A Variational Model for Simultaneously Image Denoising and Luminance Adjustment

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Abstract. In this paper, we propose and develop a saturation value total variation (SV-TV) regularization model for simultaneously image denoising and luminance adjustment. The idea is to propose a variational approach containing an energy functional to adjust the luminance between image patches, and the noise of the image can be removed. In the proposed model, we establish the adjustment term based on the concept of structure, luminance, and contrast similarity, and we make use of the SV-TV regularization to remove the noise simultaneously. We present an efficient and effective algorithm with convergence guaranteed to solve the proposed minimization model. Experimental results are presented to show the effectiveness of the proposed model compared with existing methods.

AMS subject classifications: 68U10, 65K10, 65J22, 90C25

Key words: Luminance adjustment, structure similarity, HSV color space, saturation, value, total variation, image denoising.

1 Introduction

In this paper, we focus on adjusting inconsistent luminance of noisy images. The purpose of luminance adjustment is to intensify the visibility of images and make images more suitable for other image processing applications.

In the literature, there are a variety of methods for enhancing consistent low contrast of images. Histogram equalization (HE) [7] is an effective and powerful technique for contrast enhancement. The cumulative distribution function of the normalized histogram of the input image gray-levels was selected to be the transformation function in global histogram equalization (GHE) [6] for the histogram equalization purpose. Contrast enhancement based on local information by using histogram equalization was proposed

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by Wang and Ng in [29], and the authors proposed a variational approach containing an energy functional to determine a local transformation such that the histogram can be redistributed locally, and the brightness of the transformed image can be preserved. In [28], an image pixel based histogram equalization model for image contrast enhancement was proposed. The idea was to formulate a variational model containing an energy functional to adjust the pixel values of an input image directly so that the resulting histogram can be redistributed to be uniform. The Automatic Color Enhancement (ACE) method [5] is another effective image enhancement method based on a simple model of the human visual system, and the enhancement process is consistent with perception. In [17, 18], Nikolova et al. proposed a simple image enhancement algorithm (HPE) which conserved the hue and preserved the range (gamut) of an image in an optimal way. In [4], Ferradans et al. built a general variational framework (PLCE) to perform perceptual color correction and to handle the problem of local contrast enhancement. Retinex proposed by Land and McCann [10] as a model of color perception of human vision, is another technique for illumination and contrast enhancement. Many implementations and improvements of Retinex have been studied in the literature. In [3], Elad proposed a variational framework using two special bilateral filters as the regularization terms in order to provide a non-iterative Retinex algorithm. Ma and Osher [14] established a total variation (TV) and nonlocal TV regularized model of Retinex theory that can be solved by a fast computational approach based on Bregman iteration. In [13], Ma et al. established an L1-based variational model for Retinex theory that can be solved by a fast computational approach based on Bregman iteration. In [16], Ng and Wang studied and developed a TV model for Retinex. They assumed spatial smoothness of the illumination and piecewise continuity of the reflection, where the total variation term is employed in the model.

On the other hand, image denoising is to find the unknown true image \( u \) from a noisy image \( f \). However, inverse problems are ill-posed, a regularization technique must be used to make them well-posed. This idea was introduced in 1977 by Tikhonov and Arsenin [26]. Rudin, Osher, and Fatemi proposed to use \( L_1 \) norm of the gradient of \( u \), also called total variation as the regularization (ROF model) [21, 22]. Thanh and Dvoenko proposed the modified ROF model in [23, 24] to remove mixed Poisson-Gaussian noise. In [25], Thanh et al. proposed an adaptive method based on combining the first-order and the second-order total variations with the adaptive multiscale parameter estimation, which can effectively remove noise while preserving the image structure. In [19], a new parameter estimation method for TV regularization scheme was proposed by Prasath et al. For color images, Bresson and Chan [1] established an vectorial TV (VTV) regularization method, which takes into account the coupling relationship between different channels. In [9], Jia, Ng, and Wang proposed the Saturation-Value Total Variation (SV-TV) model based on the HSV color space. The SV-TV regularization is considered in S and V channels. This method processes the image while preserving the edge and color information, so the unexpected chromatic intersection can be greatly reduced. Therefore, the SV-TV model has an excellent performance in color image restoration.

To the best of our knowledge, there is a few research work in the literature for si-
multaneously image denoising and inconsistent contrast adjustment. The related work in this direction is usually multiple step method. In [8], I_rera et al. introduced a patch-based filter for X-ray image denoising. Then they proposed to use the filtered image to define non-parametric noise containment maps which were applied in a contrast enhancement framework. In [11], a smooth base layer extracted by BM3D filter and a detail layer extracted by the first order differential of the inverted image were combined to get a noise-free image. Then an adaptive enhancement parameter was adopted into the dark channel to enhance the contrast of the restored image. In [12], Lim et al. categorized each pixel into two classes: noise-free and noisy. Then they performed the selective histogram equalization to enhance the contrast of the noise-free pixels only, and restored the missing values of the noisy pixels using the enhanced noise-free pixel values. Unfortunately, none of the above models consider adjusting inconsistent contrast and luminance of noisy images.

