

A Noise Estimation Free Framework for Robust Real Image Denoising

Anonymous CVPR submission

Paper ID ****

Abstract

Previous work all focus on noise modeling, which limit their application. However, in this paper, we first propose a framework for real image denoising. This framework doesn't need noise modeling and estimation. This framework is learning based. A new Double Semi-Couple Dictionary Learning model is proposed to learn the dictionary as well as the mapping function between real noisy images and latent clean natural images.

1. Introduction

Image denoising is an important problem in computer vision and image processing. High-quality images denoised from noisy ones is also of great importance for high-level vision tasks such as pattern recognition. Over the last several decades, there are many image denoising methods. Most existing methods are designed to deal with specific types of noise, e.g., Gaussian noise, mixed Gaussian and impulse noise, etc. Gaussian noise removal is a fundamental problem which has received intensive research interests with many representative work [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12]. Image denoising for Gaussian noise is not only an independent task but also can be incorporated into other tasks, e.g., the removal of mixed Gaussian and impulse noise. Despite of the success of these methods, they are designed specially for Gaussian noise or other specific types of noise. However, in practice, real noisy images are almost everywhere, in which the noise model is unknown and complex. The noise distribution in real images is more complex than Gaussian or mixed Gaussian and impulse noise, and is usually unknown for existing methods. This makes image denoising still a challenging problem.

In order to deal with real noise in real world images, many methods have been proposed for real or real image denoising problem [13, 14, 15, 16, 17, 18, 19]. Early methods [13, 14, 15] still assume that the noise in real images are Gaussian distributed. They first estimate the noise level and remove the noise subsequently. However, Gaussian assumption is too simple to model the noise in comprehen-

sively real images. Most recent works assume that the noise in real noisy images are Mixture of Gaussian distributed [16, 17, 18] or tensor Gaussian cross multiple channels [19].

Despite the success of these methods, they have some limitations. First of all, all these methods perform real image denoising in the framework of conjunction of a thorough noise estimation method followed by an adapted denoising method [17]. However, the real camera noise is far from being Gaussian, signal dependent, and hard to estimate [19]. For instance, the in-camera imaging pipeline in [19] include image demosaicing, white balance and color space transform, gamut mapping, tone mapping, and JPEG compression. During these procedures, at least five different types of noise are added, including fixed pattern noise, dark current noise, short noise, amplifier noise and quantization noise [20]. Although the Mixture of Gaussian model can be used to approximate any continuous distribution [], its parameters are often time consuming to be fit on the test noisy image no matter the EM [21] algorithm or variational inference [22] is used. Hence, it is hard to predict Secondly, the methods of Portilla [13], Rabie et al. [14], and Liu et al. [15] assumes that the noise is of Gaussian distribution. This is not true in real world noisy images. As suggested in [15, 17], Gaussian noise may be inflexible for more complex noise in real images. On the other hand, the method [16] needs tune specific parameters for different types of noise. This makes the proposed method not a strictly real image denoising. Hence, it is still desirable to design an robust and effective model for real image denoising, which bases on few assumptions and can deal with unknown noise without any parameter tuning procedure.

In this paper, we avoid the challenge problem of noise estimation. We therefore propose a cross domain synthesis solution for real image denoising. In fact, we propose a novel double semi-couple dictionary learning algorithm for real image denoising problem. In the training stage, given the training patches (noisy ones and clean ones), the dictionaries and coefficients of both the clean and noisy patches. The mapping between the clean and noisy coefficients matrices are also learned in our model. Given a real noisy image, we first extract overlapping patches from it. Then we obtain

the clean coefficient from an optimization framework similar to the training stage. The recovered patches are reconstructed by the obtained coefficients on corresponding clean dictionary atoms. We perform comprehensive experiments on real noisy images from multiple different CMOS or CCS sensors. The results demonstrate that our method achieves comparable or even better denoising performance (PSNR, SSIM, and visual quality) on most real noisy images. This reveals that the proposed method has the substantial effect of cross domain image synthesis framework for real image denoising task.

