

Supplementary Material to “External Prior Guided Internal Prior Learning for Real Noisy Image Denoising”

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In this supplementary material, we provide:

1. The closed-form solution of the proposed weighted sparse coding model in the main paper.
2. More denoising results on the real noisy images (with no “ground truth”) provided in the dataset [1].
3. More denoising results on the 15 smaller real noisy images (with “ground truth”) used in the dataset [2].
4. More denoising results on the 60 real noisy images (with “ground truth”) cropped from [2].

1. Closed-Form Solution of the Weighted Sparse Coding Problem

The weighted sparse coding problem in the main paper is:

$$\min_{\alpha} \|\mathbf{y} - \mathbf{D}\alpha\|_2^2 + \|\mathbf{w}^T \alpha\|_1. \quad (1)$$

Since \mathbf{D} is an orthonormal matrix, problem (1) is equivalent to

$$\min_{\alpha} \|\mathbf{D}^T \mathbf{y} - \alpha\|_2^2 + \|\mathbf{w}^T \alpha\|_1. \quad (2)$$

For simplicity, we denote $\mathbf{z} = \mathbf{D}^T \mathbf{y}$. Since $\mathbf{w}_i = c * 2\sqrt{2}\sigma^2 / (\Lambda_i + \varepsilon)$ is positive (please refer to Eq. (18) in the main paper), problem (2) can be written as

$$\min_{\alpha} \sum_{i=1}^{p^2} ((\mathbf{z}_i - \alpha_i)^2 + \mathbf{w}_i |\alpha_i|). \quad (3)$$

The problem (3) is separable w.r.t. α_i and can be simplified to p^2 scalar minimization problems

$$\min_{\alpha_i} (\mathbf{z}_i - \alpha_i)^2 + \mathbf{w}_i |\alpha_i|, \quad (4)$$

where $i = 1, \dots, p^2$. Taking derivative of α_i in problem (4) and setting the derivative to be zero. There are two cases for the solution.

(a) If $\alpha_i \geq 0$, we have

$$2(\alpha_i - \mathbf{z}_i) + \mathbf{w}_i = 0. \quad (5)$$

The solution is

$$\hat{\alpha}_i = \mathbf{z}_i - \frac{\mathbf{w}_i}{2} \geq 0. \quad (6)$$

So $\mathbf{z}_i \geq \frac{\mathbf{w}_i}{2} > 0$, and the solution $\hat{\alpha}_i$ can be written as

$$\hat{\alpha}_i = \text{sgn}(\mathbf{z}_i) * (|\mathbf{z}_i| - \frac{\mathbf{w}_i}{2}), \quad (7)$$

where $\text{sgn}(\bullet)$ is the sign function.

(b) If $\alpha_i < 0$, we have

$$2(\alpha_i - \mathbf{z}_i) - \mathbf{w}_i = 0. \quad (8)$$

The solution is

$$\hat{\alpha}_i = \mathbf{z}_i + \frac{\mathbf{w}_i}{2} < 0. \quad (9)$$

So $\mathbf{z}_i < -\frac{\mathbf{w}_i}{2} < 0$, and the solution $\hat{\alpha}_i$ can be written as

$$\hat{\alpha}_i = \text{sgn}(\mathbf{z}_i) * (-\mathbf{z}_i - \frac{\mathbf{w}_i}{2}) = \text{sgn}(\mathbf{z}_i) * (|\mathbf{z}_i| - \frac{\mathbf{w}_i}{2}). \quad (10)$$