In this paper, we propose and develop a variational model for simultaneously inconsistent luminance adjustment and image denoising. The contribution of this paper is to propose and develop an SV-TV regularization model containing the energy functional for adjusting luminance. We establish the adjustment term based on the concept of structure similarity in SSIM [32]. Meanwhile, we use the SV-TV regularization term to remove the noise of the original image. We also present a fast and effective algorithm to solve the proposed minimization model. Experimental results are presented to demonstrate the efficiency of the proposed model.

The outline of this paper is as follows. In Section 2, we review the related work about luminance adjustment and SV-TV regularization model. In Section 3, we introduce the proposed variational models for image denoising and luminance adjustment as well as the proposed algorithm. In Section 4, some experimental results are given to demonstrate the effectiveness of the proposed models. Finally, the concluding remarks are presented in Section 5.

2 Related work

2.1 Luminance adjustment

An adjustment method was proposed in [20] inspired by the ideas in SSIM [32]. This adjustment has the effect on eliminating the bias on illumination and contrast between different patches. Choose a reference patch \( R \), the adjust value of another patch \( X \) is given by

\[
X' = \sigma_R + \frac{X - \mu_X}{\sigma_X + c}(\sigma_X + c) + \mu_R,
\]

where \( \mu_X \) is the mean intensity of patch \( X \), and \( \sigma_X \) is the standard deviation of patch \( X \). \( \mu_R \) is the mean intensity of the reference patch \( R \), and \( \sigma_R \) is the standard deviation of the reference patch \( R \). The constant \( c \) is used to avoid instability when the denominator
is close to zero. In order to understand the proposed adjustment, we rewrite the above equation as follows,

$$\frac{X' - \mu_R}{\sigma_R + c} = \frac{X - \mu_X}{\sigma_X + c}. \quad (2.1)$$

Based on the construction of structural similarity measurement system [32], the luminance of patch \(X\) is estimated by the mean intensity \(\mu_X\), the contrast of \(X\) can be described by the standard deviation \(\sigma_X\) and the structure can be estimated by \((X - \mu_X)/\sigma_X\). Therefore, in the adjusted patch, we make use of the luminance and the contrast of the reference patch while keep the structure of the original patch by applying adjustment (2.1). Assume that the reference patch \(R\) is in a bright region, then the adjusted version of a dark patch \(X\) will be balanced by using the adjustment (2.1).

In order to illustrate the effect of the proposed adjustment, we give an example as shown in Fig. 1. The green labeled patch in Fig. 1(a) is chosen as a reference patch \(R\). We adjust every other patch in Fig. 1(a) by using the proposed adjustment (2.1). As expected, we see from the adjusted result in Fig. 1(b) that the luminance and contrast are well-balanced.

### 2.2 Saturation-value total variation

As is discussed in [9], the SV-TV regularization is defined by

$$\text{SV-TV}(u) = \int_{\Omega} \sqrt{\left| \partial_x u(x,y) \right|_s^2 + \left| \partial_y u(x,y) \right|_s^2 + \alpha \sqrt{\left| \partial_x u(x,y) \right|_v^2 + \left| \partial_y u(x,y) \right|_v^2}} \, dx \, dy,$$

where \(u(x,y) = [u_r, u_g, u_b]^T\). The saturation norm \(\left| \partial_x u(x,y) \right|_s\), \(\left| \partial_y u(x,y) \right|_s\) and the value norm \(\left| \partial_x u(x,y) \right|_v\), \(\left| \partial_y u(x,y) \right|_v\) are given as follows,

$$\left| \partial_x u(x,y) \right|_s = \frac{1}{3} \left\| C_{\partial x} u(x,y)^T \right\|_2,$$

$$\left| \partial_y u(x,y) \right|_s = \frac{1}{3} \left\| C_{\partial y} u(x,y)^T \right\|_2.$$
\[
C = \begin{bmatrix}
2 & -1 & -1 \\
-1 & 2 & -1 \\
-1 & -1 & 2 \\
\end{bmatrix},
\]

and

\[
|\partial_x u(x,y)|_v = \frac{1}{\sqrt{3}}|\partial_x u_r(x,y) + \partial_x u_g(x,y) + \partial_x u_b(x,y)|,
\]

\[
|\partial_y u(x,y)|_v = \frac{1}{\sqrt{3}}|\partial_y u_r(x,y) + \partial_y u_g(x,y) + \partial_y u_b(x,y)|.
\]

As is demonstrated in [9], we see from the above formulations that there is strong coupling among three channels in the coefficients and thus in the diffusion equations. Therefore, SV-TV model has very good performance for color image restoration.

