Improving the quality of low SNR images using high SNR images

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Abstract *It is important to get data with Signal-Noise-Ratios (SNR) as high as possible. Compared to other techniques, filtering methods are fast. But they do not make full use of the characteristics of sample structure which reflected by relevant high SNR images. In this study, we propose a technique termed "TransFiltering". It transplants the characteristics of a high SNR image to the frequency spectrum of a low SNR image by filtering. Usually, the high SNR and the low SNR image should have similar structure pattern. For example, they all come from the same image sequence. In the proposed method, Fourier transform is first performed on both of the images. Then, the frequency spectrum of the low SNR image is filtered according to that of the high SNR image. Finally, inverse Fourier transform is performed to get the image with improved SNR. Experiment results show that the proposed method is both effective and efficient.*

Signal-Noise-Ratio (SNR) is one of the key factors in many fields[1], such as Signal Processing[2], Image Processing[3], and Microscopy[4]. Sometimes, SNR may be the biggest barrier that prevent theoretical results to be achieved in practice. Conventional filtering technique[5] and optimization technique[6-8] are common approaches for improvement of SNR. Usually, the former (e.g., Gaussian filtering) is more efficient but less effective, and the latter (e.g., regularization method) is more effective but less efficient.

Conventional filtering techniques decrease the amplitudes of a signal's high frequency components. By doing so, noises are decreased because noises are mainly comprised of high frequency components. But the results may not be satisfying enough without a more thorough criterion to design the filters. When a sample is observed by a microscope, the SNR often changes gradually with time. For example, its fluorescence becomes weaker and weaker. As a result, the first image in a sequence may have the highest SNR, and the others have lower and lower ones. But the sample's structure pattern is relatively stable although there are some differences between frames. Therefore, we propose to adjust the frequency components of low SNR images according to those of the highest SNR image. Compared to decreasing the high frequency component, this will lead to a more realistic frequency spectrum.

Assume that an image sequence includes many images with different SNRs. One of the low SNR images needs to be processed, and the image with highest SNR is used as the criterion. The proposed method is termed "TransFiltering" because it transplant the characteristics of frequency spectrum from a high SNR image to low SNR ones using a filter. It could be treated as the extension of conventional filtering methods such as Gaussian filtering.

First of all, Fourier transform is performed on both the low SNR image (LSNRI) and high SNR image (HSNRI). Each of the frequency spectrum is the combination of amplitude spectrum and phase spectrum. Similar to conventional filtering techniques, the proposed method also handles the phase spectrum only. By changing the amplitude of components, the ratio of signal and noise will change accordingly.

After that, the LSNRI's frequency spectrum is filtered according to the HSNRI's frequency spectrum. One

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simple way is to directly set the amplitude of the LSNRI's spectrum same as that of the HSNRI's spectrum. This is a way of implicit filtering. Another way is to explicitly build a filter from the amplitude spectrums of the LSNRI and HSNRI. For example, smooth both the amplitude spectrums properly, and then divide the LSNRI's amplitude spectrum by HSNRI's. After the filter is built, it can be used to filter the LSNRI, or other low SNR images. As shown by the examples in Fig. 1, the amplitude spectrum of LSNRI has greater components of high frequency, while those of HSNRI are much smaller. After filtered by a Gaussian filter, the LSNRI's high frequency components decrease. If filtered by the proposed method, the resulting amplitude spectrum would be very similar to that of HSNRI.

Finally, inverse Fourier transform is performed on the filtered frequency spectrum, so as to get the spatial image with improved SNR.