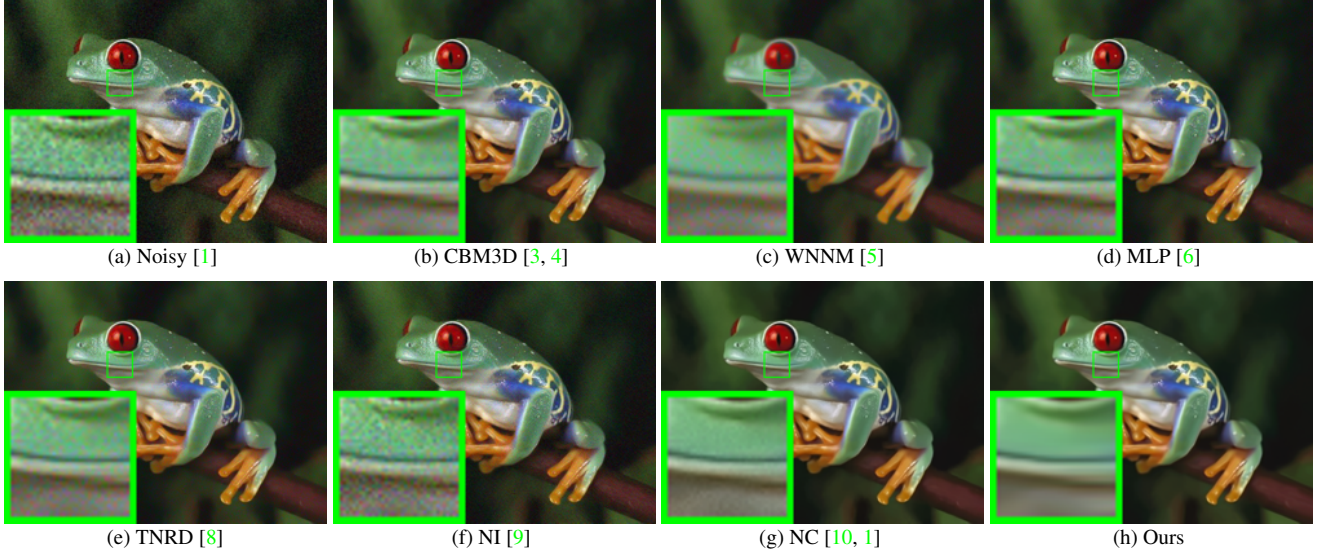


Figure 1. Denoised images of the real noisy image “Frog” [1] by different methods. The images are better to be zoomed in on screen.

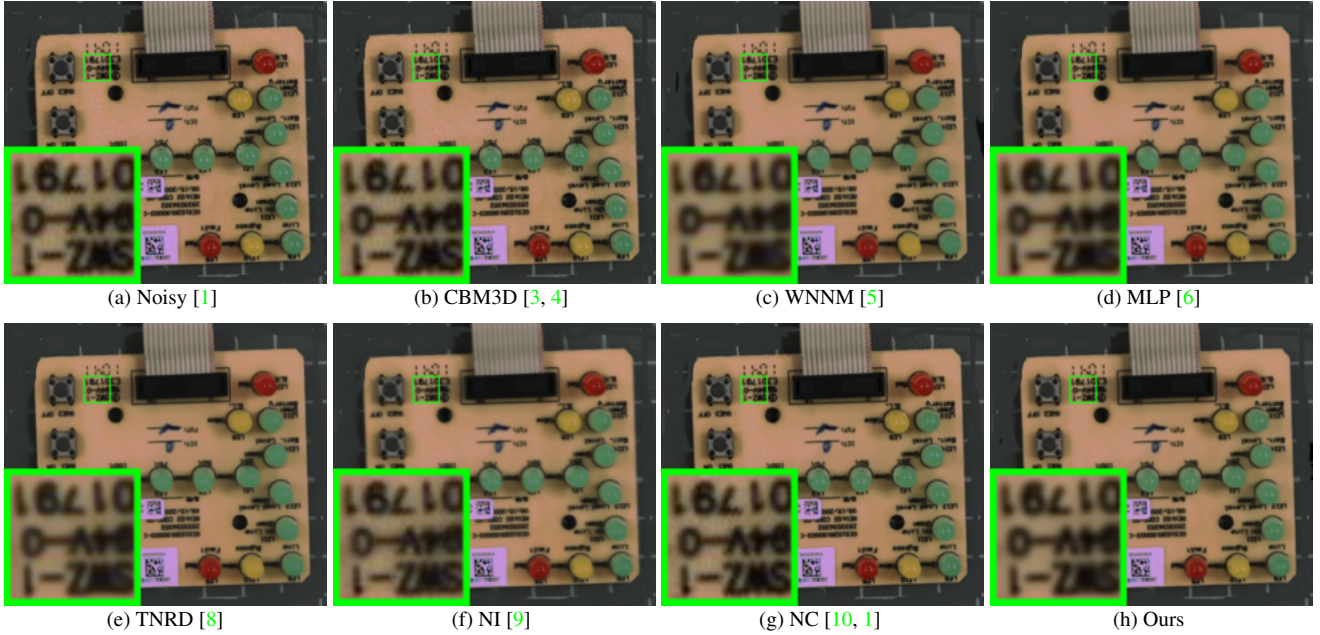


Figure 2. Denoised images of the real noisy image “Circuit” [1] by different methods. The images are better to be zoomed in on screen.

In summary, we have the final solution of the weighted sparse coding problem (1) as

$$\hat{\alpha} = \text{sgn}(\mathbf{D}^T \mathbf{y}) \odot \max(|\mathbf{D}^T \mathbf{y}| - \mathbf{w}/2, 0), \quad (11)$$

where \odot means element-wise multiplication and $|\mathbf{D}^T \mathbf{y}|$ is the absolute value of each entry of the vector $\mathbf{D}^T \mathbf{y}$.

2. More Results on Dataset [1]

In this section, we give more visual comparisons of the competing methods on the real noisy images provided in [1]. As can be seen from Figures 1-??, our proposed method is much better than the state-of-the-art denoising methods. This validates the effectiveness of our proposed external prior guided internal prior learning framework for real noisy image denoising.



Figure 3. Denoised images of the real noisy image “Woman” [1] by different methods. The images are better to be zoomed in on screen.

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