3 The proposed model

3.1 The proposed SV-TV model

Based on the above discussion, we consider the following constrained minimization problem in this paper,

\[
\min_{u} \text{SV-TV}(u), \quad \text{s.t.} \quad \frac{u(x,y) - \mu_R}{\sigma_R + c} = \frac{f(x,y) - \mu_X}{\sigma_X + c}, \quad \forall (x,y) \in \Omega,
\]

where \(\Omega\) is the image domain, \(u\) is the objective image, and \(f\) is the original image. \(X\) is the patch centered at position \((x,y)\) of the original image \(f\), \(R\) is the reference patch extracted from the original image \(f\). Recall that \(\mu_X\) is the mean intensity of patch \(X\), and \(\sigma_X\) is the standard deviation of patch \(X\). \(\mu_R\) is the mean intensity of the reference patch \(R\), and \(\sigma_R\) is the standard deviation of the reference patch \(R\). The constant \(c\) is used to avoid instability when the denominator is close to zero. The proposed model (3.1) is formulated based on the following motivations.

- The patch centered at each position \((x,y)\) of the objective image \(u\) is the adjusted version of the corresponding patch centered at each position \((x,y)\) of the original image \(f\). Meanwhile, the structure of the patch centered at \((x,y)\) of the original image will be kept in the corresponding adjusted patch of the objective image.

- The objective image is regularized by using saturation-value total variation which has been proved to be very effective for color image restoration.

By solving the proposed minimization problem (3.1), we derive the adjusted image whose luminance can be balanced locally by applying the adjustment to the objective patch and
the reference patch. Meanwhile, the structure will be kept during the adjusting procedure and the noise will be removed by using the SV-TV regularization. We then consider the following unconstrained minimization problem which is equivalent to (3.1),

$$
\min_{u} \text{SV-TV}(u) + \frac{\lambda}{2} \int_{\Omega} (u - h)^2 dx dy,
$$

(3.2)

where $h$ is defined by

$$
h(x, y) = \sigma_R + c \sigma_X + c (f(x, y) - \mu_X) + \mu_R.
$$

We emphasize that the penalty term $\int_{\Omega} (u - h)^2 dx dy$ is used for luminance adjustment and structure preservation. It is clear that the minimization problem (3.2) has at least one solution. The detailed proof can refer to the discussion about SV-TV color image restoration model in [9].

### 3.2 The proposed algorithm

In this section, we will introduce a feasible algorithm based on the classical ADMM iteration. We consider the discrete version of the proposed model (3.2) as follows

$$
\min_{u} \sum_{i=1}^{m} \sum_{j=1}^{n} \left( \sqrt{\left(\nabla_x u_{ij}\right)^2 + \left(\nabla_y u_{ij}\right)^2} + a \sqrt{\left(\nabla_x q_{1ij}\right)^2 + \left(\nabla_y q_{1ij}\right)^2} + \frac{\lambda}{2} \|u - h\|^2 \right),
$$

(3.3)

where $m$ and $n$ are the number of horizontal and vertical pixels of the discrete image $f$. By using the similar argument as in [9], the optimization problem in (3.3) is equal to

$$
\min_{q} \sum_{i=1}^{m} \sum_{j=1}^{n} \left( \sqrt{\left(\nabla_x q_{1ij}\right)^2 + \left(\nabla_y q_{2ij}\right)^2} + \left(\nabla_x q_{3ij}\right)^2 + \left(\nabla_y q_{3ij}\right)^2 \right)

+ a \sqrt{\left(\nabla_x q_{3ij}\right)^2 + \left(\nabla_y q_{3ij}\right)^2} + \frac{\lambda}{2} \|q - \tilde{h}\|^2,
$$

where

$$
q(x, y) = \begin{bmatrix} q_1(x, y) \\ q_2(x, y) \\ q_3(x, y) \end{bmatrix} = P \begin{bmatrix} u_r(x, y) \\ u_g(x, y) \\ u_b(x, y) \end{bmatrix}, \quad \tilde{h}(x, y) = Ph(x, y),
$$

and

$$
P = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 \\ \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{6}} \\ \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{bmatrix}.
$$
Lagrangian multipliers $\tau$ operator \[31\], the corresponding closed form solutions are given below using generalized shrinkage for the subproblem to solve iterations are described in the Algorithm 1.

where $\mathbf{w} = [\mathbf{w}_x(1), \mathbf{w}_x(2), \mathbf{w}_x(3), \mathbf{w}_y(1), \mathbf{w}_y(2), \mathbf{w}_y(3)]^T$, $\mathbf{\tau} = [\mathbf{\tau}_x(1), \mathbf{\tau}_x(2), \mathbf{\tau}_x(3), \mathbf{\tau}_y(1), \mathbf{\tau}_y(2), \mathbf{\tau}_y(3)]^T$, and the scalar product $<\cdot,\cdot>$ denotes the corresponding inner product. Then the ADMM iterations are described in the Algorithm 1.