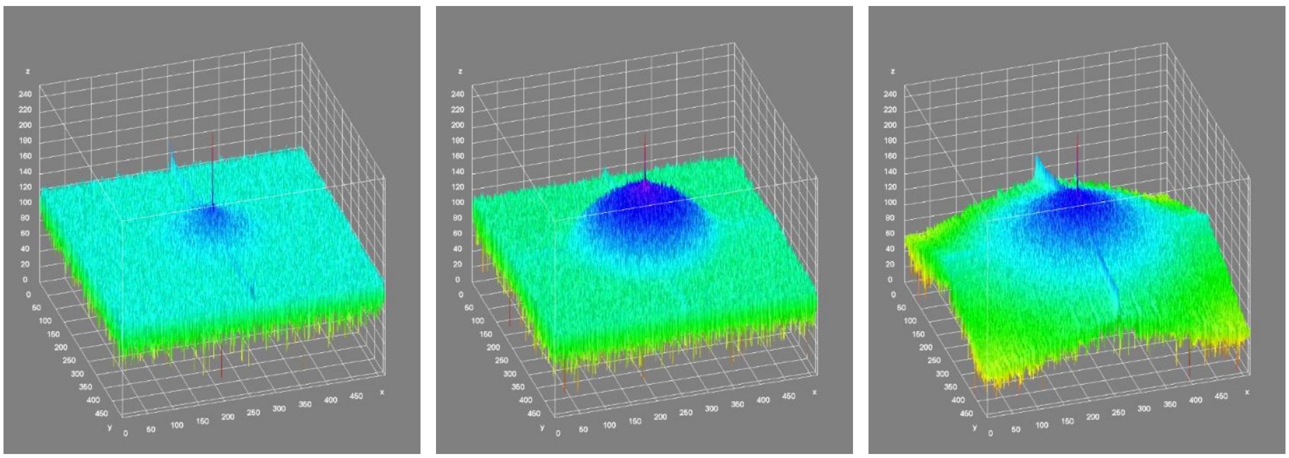

Figure 1. (a) The amplitude spectrum of LSNRI (b) The amplitude spectrum of HSNRI (c) The amplitude spectrum of LSNRI filtered by a Gaussian filter.

Experiments are performed on some biological images. Fig. 2 shows the experiment result on an image of fly brain. Fig. 2(a) is a HSNRI which is used as the criterion for filtering the LSNRI's frequency spectrum. Fig. 2(b) is the expected image if the LSNRI was not contaminated by noises. Such an image cannot be got in real observations. But in this experiment, the LSNRI is generated by adding noised to this image. Please note that Fig. 2(a) and Fig. 2(b) are picked from the same image sequence, but they are somewhat different. Fig. 2(c) is the LSNRI which includes dense and large noises. Fig. 2(d) is the result of the LSNRI filtered by the proposed method. Fig. 2(e) is the result of the LSNRI filtered by a Gaussian Filter. Fig. 3 shows the results of another situation, where the LSNRI includes severe artifacts. Fig. 4 shows the results of an experiment on another image.

As a filtering method, the proposed technique runs fast. The experiment is run in a common laptop, with AMD A9-9410 RADEON R5 2.90GHz CPU, 8 GB memory, x64 Windows 10. The experimental program is implemented with Matlab R2017b. Usually, less than 0.4 seconds are needed for the whole procedure: reading the images, building the filter, filtering the LSNRI, etc.

As demonstrated by the experiments, the proposed technique is an efficient filtering approach, and at the same time is also effective.