1.1. Our Contributions

To summarize, the contributions of this paper are as follows:

- To the best of our knowledge, we are among the first attempts for real image denoising which regard image denoising as a cross domain transfer problem.
- We also propose a new coupled dictionary learning framework for image restoration problems.
- We demonstrate that our method achieves the state-of-the-art performance on real image denoising problem, both on objective and subjective measurements.
- We construct paired dataset by transforming the unpaired dataset via k-Nearest Neighbor algorithm [?].
- We introduce the Gating Network to speed up the model selection and overall testing speed.

2. Related Work

2.1. Couple dictionary learning

Coupled dictionary learning (CDL) is frequently used in cross-style image synthesis problems such as image super-resolution. CDL assumes that the source and target styles of image have close relationships. CDL aims at learning a pair of dictionaries as well as the relationships between the two cross-domain image styles. Hence, the information from the source image style can be applied to synthesize the image at the target style. The relationships are often assumed to be identical mapping (coupled) [23], linear mapping (semi-coupled) [24]. Yang et al. [23] assumed that LR image patches have the same sparse representations as their HR versions do, and proposed a joint dictionary learning model for SR using concatenated HR/LR image features. They later imposed relaxed constraints on the observed dictionary/coefficient pairs across image domains for improved performance. Wang et al. [24] further proposed a semi-coupled dictionary learning (SCDL) scheme by advancing a linear mapping for cross-domain image sparse representation. Their method has been successfully applied to applications of image SR and cross-style synthesis.

2.2. Real Image Denoising

To the best of our knowledge, the study of real image denoising can be dated back to the BLS-GSM model [25], in which Portilla et al. proposed to use scale mixture of Gaussian in overcomplete oriented pyramids to estimate the latent clean images. In [13], Portilla proposed to use a correlated Gaussian model for noise estimation of each wavelet subband. Based on the robust statistics theory [?], the work of Rabie [14] modeled the noisy pixels as outliers, which could be removed via Lorentzian robust estimator. In [15], Liu et al. proposed to use 'noise level function' (NLF) to estimate the noise and then use Gaussian conditional random field to obtain the latent clean image. Recently, Gong et al. proposed an optimization based method [16], which models the data fitting term by weighted sum of ℓ_1 and ℓ_2 norms and the regularization term by sparsity prior in the wavelet transform domain. Later, Lebrun et al. proposed a multiscale denoising algorithm called 'Noise Clinic' [17] for real image denoising task. This method generalizes the NL-Bayes [26] to deal with signal, scale, and frequency dependent noise. Recently, Zhu et al. proposed a Bayesian model [18] which approximates the noise via Mixture of Gaussian (MoG) model [22]. The clean image is recovered from the noisy image by the proposed Low Rank MoG filter (LR-MoG). However, noise level estimation is already a challenging problem and denoising methods are quite sensitive to this parameter. Moreover, these methods are based on shrinkage models that are too simple to reflect reality, which results in over-smoothing of important structures such as small-scale text and textures.

3. Double Semi-Couple Dictionary Learning

In this section, we first formulate the real image denoising problem from the perspective of learning based model and then provide the optimization for the problem.

3.1. Problem Formulation

For real image denoising, we first collect clean natural images and real noisy images for training. Assume the \mathbf{X} and \mathbf{Y} are unpaired clean image patches and real noisy patches. Let the $\mathbf{X} = \mathbf{D}_x \mathbf{A}_x$ and $\mathbf{Y} = \mathbf{D}_y \mathbf{A}_y + \mathbf{V}_y$, where \mathbf{V}_y is the real noise of which we don't know the distribution.