3.2.1 The solutions of the subproblems

For the subproblem to solve $\mathbf{w}^{k+1}$ in (3.5), let $\mathbf{w}_{(1,2)} = [\mathbf{w}_x(1), \mathbf{w}_x(2), \mathbf{w}_y(1), \mathbf{w}_y(2)]^T$ and $\mathbf{w}_{(3)} = [\mathbf{w}_x(3), \mathbf{w}_y(3)]^T$, the original problem can be divided into the following two parts:

\[
\mathbf{w}_{(1,2)}^{k+1} = \arg\min_{\mathbf{w}_{(1,2)}} \sum_{i=1}^{m} \sum_{j=1}^{n} \sqrt{|(\mathbf{w}_x(i))_j|^2 + |(\mathbf{w}_x(2))_j|^2 + |(\mathbf{w}_y(1))_j|^2 + |(\mathbf{w}_y(2))_j|^2} \\
+ \frac{\gamma}{2} \sum_{c=1}^{3} \left( \|\mathbf{w}_x(c) - \nabla_x \mathbf{q}_c^k + \tau_x(c)\|^2 + \|\mathbf{w}_y(c) - \nabla_y \mathbf{q}_c^k + \tau_y(c)\|^2 \right),
\]

\[
\mathbf{w}_{(3)}^{k+1} = \arg\min_{\mathbf{w}_{(3)}} \sum_{i=1}^{m} \sum_{j=1}^{n} \alpha \sqrt{|(\mathbf{w}_x(3))_j|^2 + |(\mathbf{w}_y(3))_j|^2} \\
+ \frac{\gamma}{2} \left( \|\mathbf{w}_x(3) - \nabla_x \mathbf{q}_3^k + \tau_x(3)\|^2 + \|\mathbf{w}_y(3) - \nabla_y \mathbf{q}_3^k + \tau_y(3)\|^2 \right).
\]

The corresponding closed form solutions are given below by using generalized shrinkage operator [31],

\[
\mathbf{w}_{(1,2)}^{k+1} = \text{shrink} \left( \nabla \mathbf{q}_{(1,2)}^k - \tau_{(1,2)}^k, \frac{1}{\gamma} \right),
\]

\[
\mathbf{w}_{(3)}^{k+1} = \text{shrink} \left( \nabla \mathbf{q}_{(3)}^k - \tau_{(3)}^k, \frac{1}{\gamma} \right),
\]

where the definitions of $\mathbf{q}_{(1,2)}, \mathbf{q}_{(3)}, \tau_{(1,2)}$ and $\tau_{(3)}$ are similar to those of $\mathbf{w}_{(1,2)}$ and $\mathbf{w}_{(3)}$. 

$I$ is an identity matrix. By introducing the auxiliary variables $\mathbf{w}_x(c), \mathbf{w}_y(c)$ ($c = 1, 2, 3$), the Lagrangian multipliers $\mathbf{\tau}_x(c), \mathbf{\tau}_y(c)$ ($c = 1, 2, 3$), and a penalty parameter $\gamma > 0$, the augmented Lagrangian function is given as:

\[
\mathcal{L}(\mathbf{w}, \mathbf{q}, \mathbf{\tau}) = \mathcal{L}(\mathbf{w}, \mathbf{\tau}_x(1), \mathbf{\tau}_x(2), \mathbf{\tau}_x(3), \mathbf{\tau}_y(1), \mathbf{\tau}_y(2), \mathbf{\tau}_y(3)) \\
= \sum_{i=1}^{m} \sum_{j=1}^{n} \sqrt{|(\mathbf{w}_x(1))_j|^2 + |(\mathbf{w}_x(2))_j|^2 + |(\mathbf{w}_y(1))_j|^2 + |(\mathbf{w}_y(2))_j|^2} \\
+ \alpha \sqrt{|(\mathbf{w}_x(3))_j|^2 + |(\mathbf{w}_y(3))_j|^2} + \frac{\lambda}{2} \|\mathbf{q} - \mathbf{h}\|^2 \\
+ \sum_{c=1}^{3} \frac{\gamma}{2} \left( \|\mathbf{w}_x(c) - \nabla_x \mathbf{q}_c + \mathbf{\tau}_x(c)\|^2 + \|\mathbf{w}_y(c) - \nabla_y \mathbf{q}_c + \mathbf{\tau}_y(c)\|^2 \right), \tag{3.4}
\]
Algorithm 1

