Image Deblurring in the presence of Salt-and-Pepper Noise

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Motivation

Deblurring the image in the presence of Salt-and-Pepper Noise by exploring the signal sparse property.

Traditional algorithms

The classical methods developed for Gaussian noise produces very poor results. To benefit from the fact that parts of the pixels are noise-free, a two-phase method that includes first noise detection and then deblur based on the noise-free pixels was proposed in [1], and after that two improved versions based on the similar idea were developed in [2] and [3]. Unfortunately, there are two unavoidable issues. First, the blurring kernel is assumed to be known while it is not the case in practice. Second, there is a rapid descend in performance when the noise level is high because of the limited noise-free pixels.

References

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Conclusions

In this work, the image and the kernel are sparsely represented by the framelet domain, and the noise is sparsely represented by the spatial domain. To perform robust recovery, the estimation error in blur kernel is also considered and sparely represented by spatial domain. Based on the sparse properties, a joint estimation is devised that simultaneously recovers the image, suppresses the noise, and estimates the unknown blurring kernel. A two-step process is developed to obtain the solution in which the APG approach is applied to efficiently solve ℓ_1-norm constrained problem. Numerical studies demonstrate that the proposed proposed joint estimation approach offers great performance improvements compared with other state-of-the-art algorithms.

Proposed method

To explore the sparse property of the clean image and the blur kernel, the following optimization problem is proposed to jointly perform image reconstruction and blurring kernel estimation under the salt-and-pepper noise. That is

$$\begin{aligned} &\text{minimize} && \|\alpha_{\mathbf{x}}\|_1 + \lambda_1\|\alpha_{\mathbf{H}}\|_1 + \lambda_2\|\mathbf{n}\|_1 + \lambda_3\|\mathbf{u}\|_1 \\ &\text{subject to} && \|\mathbf{y} - (\mathbf{W}^{\mathbf{T}}\alpha_{\mathbf{x}})(\mathbf{W}^{\mathbf{T}}\alpha_{\mathbf{H}}) - \mathbf{u} - \mathbf{n}\|_2 < \epsilon, \end{aligned} \tag{1}$$

where $\mathbf{u} = \delta(W^T\alpha_x)$ is the residual term, and it has been shown to be sparse in the spatial domain.To efficiently solve the optimization problem, a two-step iterative process is utilized. In details, the two-step procedure works as follows

- **Step 1**: solve the convex optimization problem with the initialized/estimated blurring kernel as

$$\begin{aligned} &\text{minimize} && \|\alpha_{\mathbf{x}}\|_1 + \lambda_2\|\mathbf{n}\|_1 \\ &\text{subject to} && \|\mathbf{y} - (\mathbf{W}^{\mathbf{T}}\alpha_{\mathbf{x}})(\mathbf{W}^{\mathbf{T}}\hat{\alpha}_{\mathbf{H}}) - \hat{\mathbf{u}} - \mathbf{n}\|_2 < \epsilon, \end{aligned} \tag{2}$$

- **Step 2**: Using the estimations from Step 1, solving the same convex optimization problem produces blurring kernel estimation as