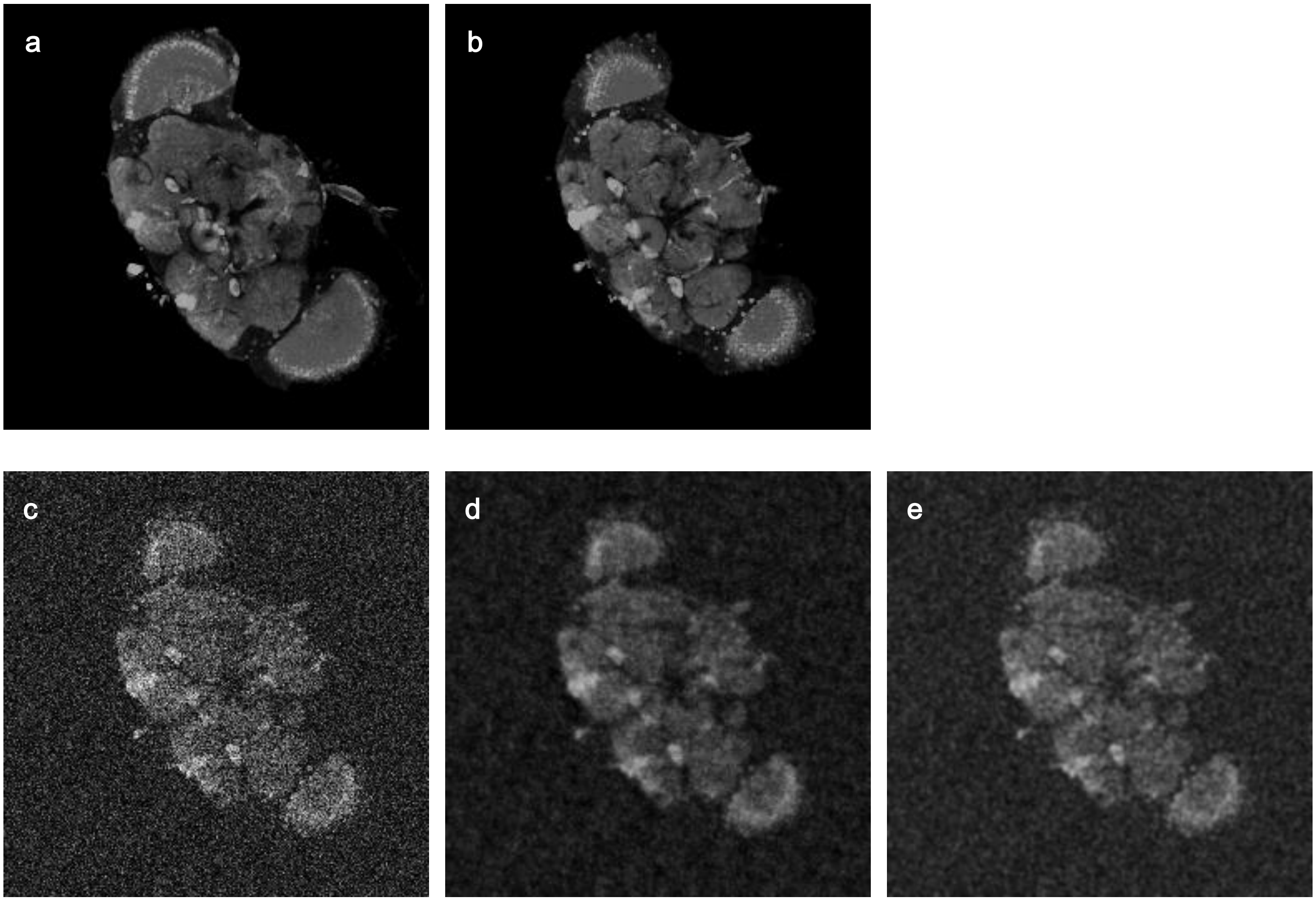

Figure 2. (a) HSNRI (frequency criterion) (b) Image without noise (c) LSNRI with noises (d) Filtered by the proposed method (e) Filtered by a Gaussian Filter.

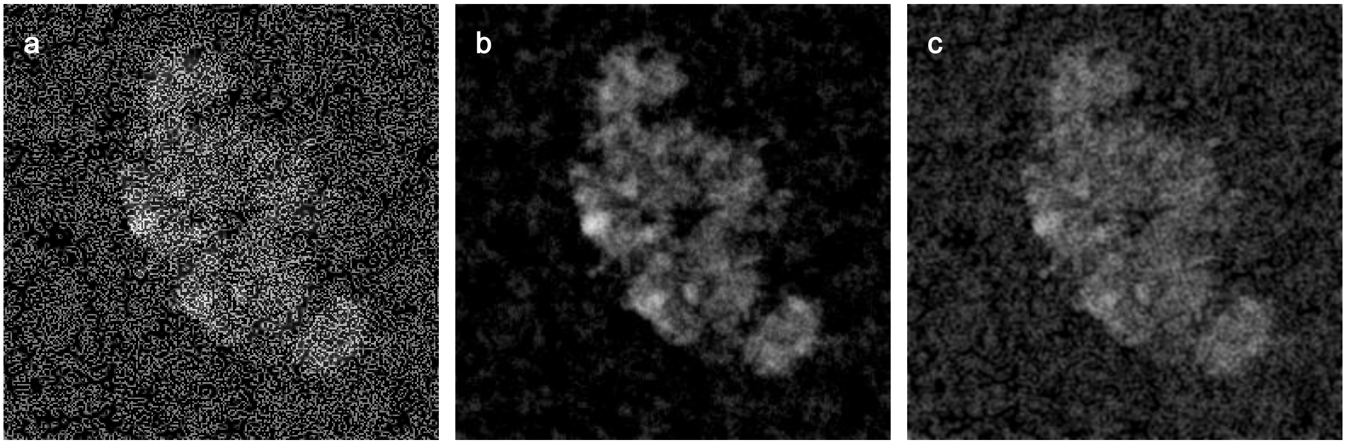

Figure 3. (a) LSNRI with artifacts (b) Filtered by the proposed method (c) Filtered by a Gaussian Filter.

