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Edge-Preserving Image Smoothing Via a Total Variation Regularizer and a Nonconvex Regularizer

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Abstract

Image smooth plays an important role in image pre-processing. For classical image smoothing models, a convex total variation regularizer or a nonconvex regularizer has been widely used to protect image edges and to smooth noise. In this paper, we propose a new effective model in which the total variation regularizer and the nonconvex regularizer are combined to be a new weighted regularizer. The main advantage of our combined regularizer is that some undesirable details such as noise can be removed more effectively, while some important edge details can be preserved better. In addition, an efficient algorithm is designed to solve our model. In our algorithm, an iteratively reweighted process with the Chambolle's projection algorithm are coupled with each other. Numerical results demonstrate that our proposed model can generate better image smoothing results than those generated by total variation based models and those generated by nonconvex regularizer based models.

Keywords: Image smoothing; total variation; nonconvex regularizer; Chambolle's projection; iteratively reweighted processing

1. Introduction

Edge-protecting image smooth which plays a significant role in computer vision and image process, aims to eliminate unimportant details of the image while preserving salient edges. Historically, smoothing images is implemented by using lots of filters. The earliest Gaussian filter as a linear smoothing filter shows great performance when smoothing an input image at a steady speed in all direction. But it cannot protect the image edges very well.

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The nonlinear image smoothing filters such as Anisotropic diffusion filter, Total Variation model, Bilateral filter, NL-means filter, Weighted Least Square filter, can overcome the image blurring problem caused by the linear filters, and smooth the image while protecting the image edges, because those filters utilize prior edge information to remove certain image details and create a scale space representation consisting of simplified image to preserve edges. Anisotropic diffusion filter employs edge-stopping diffusion coefficient to detect edges, so it is able to protect edges from over-smoothing while curbing noise and some unimportant details. Total Variation model is known as its simplicity and high-efficiency which utilizes L1-norm regularization to penalize large gradient magnitudes. Bilateral filters another widely used model can concurrently achieve the goal of detail fattening and edge preservation. Because it takes the geometric distance and the color distance between pixels into consideration in smoothing process. Weighted Least Square filter can overcome some halo artifacts caused by continuous coarsening process due to the model's robust edge protecting regularization. In recent work, Xu et al. proposed a robust filtering methods making use of L0 gradient minimization to count non-zero gradient which can globally maintain the most prominent edges [1]. Later, Xu et al. introduced Relative Total Variation to extract main structures from texture to complete image smooth, but it cannot distinguish similar texture and structure [2]. Caixia Liu, Xiaofei Yan et al. introduced an image smoothing method based on adaptive anisotropic equation which can maintain significant details and reduce noise [9]. Bolun Cai, Xiaofen Xing et al. proposed a structure-preserving smoothing model based on cross-scale relative which obtains the weak textures from the most salient edges [10].

In order to ensure that the model has a globally optimal solution, the regularizer is usually convex in an adaptive total variation model. However, nonconvex regularizer performs better in maintaining edges of image and texture details. In this paper, we are inspired by Han's work [5], and propose an original edge-protecting image smoothing method which simultaneously eliminates some certain details like noise and preserves significant edges by using a weighted regularizer which can be regarded as a balance between the TV regularizer and the nonconvex regularizer. For one thing the weighted regularizer can eliminate certain details from TV regularizer; for another it can maintain edge details from nonconvex regularizer [3]. Moreover, numerical experiments demonstrate that the classical TV model tends to blur the details of image as the number of iterations increases, and our proposed model overcomes this problem with a non-convex regularizer. In the meanwhile, our model also guarantees the uniqueness of solution, which remains uncertainty for Han’s model. The rest of this paper is organized as follow: Section 2 introduces the preliminaries of the proposed model. Section 3 derives the proposed model and presents its mathematical study. In section 4, we demonstrate the experimental results. Section 5 concludes the whole paper.