$$\min_{\mathbf{D}_x, \mathbf{D}_y, \mathbf{A}_x, \mathbf{A}_y} E_{data}(\mathbf{X}, \mathbf{D}_x, \mathbf{A}_x) + E_{data}(\mathbf{Y}, \mathbf{D}_y, \mathbf{A}_y, \mathbf{V}_y) + E_{map}(f_1(\mathbf{A}_x), f_2(\mathbf{A}_y)) + E_{reg}(\mathbf{A}_x, \mathbf{A}_y, f_1, f_2, \mathbf{D}_x, \mathbf{D}_y, \mathbf{V}_y) \quad (1)$$

This framework doesn't need noise modeling and estimation. However, we still model the noise by \mathbf{V}_y for visualization what we have removed during training. The regularization of the noise by $\|\mathbf{V}_y\|_p^p$ can be flexible, that we can

penalize it by Frobenius norm, ℓ_1 norm, or any other norms. We employ Frobenius norm here for modeling simplicity. To model the relationship between the representational coefficients, we propose to use two inversible mapping functions f_1 and f_2 . To measure the error, we employ a penalty function F .

$$\begin{aligned} & \min_{\mathbf{D}_x, \mathbf{D}_y, \mathbf{A}_x, \mathbf{A}_y, \mathbf{U}_x, \mathbf{U}_y, \mathbf{V}_y} \|\mathbf{X} - \mathbf{D}_x \mathbf{A}_x\|_F^2 \\ & + \|\mathbf{Y} - \mathbf{D}_y \mathbf{A}_y - \mathbf{V}_y\|_F^2 + \alpha F(f_1(\mathbf{A}_x), f_2(\mathbf{A}_y)) \quad (2) \\ & + \beta_x \|\mathbf{A}_x\|_1 + \beta_y \|\mathbf{A}_y\|_1 + \gamma_y \|\mathbf{V}_y\|_p^p \\ & \text{s.t. } \|\mathbf{d}_{x,i}\|_2 = 1, \|\mathbf{d}_{y,i}\|_2 = 1, \forall i. \end{aligned}$$

Here, we want to discuss more on the mapping functions f_1, f_2 and the measure function F . The mapping function can be linear or nonlinear transformations. The linear function can be defined as a mapping matrix $f_1(\mathbf{A}_x) = \mathbf{U}_x \mathbf{A}_x$ and $f_2(\mathbf{A}_y) = \mathbf{U}_y \mathbf{A}_y$. The corresponding penalty terms on the mapping matrices are $\|\mathbf{U}_x\|_F^2$ and $\|\mathbf{U}_y\|_F^2$. The nonlinear function can be defined as sigmoid function $f_1(\mathbf{A}_x) = 1/(1 + \exp\{-\mathbf{A}_x\})$. We can also employ "first-linear-then-nonlinear" or "first-nonlinear-then-linear" strategies. Here, we don't have explicit penalty terms for the nonlinear mapping functions. The derivatives of the nonlinear case also need further discussions since it is not easy to obtain closed-form solutions with sigmoid functions. In this paper, we utilize linear transformation matrices as the mapping functions f_1 and f_2 . The measure penalty function is simply defined by Frobenius norm. Hence, the term is defined as $\|\mathbf{U}_x \mathbf{A}_x - \mathbf{U}_y \mathbf{A}_y\|_F^2$. However, this would generate a trivial solution of $\mathbf{U}_x = \mathbf{U}_y = \mathbf{0}$. In order to avoid this case, we propose to use the inverse of the mapping matrices, i.e., \mathbf{U}_x^{-1} and \mathbf{U}_y^{-1} .