1. Initializing: $\mathbf{u}^0 = 0$, $\mathbf{q}^0 = \mathbf{P} \mathbf{u}^0 = 0$, $\mathbf{r}^0 = 0$.

2. While $\frac{\|\mathbf{q}^k - \mathbf{q}^{k-1}\|}{\|\mathbf{q}^k\|} \leq \varepsilon$, at the $k$th iteration:
   
   - For given $\mathbf{q}^k$ and $\mathbf{r}^k$, $\mathbf{w}^{k+1}$ is updated by solving
     \[
     \min_{\mathbf{w}} \sum_{i=1}^m \sum_{j=1}^n \left( \sqrt{|(\mathbf{w}_x(1))_{ij}|^2 + |(\mathbf{w}_x(2))_{ij}|^2 + |(\mathbf{w}_y(1))_{ij}|^2 + |(\mathbf{w}_y(2))_{ij}|^2} 
     + \alpha \sqrt{|(\mathbf{w}_x(3))_{ij}|^2 + |(\mathbf{w}_y(3))_{ij}|^2} 
     + \frac{\gamma}{2} \sum_{c=1}^3 \left( |\mathbf{w}_x(c) - \nabla_x \mathbf{q}_c^k + \mathbf{r}_x(c)|^2 + |\mathbf{w}_y(c) - \nabla_y \mathbf{q}_c^k + \mathbf{r}_y(c)|^2 \right) \right); 
     \] (3.5)

   - For given $\mathbf{r}^k$ and $\mathbf{w}^{k+1}$, $\mathbf{q}^{k+1}$ is updated by solving
     \[
     \min_{\mathbf{q}} \frac{\lambda}{2} \|\mathbf{q} - \tilde{\mathbf{h}}\|^2 + \frac{\gamma}{2} \sum_{c=1}^3 \left( |\mathbf{w}^{k+1}_x(c) - \nabla_x \mathbf{q}_c + \mathbf{r}^k_x(c)|^2 + |\mathbf{w}^{k+1}_y(c) - \nabla_y \mathbf{q}_c + \mathbf{r}^k_y(c)|^2 \right); \] (3.6)

   - For given $\mathbf{w}^{k+1}$ and $\mathbf{q}^{k+1}$, $\mathbf{r}^{k+1}$ is updated by using
     \[
     \begin{align*}
     \tau_{x(c)}^{k+1} &= \tau_{x(c)}^k + \gamma (\mathbf{w}^{k+1}_x(c) - \nabla_x \mathbf{q}_c^{k+1}), \\
     \tau_{y(c)}^{k+1} &= \tau_{y(c)}^k + \gamma (\mathbf{w}^{k+1}_y(c) - \nabla_y \mathbf{q}_c^{k+1}), \quad c = 1,2,3. 
     \end{align*} \] (3.7)

3. Convert the numerical result $\mathbf{q}$ back into RGB color space by using
   \[
   \mathbf{u} = \mathbf{P}^{-1} \mathbf{q}. 
   \]

For the subproblem to solve $\mathbf{q}^{k+1}$ in (3.6), noting that the three channels are decoupled in this term, the solution can be separately solved by using fast Fourier transform (FFT). Specifically, the solution can be expressed as follows,

\[
\mathbf{q}_c^{k+1} = \mathcal{F}^{-1} \left( \frac{\lambda \mathcal{F}(\tilde{h}_c) + \gamma (\mathcal{F}^*(\nabla_x) \mathcal{F}(\mathbf{w}^{k+1}_x(c) + \mathbf{r}^k_x(c)) + \mathcal{F}^*(\nabla_y) \mathcal{F}(\mathbf{w}^{k+1}_y(c) + \mathbf{r}^k_y(c)))}{\gamma (\mathcal{F}^*(\nabla_x) \mathcal{F}(\nabla_x) + \mathcal{F}^*(\nabla_y) \mathcal{F}(\nabla_y)) + \lambda} \right),
\]

$c = 1,2,3.$

3.2.2 Convergence analysis

For the proposed algorithm (Algorithm 1) based on ADMM iteration, we note that the result of the convergence analysis for ADMM can be used here, see the detail information.
in [2]. We conclude it in the following theorem.

**Theorem 3.1.** Let \( q^0, \tau^0 \) be arbitrary and let \( \gamma > 0 \), then the sequence \( \{w^k, q^k, \tau^k\} \) generated by (3.5)-(3.7) converges to \( (w^*, q^*, \tau^*) \), which is a saddle point of \( L \) (i.e., the unique solution of the problem in (3.1)).

### 3.2.3 Complexity analysis

In this subsection, we give a brief analysis about the computational complexity of Algorithm 1. Assuming that the size of the original image is \( m \times n \), and the patch size is \( p \times p \). For each iteration in the proposed algorithm, we need to calculate \( w, q \) and the Lagrangian multiplier \( \tau \). The main computational cost comes from the calculations in the \( q \)-subproblem. Note that the computation process of the \( q \)-subproblem can be divided into two parts: the calculation of \( \tilde{h} \) and the updating of \( q \) by using FFT. We remark that the computational complexity is in the order of \( O(mnq^2) \) and \( O(mn \cdot \log(mn)) \) corresponding to the calculation of \( \tilde{h} \) and the updating of \( q \) respectively.