2. Preliminaries

Image distortion may occur in the process of transmission and storage, resulting in degradation of image quality. Image restoration is to reduce or eliminate the distortion of the observed image as much as possible, and get a high quality image. Given an input image u0, we search for a new image u which is as similar as possibly to u0. An approximation to u0 can be found by solving the follow minimization problem using the Equation (1):

$$\min_u \int_\Omega |u-u_0|^2 \, dx \tag{1}$$

The minimization problem is a typically ill-posed problem. A classical way to solve ill-posed minimization problem is to add a regularization term to the energy. The most classical model, the Equation (2), is TV (ROF) regularization model proposed by Rudin et al.in 1992.

$$J(u)=\min_u \{\int_\Omega |u-u_0|^2 \, dx + \lambda \int_\Omega |\nabla u| \, dx\} \tag{2}$$

The first term is known as fidelity term which is used to minimize the distance of u and u0. The second term is a smoothing term. λ is a positive weighting constant which maintains the tradeoff between fidelity and smoothing term.

However, TV regularization cannot distinguish some structural edges and details (noise) due to its isotropic effect. In order to overcome this problem, Han at el. proposed Equation (3) as a nonconvex regularizer to preserve edges.

$$\int_{\Omega} \varphi(|\nabla u|)dx \tag{3}$$

In Equation (3), the function $\varphi(s) = \alpha s / (1+\alpha s)$, α is a positive parameter. The nonconvex regularizer is efficient in preserving edges, but because of its nonconvex characteristic, high-intensity noise is likely to be preserved in a homogeneous region of an image rather than be removed, since it is regarded as true details. But TV regularizer can eliminate noise efficiently due to its robust polishing effect. In order to combine both of their merits, we fuse the TV regularizer and the nonconvex regularizer into a unified model.

3. The Proposed Model

For this propose, we derive a functional Equation (4):

$$\min_{u}\{\int_{\Omega} |u-u_0|^2\, dx + \varepsilon\int_{\Omega} |\nabla u|\, dx + (1-\varepsilon)\int_{\Omega} \varphi(|\nabla u|)dx\} \tag{4}$$

It is easy to find that Equation (4) inherits the advantages of Equation (2) and Equation (3). When comparing Equation (2) and (3) with (4), we can find that ε is a positive tradeoff parameter. When ε = 1 (resp. ε = 0), Equation (4) is degenerated Equation (2) (resp. Equation (3)).

As section 2 mentioned, because of the nonconvexity of the function $\varphi(s) = \alpha s / (1+\alpha s)$, the existence and uniqueness of the solutions of the minimization problem Equation (4) cannot be guaranteed. In order to obtain the solution efficiently, an iteratively reweighted method [5] is proposed as:

$$\varphi(|\nabla u|) = \frac{\alpha |\nabla u|}{1+\alpha |\nabla u|} = b|\nabla u| \tag{5}$$

In Equation (5), the b is defined as:

$$b = \frac{\alpha}{1+\alpha |\nabla u|} \tag{6}$$

Then, the TV regularizer and the nonconvex regularizer can be represented as a weighted regularizer:

$$\varepsilon\int_{\Omega} |\nabla \mathrm{u}|\, dx + (1-\varepsilon)\int_{\Omega} b|\nabla u|\, dx = \int_{\Omega} (\varepsilon + (1-\varepsilon)b)|\nabla u|\, dx \tag{7}$$

Based on the above discussion, we derive the following formula:

$$\min_{u,b}\{\int_{\Omega} |u-u_0|^2\, dx + \int_{\Omega} (\varepsilon + (1-\varepsilon)b)|\nabla u|\, dx\} \tag{8}$$

The problem (8) can be solved by utilizing the alternative iteration method with respect to variables u and b. If we can obtain $u^{(k-1)}$ from the last iteration, an appropriate solution of $b^{(k-1)}$ can also be obtained by using the Equation (9):

$$b^{(k-1)} = \frac{\alpha}{1+\alpha\,|\nabla u^{(k-1)}|} \tag{9}$$

Then the solution of minimization problem (10) is the final goal.

$$u^{(k)} = \arg\min_{u}\{\int_\Omega |u-u_0|^2\,dx + \int_\Omega (\varepsilon+(1-\varepsilon)b^{(k-1)})\,|\nabla u|\,dx\} \tag{10}$$