In summary, we propose a Doubly Inversible and Semi-Coupled Dictionary Learning (DISCDL) model to learn the dictionaries and mapping functions between real noisy images and latent clean natural images.

$$\begin{aligned} & \min_{\mathbf{D}_x, \mathbf{D}_y, \mathbf{A}_x, \mathbf{A}_y, \mathbf{U}_x, \mathbf{U}_y, \mathbf{V}_y} \|\mathbf{X} - \mathbf{D}_x \mathbf{A}_x\|_F^2 \\ & + \|\mathbf{Y} - \mathbf{D}_y \mathbf{A}_y - \mathbf{V}_y\|_F^2 + \alpha \|\mathbf{U}_x^{-1} \mathbf{A}_x - \mathbf{U}_y^{-1} \mathbf{A}_y\|_F^2 \\ & + \beta_x \|\mathbf{A}_x\|_1 + \beta_y \|\mathbf{A}_y\|_1 + \gamma_y \|\mathbf{V}_y\|_p^p \quad (3) \\ & + \lambda_x \|\mathbf{U}_x^{-1}\|_F^2 + \lambda_y \|\mathbf{U}_y^{-1}\|_F^2 \\ & \text{s.t. } \|\mathbf{d}_{x,i}\|_2 = 1, \|\mathbf{d}_{y,i}\|_2 = 1, \forall i. \end{aligned}$$

This model has three major differences when compared with SCDL model.

- We use a matrix \mathbf{V}_y to model the noise, and we don't set any prior distribution on it. This term can help us visualize the noise we learned from the data, i.e., the real noisy images. This make our model fully data-driven. Since our assumption (we have no assumption at all) on noise is more flexible than others', the

noise we obtain in our model can be more accurate than other statistical models such as Gaussian or Mixture of Gaussians. Besides, it is time-consuming to fit the noise model from the online data.

- We use two inversible matrices as the mapping transformations between the coefficients of the real noisy patches and the latent clean patches. This makes our model more flexible than SCDL in which the mapping matrix not explicitly inversible. Besides, the SCDL can only transform LR images into HG images while our model can transform two different image styles in both direction.
- The constraints on dictionary atoms in our model is strictly $\|\mathbf{d}_{x,i}\|_2 = 1, \|\mathbf{d}_{y,i}\|_2 = 1$ while the CDL model and SCDL model are $\|\mathbf{d}_{x,i}\|_2 \leq 1, \|\mathbf{d}_{y,i}\|_2 \leq 1$. This makes our model more robust on the dictionary learning since both the dictionary atoms and sparse coefficients are interacted with each other. The ≤ 1 constraints would like to make the coefficients larger and dictionary atoms smaller or even vanish. However, in the training stage, we care more about the dictionary atoms and would rather ignore the sparse coefficients.

3.2. Model Optimization

While the objective function in (3) is not convex, it is convex with each variable when other variables are fixed. We employ alternating direction method of multipliers (ADMM) algorithm here. Specifically, we divide the objective function into four sub-problems: 1) updating the sparse coefficients $\mathbf{A}_x, \mathbf{A}_y$; 2) updating the normalized dictionaries $\mathbf{D}_x, \mathbf{D}_y$; 3) updating the noise matrix \mathbf{V}_y ; 4) updating the mapping matrices $\mathbf{U}_x, \mathbf{U}_y$. We discuss the four steps as follows.

3.2.1 Updating \mathbf{A}_x and \mathbf{A}_y

$$\min_{\mathbf{A}_x} \|\mathbf{X} - \mathbf{D}_x \mathbf{A}_x\|_F^2 + \alpha \|\mathbf{U}_x^{-1} \mathbf{A}_x - \mathbf{U}_y^{-1} \mathbf{A}_y\|_F^2 + \beta_x \|\mathbf{A}_x\|_1, \quad (4)$$

$$\begin{aligned} & \min_{\mathbf{A}_y} \|\mathbf{Y} - \mathbf{D}_y \mathbf{A}_y - \mathbf{V}_y\|_F^2 \\ & + \alpha \|\mathbf{U}_x^{-1} \mathbf{A}_x - \mathbf{U}_y^{-1} \mathbf{A}_y\|_F^2 + \beta_y \|\mathbf{A}_y\|_1. \end{aligned} \quad (5)$$