### 3.3 The vectorial total variation (VTV) model and the V channel restoration

In order to illustrate the effectiveness of the proposed SV-TV model, we compare the proposed model with the vectorial total variation (VTV) model [1] by replacing the SV-TV regularization with the VTV regularization. The formulation of the proposed VTV model is given as follows,

\[
\min_u \text{VTV}(u) + \frac{\lambda_1}{2} \int_{\Omega} (u - h)^2 dx dy,
\]

where

\[
\text{VTV}(u) = \int_{\Omega} \sqrt{\sum_{c=1}^{3} (\partial_x u_c)^2 + (\partial_y u_c)^2} dx dy.
\]

Meanwhile, we consider the proposed model in the Value component, and keep the saturation information unchanged. The proposed V channel restoration model is given as follows,

\[
\min_u \text{SV-TV}(u) + \frac{\lambda_2}{2} \int_{\Omega} |u - h|^2 dx dy + \frac{\lambda_2}{2} \int_{\Omega} |u - f|^2 dx dy.
\]

The second term of (3.8) is used for adjusting the value of V component, and the third term is used for maintaining the original saturation information. By using the same transformation mentioned in Section 3.2, we can rewrite the fidelity term of (3.8) in the discrete form as

\[
\frac{\lambda_2}{2} \|q - \hat{h}\|_2^2, \quad \text{with} \quad \hat{h} = \begin{bmatrix} \langle Pf, 1 \rangle \\ \langle Pf, 2 \rangle \\ \langle Ph, 3 \rangle \end{bmatrix}.
\]

We remark that both the VTV model and the V channel restoration model can be solved efficiently by using the similar algorithms as discussed in Section 3.2.
4 Numerical experiments

In this section, we present the experimental results, and compare the proposed SV-TV model with the proposed VTV model, SIDCE model [30], $L_1$-Retinex model [13], TV-Retinex model [16], ACE model [5], PLCE model [4] and ATVBH model [25]. In the numerical experiments, the maximum number of iterations are set to be 300. For the stopping criteria, we set $\varepsilon$ to be $1 \times 10^{-6}$ in Algorithm 1. The penalty parameter $\beta$ is set to be 0.01 when the ADMM method is employed. All the computations are performed under the MATLAB implementation on a personal computer with a 1.19 GHz Intel Core i5 CPU.

4.1 The parameter $\lambda$ and patch size

In Fig. 2, we display the restored images by setting different patch sizes and values of the parameter $\lambda$. We make use of the original image given in Fig. 3. The original image was degraded by adding Gaussian noise with standard deviation $\sigma = 20$ in each channel. Both RGB-channels adjustment and V-channel adjustment are tested.

Recall that $\lambda$ is a penalty weight parameter of the fidelity term, we see from the results that the image becomes smoother and the denoising effect is better as $\lambda$ decreases. Meanwhile, by comparing the results with different patch sizes, we see that the contrast of the restored image is nearly uniform with extremely small patch size ($21 \times 21$). However, the color information and the structure information are lost in the restored results. On the other hand, the contrast of the restored results is enhanced by balancing the color/texture preservation and the contrast adjustment by using large patch size (e.g., $81 \times 81$). We remark here that an appropriate patch size is important to keep the color/structure information of the input images and to avoid high computational cost. Meanwhile, It’s interesting to note that more color information is maintained by using V channel adjusting in HSV color space, while the overall color of the image tend to be consistent by using RGB adjusting. We remark here that we set the range of the parameter $\lambda$ to be $0.1 \sim 2.0$ numerically in the following experiments.

4.2 Tests for different noise levels

In this test, we demonstrate the performance of the proposed SV-TV model with respect to different noise levels. We compare the proposed SV-TV model with the VTV model introduced in Section 3.3. In this subsection, we consider the RGB-channels restoration method.

The original image is given in Fig. 3. The original image is artificially added zero-mean Gaussian noise with different standard deviations which are $\sigma = 5, 10, 15, 20, 25$. The patch size is set to be $61 \times 61$ and the parameter $\lambda$ is chosen to be $2.0, 0.50, 0.40, 0.30, 0.20, 0.15$ respectively in the proposed SIDLA model. In the VTV model, we set different parameter values as: $\lambda_{VTV} = 1, 0.06, 0.05, 0.04, 0.03, 0.02$, where $\lambda_{VTV}$ is the parameter
Figure 2: From the first row to the last row, the patch size is chosen to be $81 \times 81$, $71 \times 71$, $61 \times 61$, $51 \times 51$, $41 \times 41$, $31 \times 31$, $21 \times 21$ respectively. (a) The reference patch; (b)-(e) The RGB-channels adjusted results by setting $\lambda = 0.8, 0.6, 0.4, 0.2$; (f)-(i) The V-channel adjusted results by setting $\lambda = 0.8, 0.6, 0.4, 0.2$.