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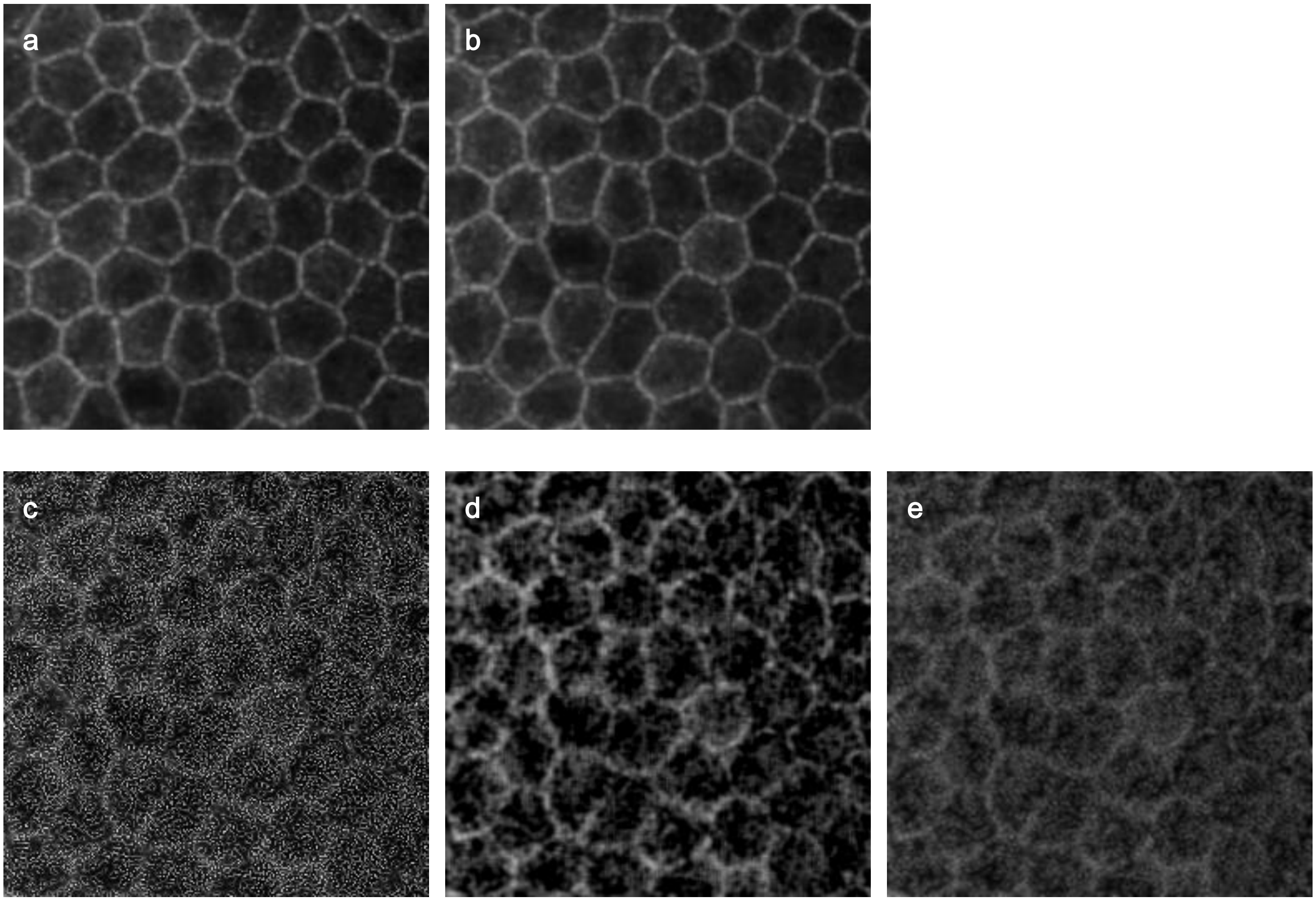

Figure 4. (a) HSNRI (frequency criterion) (b) Image without noise (c) LSNRI with severe artifacts (d) Filtered by the proposed method (e) Filtered by a Gaussian Filter.

References

1. García, E., et al., *Spreading sequences in active sensing: A review.* Signal Processing, 2015. **106**: p. 88-105.
2. Oppenheim, A.V. and R.W. Schafer, *Digital Signal Processing*. 2015: PEARSON.
3. Gonzalez, R.C. and R.E. Woods, *Digital Image Processing (3rd Edition)*. 2014: PEARSON.
4. Lin, K.T., et al., *A high signal-to-noise ratio passive near-field microscope equipped with a helium-free cryostat.* Rev Sci Instrum, 2017. **88**(1): p. 013706.
5. Brailean, J.C., et al., *Noise reduction filters for dynamic image sequences: a review.* Proceedings of the IEEE, 1995. **83**(9): p. 1272-1292.
6. Orieux, F., et al., *Bayesian Estimation for Optimized Structured Illumination Microscopy.* IEEE Transactions on Image Processing, 2012. **21**(2): p. 601-614.
7. Lefkimmiatis, S. and M. Unser, *Poisson Image Reconstruction With Hessian Schatten-Norm Regularization.* IEEE Transactions on Image Processing, 2013. **22**(11): p. 4314-4327.
8. Bioucas-Dias, J.M., M.A.T. Figueiredo, and J.P. Oliveira. *Total Variation-Based Image Deconvolution: a Majorization-Minimization Approach*. in *2006 IEEE International Conference on Acoustics Speech and Signal Processing Proceedings*. 2006.

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