Take \mathbf{A}_x as an example, the first and second terms above can be combined to form a new optimization problems as follows:

$$\min_{\mathbf{A}_x} \|\tilde{\mathbf{X}} - \tilde{\mathbf{D}}_x \mathbf{A}_x\|_F^2 + \beta_x \|\mathbf{A}_x\|_1, \quad (6)$$

where $\tilde{\mathbf{X}} = \begin{pmatrix} \mathbf{X} \\ \sqrt{\alpha} \mathbf{U}_y^{-1} \mathbf{A}_y \end{pmatrix}$ and $\tilde{\mathbf{D}} = \begin{pmatrix} \mathbf{D}_x \\ \sqrt{\alpha} \mathbf{U}_x^{-1} \end{pmatrix}$. For \mathbf{A}_y , it is similar with \mathbf{A}_x .

$$\min_{\mathbf{A}_y} \|\tilde{\mathbf{Y}} - \tilde{\mathbf{D}}_y \mathbf{A}_y\|_F^2 + \beta_y \|\mathbf{A}_y\|_1, \quad (7)$$

where $\tilde{\mathbf{Y}} = \begin{pmatrix} \mathbf{Y} - \mathbf{V}_y \\ \sqrt{\alpha} \mathbf{U}_x^{-1} \mathbf{A}_x \end{pmatrix}$ and $\tilde{\mathbf{D}} = \begin{pmatrix} \mathbf{D}_y \\ \sqrt{\alpha} \mathbf{U}_y^{-1} \end{pmatrix}$. These simplified versions have the exactly same formulation as standard sparse coding and can be simply solved by tools such as SPAMS.

The \mathbf{U}_x^{-1} and \mathbf{U}_y^{-1} are invertible. This will be discussed in subsection "Updating U".

3.2.2 Updating \mathbf{D}_x and \mathbf{D}_y

$$\min_{\mathbf{D}_x} \|\mathbf{X} - \mathbf{D}_x \mathbf{A}_x\|_F^2 \quad \text{s.t.} \quad \|\mathbf{d}_{x,i}\|_2 = 1, \forall i. \quad (8)$$

$$\min_{\mathbf{D}_y} \|\mathbf{Y} - \mathbf{D}_y \mathbf{A}_y - \mathbf{V}_y\|_F^2 \quad \text{s.t.} \quad \|\mathbf{d}_{y,i}\|_2 = 1, \forall i. \quad (9)$$

These two are quadratically constrained quadratic program (QCQP) problem and can be solved by Lagrange dual techniques.

3.2.3 Updating \mathbf{V}_y

The noise matrix is initialized as a zero matrix and updated by solving the following problem:

$$\min_{\mathbf{V}_y} \|\mathbf{Y} - \mathbf{D}_y \mathbf{A}_y - \mathbf{V}_y\|_F^2 + \gamma_y \|\mathbf{V}_y\|_F^2 \quad (10)$$

This is a ridge regression problem. We can obtain the analytical solution of \mathbf{V}_y by

$$\mathbf{V}_y = (\mathbf{Y} - \mathbf{D}_y \mathbf{A}_y) / (1 + \gamma_y). \quad (11)$$

3.2.4 Updating \mathbf{U}_x and \mathbf{U}_y

$$\begin{aligned} \min_{\mathbf{U}_x^{-1}} \alpha \|\mathbf{U}_y^{-1} \mathbf{A}_y - \mathbf{U}_x^{-1} \mathbf{A}_x\|_F^2 + \lambda_x \|\mathbf{U}_x^{-1}\|_F^2 \\ \min_{\mathbf{U}_y^{-1}} \alpha \|\mathbf{U}_x^{-1} \mathbf{A}_x - \mathbf{U}_y^{-1} \mathbf{A}_y\|_F^2 + \lambda_y \|\mathbf{U}_y^{-1}\|_F^2 \end{aligned} \quad (12)$$