The restored results are displayed in Fig. 3. We observe that the proposed SIDLA model is very good in terms of the effectiveness of denoising and luminance adjustment. Meanwhile, as expected, the proposed SIDLA model can also handle color disturbance compared with VTV model, see especially the restored results with high standard deviation in Fig. 3 (the last row).
Figure 3: (a) The degraded images; (b)-(c) The restored results by using the proposed VTV model and the proposed SV-TV model.
4.3 Comparisons with image enhancement methods I

In this subsection, we compare the proposed SIDLA model with other image enhancement methods. Both noise-free images and noisy images were tested in this experiment. The noisy images were generated by adding Gaussian noise of standard deviation $\sigma = 12$ to the noise-free images. In the following experiments, we set the patch size to be $61 \times 61$, and for each test image, the reference patch are shown in Fig. 4(a). For the proposed SV-TV model, we set the parameter $\lambda = 2.0$ for all noise-free images, and we set $\lambda$ to be 0.6, 0.5, 1.8, 0.9, 0.3, 0.4, 0.4 respectively in the test of noisy images. For the proposed VTV model, the parameter is chosen to be $\lambda_{VTV} = 1$ for all noise-free images, and $\lambda_{VTV}$ is set to be 0.06, 0.05, 0.08, 0.07, 0.04, 0.04 for noisy images respectively. For SCIDE model, the parameter $\mu$ is always set to be 0.005 in the first test, the parameter $\alpha$ is chosen to be 1, 1, 4 for the third, fourth, fifth test images respectively, and $\alpha = 2.5$ for the rest images. In the second test we choose the parameters $(\mu, \alpha)$ to be $(0.09, 2.5), (0.12, 2.5), (0.12, 1), (0.18, 1), (0.20, 2.5), (0.16, 2.5), (0.18, 2.5)$ in practice. For $L_1$-Retinex Model, we set the threshold $t$ to be 6, 6, 10, 2, 8, 5, 4 in the first test and set it to be 17, 15, 18, 15, 25, 25, 11 in the second test. For TV-Retinex Model and PLCE Model, we use the default values of the parameters in both tests. For ACE Model, the parameter $\alpha$ is set to be the default value ($\alpha = 5$) for all the testing images. For ATVBH model, we set the proportional parameter to be $k = 1/10$ for all the experiments.

In Fig. 4 and Fig. 5, we show the restored results by using the proposed SV-TV model, VTV model, $L_1$-Retinex Model, TV-Retinex Model, SCIDE Model, ACE model, PLCE model and ATVBH model. As illustrated in Fig. 4, we find that the luminance of the restored results by using $L_1$-Retinex Model, TV-Retinex Model, SCIDE Model, ACE Model, PLCE model and ATVBH model is uniformly enhanced. Therefore, some parts are over-enhanced and visually unpleasant, see especially the grass picture. However, the proposed SV-TV model and VTV model aim to do adjustment in order to make the luminance be consistent. For noisy images in Fig. 5, we find that $L_1$-Retinex Model, TV-Retinex Model, ACE Model and PLCE Model fail in denoising and cause more disturbance. The SIDCE model and ATVBH model are able to reduce the noise, but fail in adjusting the luminance. The proposed VTV model is better by balancing the denoising and luminance adjustment, but fail to reduce color disturbance. Again we see from the results that the proposed SV-TV Model is very good in simultaneously denoising and luminance adjustment for color images.

In order to further demonstrate the effectiveness of the proposed model in adjusting luminance, we consider two patches with different luminance conditions in the original images. We then calculate the mean brightness ratio of these patch pairs. After normalizing the ratio, we can easily deduce that a high ratio corresponds to the similar luminance condition, and vice versa. As shown in Fig. 5, the patch pairs are marked by using red squares and blue squares. We can see that the red squares correspond to better luminance condition, while the blue squares correspond to worse luminance condition. We consider the proposed ratio in $S$ channel for measuring the color consistency, and we consider the
ratio in V channel for measuring the luminance consistency. In Table 1, we report the mean brightness ratios of the images displayed in Fig. 4, and we see from the values that the proposed models (with SV-TV and VTV regularizations) give the best numbers which illustrate the effectiveness of the luminance adjustment by using the proposed models. In Table 2, we report the mean brightness ratios of the images displayed in Fig. 5. Again we see from the numbers that the proposed models outperform other testing methods in terms of luminance adjustment.
Figure 5: Testing results for noisy images. (a) The original images and the patches with different luminance conditions; (b)-(c) The restored results by using the proposed SV-TV model and VTV model; (d)-(h) The restored results by using SCIDE Model, $L_1$-Retinex Model, TV-Retinex Model, ACE Model, PLCE Model and ATVBH model respectively.

