

# Algorithm Description

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We have a speckle backscatter intensity image  $I_0$  and we want to find  $R$  such that:

$$R = \arg \min_{I \in \mathbb{R}^{M \times N}} \mathcal{R}(I) + P(I | I_0).$$

Above  $\mathcal{R}:\mathbb{R}^{M \times N} \rightarrow \mathbb{R}$  is an image regularizer such as the [total-variation norm](#)  $\|I\|_1$  or [BM3D](#). The noise model  $P(I | I_0)$  is the fully-developed speckle model (see this [paper](#) and references therein). This tool is then applied to:

- the "reference image" (called the super-image in the paper): the temporally averaged image from the intensity stack.
- the ratio of each intensity image with the reference image (using a slightly different noise model than the fully developed speckle model).

The final de-speckled image is then the (denoised ratio)  $\times$  (the denoised reference image). Each denoising step is solved using the [Alternating Direction Method of Multipliers](#) (ADMM).

## References

### Rabasar

- Zhao, et al. [RABASAR](#), 2019.
- Zhao, et al. [Github Repo](#), 2019.

### Spatial Denoising

- Bioucas-Dias and Figueiredo. [Multiplicative Noise Removal Using Variable Splitting and Constrained Optimization](#), 2010.
- Delladelle, et al. [MuLoG: Multi-channel Logarithm with Gaussian denoising](#), 2017.

### ADMM

- Boyd, et al. [Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers](#), 2010.
- Chan, et al. [Plug-and-Play ADMM for Image Restoration: Fixed Point Convergence and Applications](#), 2016.