The above problems are also ridge regression problems and have analytical solutions of \mathbf{U}_x and \mathbf{U}_y as follows:

$$\begin{aligned} \mathbf{U}_x^{-1} &= \mathbf{U}_y^{-1} \mathbf{A}_y \mathbf{A}_x^T (\mathbf{A}_x \mathbf{A}_x^T + (\gamma_x / \alpha) \mathbf{I})^{-1} \\ \mathbf{U}_y^{-1} &= \mathbf{U}_x^{-1} \mathbf{A}_x \mathbf{A}_y^T (\mathbf{A}_y \mathbf{A}_y^T + (\gamma_y / \alpha) \mathbf{I})^{-1} \end{aligned} \quad (13)$$

Here, we verify that \mathbf{U}_x^{-1} and \mathbf{U}_y^{-1} are invertible. The \mathbf{U}_x^{-1} and \mathbf{U}_y^{-1} are both initialized as an identity matrix, of suitable dimension, which is invertible. That is, we have $\mathbf{U}_y^{(0)} = \mathbf{I}$ when we compute \mathbf{U}_x^{-1} . If $\mathbf{A}_y \mathbf{A}_x^T$ is invertible, then \mathbf{U}_x^{-1} is invertible. In fact, we have $\mathbf{A}_y, \mathbf{A}_x \in \mathbb{R}^{d \times N}$. d is the dimension of the sample. For a patch of size 8×8 , $d = 64$. The N is the number of samples in the training data. Remember that we have much more samples when compared to the dimension of patches, that is $N \gg d$. It is less likely that $\mathbf{A}_y \mathbf{A}_x^T \in \mathbb{R}^{d \times d}$ has a rank structure lower than d . In other words, $\mathbf{A}_y \mathbf{A}_x^T \in \mathbb{R}^{d \times d}$ is less likely to be

singular if we have enough training data. The experiments also confirm our conjecture. Besides, we can also add small disbursement to guarantee that $\mathbf{A}_y \mathbf{A}_x^T \in \mathbb{R}^{d \times d}$ is invertible.

Once \mathbf{U}_x^{-1} is invertible, we can also verify that \mathbf{U}_y^{-1} is invertible in a similar way.

3.3. Real Image Denoising

Two methods:

The first one is that

$$\begin{aligned} \min_{\mathbf{a}_{x,i}, \mathbf{a}_{y,i}} \|\mathbf{x}_i - \mathbf{D}_x \mathbf{a}_{x,i}\|_2^2 + \|\mathbf{y}_i - \mathbf{D}_y \mathbf{a}_{y,i} - \mathbf{v}_{y,i}\|_2^2 \\ + \alpha \|\mathbf{U}_x^{-1} \mathbf{a}_{x,i} - \mathbf{U}_y^{-1} \mathbf{a}_{y,i}\|_2^2 \quad (14) \\ + \beta_x \|\mathbf{a}_{x,i}\|_1 + \beta_y \|\mathbf{a}_{y,i}\|_1 + \gamma_y \|\mathbf{v}_{y,i}\|_1 \end{aligned}$$

and finally we get $\hat{\mathbf{x}}_i = \mathbf{D}_x \hat{\mathbf{a}}_{x,i}$.

The second one is to solve

$$\begin{aligned} \min_{\mathbf{a}_{y,i}, \mathbf{v}_{y,i}} \|\mathbf{y}_i - \mathbf{D}_y \mathbf{a}_{y,i} - \mathbf{v}_{y,i}\|_2^2 + \alpha \|\mathbf{U}_x^{-1} \mathbf{a}_{x,i} - \mathbf{U}_y^{-1} \mathbf{a}_{y,i}\|_2^2 \\ + \beta_y \|\mathbf{a}_{y,i}\|_1 + \gamma_y \|\mathbf{v}_{y,i}\|_1. \quad (15) \end{aligned}$$

Once we get $\hat{\mathbf{a}}_{y,i}$ from \mathbf{y}_i , $\hat{\mathbf{a}}_{x,i} \approx \mathbf{U}_x \mathbf{U}_y^{-1} \hat{\mathbf{a}}_{y,i}$ and $\hat{\mathbf{x}}_i \approx \mathbf{D}_x \hat{\mathbf{a}}_{x,i}$.