The minimization problem (10) can be solved by Chambolle's projection algorithm, and the solution is given by:

$$u^{(k)} = u_0 - \mu divp \tag{11}$$

where the divp is the divergence of the vector $p \in R^n \times R^n$, and the solution of p can be solved by fixed point iteration method: given an initial $p^{(k)(0)} = 0, n = 1$ and a time-step δ, we iterate the following formula:

$$p^{(k)(n)} = \frac{p^{(k)(n-1)} + \delta\,\nabla(divp^{(k)(n-1)} - \frac{1}{\mu}u_0{}^{(k)})}{1+(\delta/\varepsilon+(1\text{-}\varepsilon)\mathrm{b}^{(k-1)})\,|\nabla(divp^{(k)(n-1)} - \frac{1}{\mu}u_0{}^{(k)})|} \tag{12}$$

where the two superscripts k and n represent outer loop and inner loop, respectively. Based on the discussion about Equation (9), (10), (11) and (12), we can estimate the final output image u. The whole alternative iteration process is summarized in Algorithm 1.

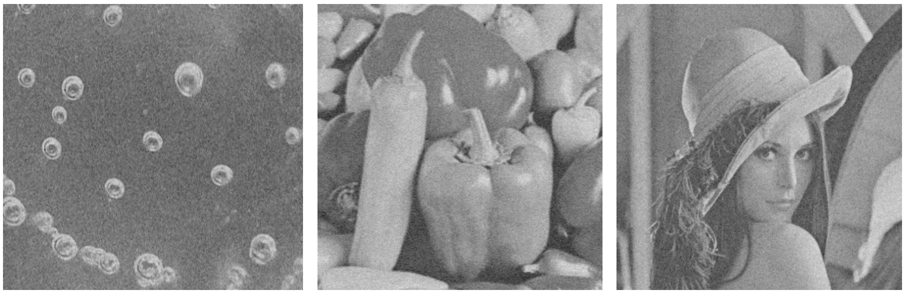
Table 1. Algorithm 1

Algorithm 1 Edge-Preserving Image Smoothing
1: input: image u_0, tradeoff parameter ε, smoothing parameter μ,δ
2: initialization: $u = u_0, p = 0$
3: for $i = 1:$ outer loop
4: compute b using Equation (9)
5: for $t = 1:$ inner loop
6: compute u using Equation (11) and Equation (12)
7: end for
8: end for
9: output: final image u

4. Experimental Analysis

In this section, more experimental analysis will be presented to demonstrate the effective performance of the proposed model. All experiments are implemented in Matlab 9.2 environment on a computer equipped with core(TM)i7- 7500U and 2.70GHz. In order to illustrate our model's efficiency, we compare our smoothing results with some classical models, including the ROF model and the model proposed by Han et al. As for the parameters that are chosen to produce the optimal results in our model, we will discuss them in the following section.

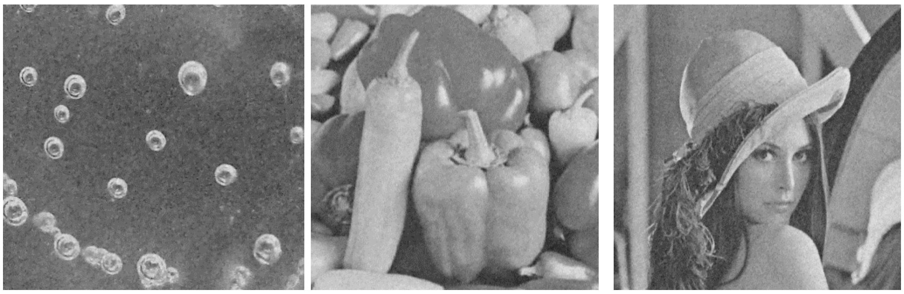
(a)



(b)

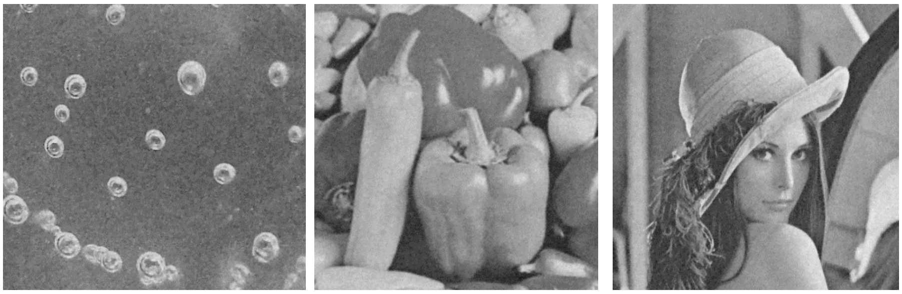
Fig. 1. Three original and noise images. (a) is three original images. (b) is noise images with L=25.

