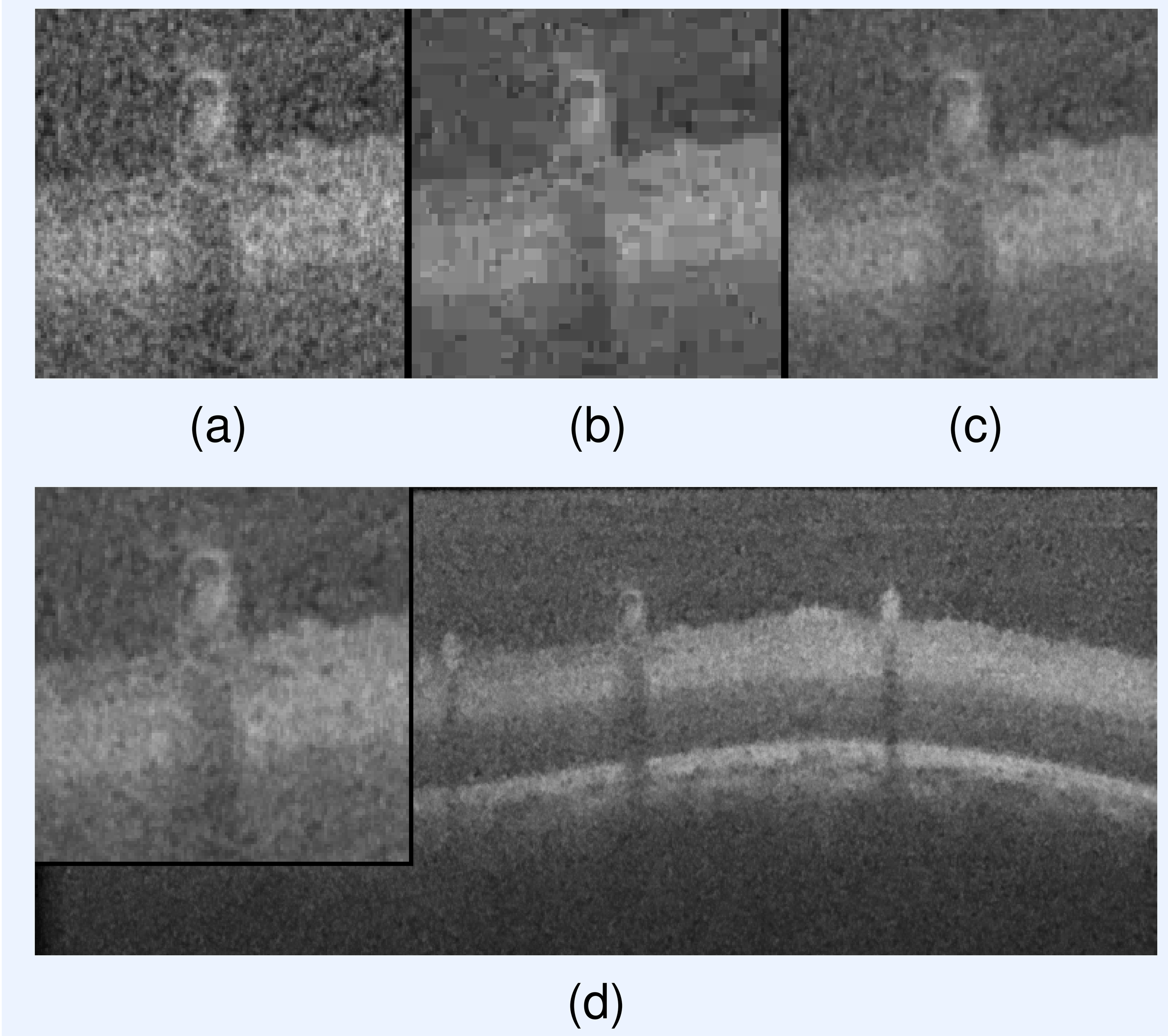

Figure 4: Example results. (a) Average from 8 frames. (b) Standard Wavelet hard thresholding applied to the average image (SNRG 99%, SR 9.6%). (c) Multiframe Wavelet denoising using only the significance weight (SNRG 98%, SR 5.9%). (d) Multiframe Wavelet denoising using the combination of significance and correlation weight (SNRG 111%, SR 8.0%).

Conclusion

1. **With 8 recorded frames we reach an SNR that is comparable to an averaging of 35 frames**.
2. A visual and quantitative evaluation shows: Nearly no detail or sharpness loss.
3. Proposed main application: Data preprocessing for segmentation tasks.

Support

The authors gratefully acknowledge funding of the Erlangen Graduate School in Advanced Optical Technologies (SAOT) by the German National Science Foundation (DFG) in the framework of the excellence initiative. The contribution was further supported by the DFG in the context of the Collaborative Research Center 539.

Commercial Relationship

M.A. Mayer, None; M. Wagner, None; J. Hornegger, None; R.P. Tornow, None.

References

[1] M. Wagner and A. Borsdorf et. al.: Wavelet Based Approach to Multiple-Frame Denoising of OCT-Images, Proceedings of the 5th Russian Bavarian Conference on Bio-Medical Engineering (RBC), 67–69, 2009