4.4 Comparisons with image enhancement methods II

In this section, we make use of the images in Fig. 6(a) taken from the Berkeley Segmentation Database5 [15] to show the effectiveness of the proposed model. We compare the proposed V-channel SV-TV model with other testing methods mentioned in the previous section. We artificially add bias on each ground-truth image. Then the images are further degraded by adding Gaussian noise with standard deviation $\sigma = 12$. We set the patch size to be $61 \times 61$ in the proposed model. The reference patches are shown in Fig. 6(b). For
Table 1: The mean brightness ratios for the results in Fig. 4.

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<th>VTV</th>
<th>SCIDE</th>
<th>L₁-Retinex</th>
<th>TV-Retinex</th>
<th>ACE</th>
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<td>0.9980</td>
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<td>0.7214</td>
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<td>0.9970</td>
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Table 2: The mean brightness ratios for the results in Fig. 5.

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<th>Channel</th>
<th>Original Image</th>
<th>SVTV</th>
<th>VTV</th>
<th>SCIDE</th>
<th>L₁-Retinex</th>
<th>TV-Retinex</th>
<th>ACE</th>
<th>PLCE</th>
<th>ATVBH</th>
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the proposed SV-TV model, we set the parameter \( \lambda \) to be 0.7, 0.7, 0.6, 0.8, 0.8 respectively in the test of degraded images. For SCIDE model, the parameters \((\mu, \alpha)\) are chosen to be \((0.14, 2), (0.16, 2), (0.3, 2), (0.18, 2), (0.15, 1.5)\) in practice. For \(L_1\)-Retinex Model, we set the threshold \(t\) to be 10, 14, 12, 12, 15 respectively. For ATVBH model, the proportional parameter is always set to be \(k = 1/10\). For TV-Retinex model, ACE model and PLCE model, we use the default values of the parameters.

We display the restored results by using the proposed SV-TV model, SCIDE model, \(L_1\)-Retinex model, TV-Retinex model, ACE model, PLCE model and ATVBH model in Fig. 6(d)-(i) respectively. We see from the results that although SCIDE model and ATVBH model are able to remove noise, they fail in balancing the image contrast. TV-Retinex
model removes the bias, however, it keeps the image noise. Meanwhile, $L_1$-Retinex, ACE model, and PLCE model can neither eliminate noise nor bias. Again we see from these results that the proposed model is the best compared with other testing methods in simultaneously image denoising and luminance adjustment.

We then compute PSNR, SSIM and S-CIELAB color error [33] between the restored results and the ground truth images, meanwhile, we also calculate the PIQE [27] value of each restored result, the numbers are given in Tables 3 and 4. We remark here that we make use of SSIM, PSNR and S-CIELAB color error to show the restoration (noise and bias removal) effect of different testing methods, and we make use of PIQE value to show the enhancement effect and the overall quality of the restored results. We see from the numbers that the PSNR, SSIM, S-CIELAB error and PIQE values by using the proposed model are very competitive.

5 Conclusion remarks

In this paper, we propose and develop a variational model for simultaneously image denoising and luminance adjustment. The idea is to formulate an energy functional
Table 3: The PSNR, SSIM and PIQE values for results in Fig. 6.

<table>
<thead>
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<th>Measures</th>
<th>Testing Image</th>
<th>SVTV (V-restoration)</th>
<th>SCIDE</th>
<th>L₁-Retinex</th>
<th>TV-Retinex</th>
<th>ACE</th>
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Table 4: Pixel numbers whose S-CIELAB errors are larger than 20, 30 for results in Fig. 6.

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<th>SVTV (V-restoration)</th>
<th>SCIDE</th>
<th>L₁-Retinex</th>
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To adjust the luminance between image patches, and the noise of the image can be removed. In the proposed model, a saturation-value total variation regularization term is incorporated to remove the noise of the input image, meanwhile, a luminance adjusting term is considered based on luminance and contrast adjustment. Numerically we propose an efficient and effective algorithm to solve the proposed minimization model. We compare the proposed model with SIDCE model [30], L₁-Retinex model [13], TV-Retinex model [16], ACE model [5], PLCE model [4] and ATVBH model [25]. Experimental results are reported to demonstrate the efficiency and effectiveness of the proposed model.

Finally, we remark that the experimental part of this paper studies Gaussian-noise based image restoration. It’s very natural to generalize the application of the proposed SV-TV model to other types of noise, such as multiplicative noise, correlated noise, pois-
son noise, real world noise, etc., by formulating appropriate data fidelity method. This could be possible research work in the future.

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References