Experiments demonstrate that the first method can get better performance than the second one while the second one can get faster speed than the first one.

We can also initialize the solution from the second one.

4. The Overall Algorithm

4.1. Pair Sample Construction from Unpaired Samples

In cross style transfer methods such as CDL and SCDL, the authors assume that the two different styles have paired data, i.e., for each data sample in one style, we can find paired data sample in the other style. However, in real world, the data from two different sources may be unpaired. For example, the real noisy images should not have groundtruth clean images of the same scene. The real low-resolution images should not have corresponding high-resolution images in the real world. The real blurry images should not have corresponding clear and high quality images in real world.

To deal with unpaired data, we could collect real noisy images and clean natural images from two different sources. The real noisy images are from the example images (18 images) of the Neat Image website while the clean natural images are from the training set (200 images) of the Berkeley Segmentation Dataset (BSDS500). To make use of the unpaired data samples, we employ searching strategy to construct the training dataset. That is, for each noisy image patch, we utilize the k-Nearest Neighbor (k-NN) algorithm

to find the most similar patch in the clean images as the paired groundtruth patch. The similarity is measured by the Euclidean distance (also called squared error or ℓ_2 norm).

4.2. Structural Clustering and Model Selection

In fact, different image structures should have different influences on dictionary as well as the mapping function. Patches with flat region should have low rank structure within dictionary elements and identity mapping between noisy and latent clean patches. Patches with complex details should have more comprehensive dictionary elements within dictionary elements and more complex mapping function between noisy and clean patches. A single mapping function cannot deal with all these complex relationships. Hence, a structural clustering procedure is needed for complex solution. In this paper, we propose to employ Gaussian Mixture Model to cluster different image patches into different groups and learn dictionary and mapping function for each group.

4.3. Adaptive Iterations of Different Noise Levels

For real image denoising, we can perform well on images which have similar noise levels with the training dataset. How can we deal with the real noisy images whose noise levels are higher than the training dataset? The answer is to remove the noise by more iterations. The input image of each iteration is the recovered image of previous iteration. This makes sense since we can still view the recovered image as a real noisy image.

This will also bring a second problem, that how we could automatically terminate the iteration. This can be solved by two methods. One way is to compare the images between two iterations and calculate their difference, the iteration can be terminated if the difference is smaller than a threshold. The other way is to estimate the noise level of the current image and terminate the iterations when the noise level is lower than a preset threshold. We employ the second way and set the threshold as 0.0001 in our experiments. In fact, most of our testing images will be denoised well in one iteration.

4.4. Efficient Model Selection by Gating Network

In the Gaussian component selection procedure, if we employ the full posterior estimation, the speed is not fast. Our algorithm can be speeded up by introducing the Gating network model.

5. Experiments

We compare with popular software NeatImage which is one of the best denoising software available. All these methods need noise estimation which is vary hard to perform if there is no uniform regions are available in the test-

ing image. The NeatImage will fail to perform automatical parameters settings if there is no uniform regions.

5.1. Parameters

We don't fine tune the parameters both in the training and testing datasets.

5.2. Real Image Denoising

5.3. Comparison on Dataset with GroundTruth

6. Conclusion and Future Work

In the future, we will evaluate the proposed method on other computer vision tasks such as single image super-resolution, photo-sketch synthesis, and cross-domain image recognition. Our proposed method can be improved if we use better training images, fine tune the parameters via cross-validation. We believe that our framework can be useful not just for real image denoising, but for image super-resolution, image cross-style synthesis, and recognition tasks. This will be our line of future work.

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