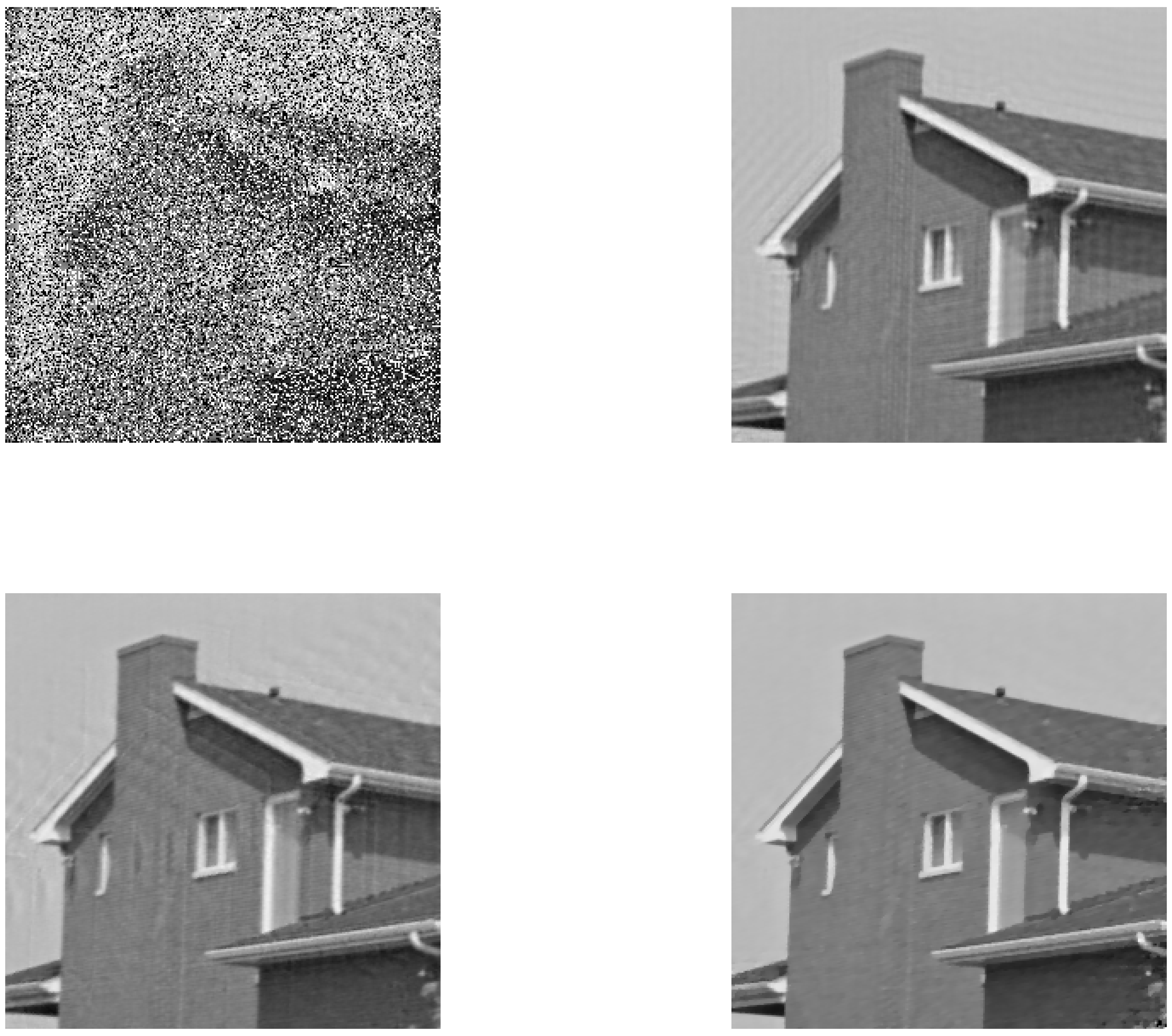
$$\begin{aligned} &\text{minimize} && \lambda_1\|\alpha_{\mathbf{H}}\|_1 + \lambda_3\|\mathbf{u}\|_1 \\ &\text{subject to} && \|\mathbf{y} - (\mathbf{W}^{\mathbf{T}}\hat{\alpha}_{\mathbf{x}})(\mathbf{W}^{\mathbf{T}}\alpha_{\mathbf{H}}) - \mathbf{u} - \hat{\mathbf{n}}\|_2 < \epsilon, \end{aligned} \tag{3}$$

- Steps 1 and 2 are proceeded recursively until a stopping rule is satisfied.

At each step of the two-step process, it solves an ℓ_1-norm constrained optimization problem, and considering the large size of the image, the algorithm of APG is tailored to solve the optimization problem.

Numerical Studies

The results of numerical studies are presented in this section to demonstrate the performance of the proposed joint estimation method. For comparison purpose, the results from TP-TV, and FTP are also provided.



The ringing artifacts are noticeable in the results obtained by the TP-TV and FTP, whereas the proposed approach preserves the details of the image.