Three original reference image named Sky, Peppers and Lena respectively are used in our experiments. These images are shown in Fig. 1. Moreover, each of the original clean image is degenerated by noise from different Gaussian distribution with different parameters L chosen from the set {15, 20, 25}. In order to demonstrate the comparable result intuitively, we use the signal to noise ratio (SNR) and the peak signal to noise ratio (PSNR) as the evaluation indicators. Both of them are used to measure the similarity between clean and the restored images.



(a)

(b)



(c)

Fig. 2. Smoothing result of different models. From (a)-(c) results are obtained from ROF model, Han’s model and proposed model, respectively.

4.1 Parameter adjustment

Before adjusting the parameters, we normalize the size of grey intensity ranges to the interval [1,256]. The parameter μ controls the smoothing degree, and a large μ will blur the image too much while a small μ cannot restore the image effectively. Therefore, μ should be proportional to the level of noise. The parameter α plays the same role with parameter μ ,and the choice of α is the fixed range [1,6]. In this paper, we set $\alpha = 1$ and it performs effectively in most experiments. The parameter δ has been proved to be smaller than 1/8 to make sure the convergence of the algorithm. In our case, we choose it from the random value from the fixed range [0.01, 0.03], which can show a superior performance in most experiments. The parameter ε reflects the influence of different regularizers in model (4) and it varies in a small ranges [0, 0.6].

4.2. Smoothing performance evaluation

We compare our method with ROF model and Han's model by the way that compares the optimal SNRs/PSNRs obtained from those models, and the results are summarized intuitively in Table 2. It is easy to find that the proposed model can averagely get higher SNRs and PSNRs than the other two models in Table 2. Moreover, from the side of running time of different models, the times of proposed model presented in table 2 are much higher in comparison with Han’s model, but by and large it still runs less time than that of the other ones. The original reference images and noise images are shown respectively in Fig. 1 (a)-(b), and the smoothing results obtained from ROF model, Han's model and our proposed model are shown in Fig. 2 (a)-(c). Comparing these restored images, we find that our proposed model outperforms the other two models, especially when our model works well in removing the noise in homogeneous regions of images and maintaining important edges across the different regions. It is noting worth that the classical ROF model will blur the image too much with the increase of the number of iterations. In Fig. 2 (a), we can observe that some visual noise is still contained. As for Han’s model, the restored results are shown in Fig. 2 (b), which indicates that the edges of the images are over smoothed and at the same time, the noise is also not removed well. Our proposed model's smoothing results are shown in Fig. 2 (c), and it can easily observe that the proposed model can achieve the two contradictory goals that noise is removed while important edges are preserved. Therefore, we can conclude that our proposed model shows a better performance than the classical ROF model and Han's model.

5. Conclusions

A nonconvex regularizer-based edge-preserving image smoothing method is proposed in this paper. The proposed combined regularizer can not only preserve the geometric structural edges from over-smoothing, but also remove the undesired details well. In order to solve the minimization problem of the proposed model efficiently, the Chambolle's projection algorithm is introduced. In numerical experiments, the proposed model is better than the classical ROF model and Han’s model.

Table 2. Quantitative evaluation(SNR(db), PSNR(db), and the running time(s)) for different smoothing models.

	L	Noise SNR	Image PSNR	Proposed SNR	Model PSNR	time	ROF SNR	Model PSNR	time	Han’s SNR	Model PSNR	time
Lena	15	9.901	24.60	9.893	31.75	9.121	9.901	30.88	8.463	9.901	28.59	1.914
	20	7.416	22.12	7.409	30.04	9.472	7.373	28.84	8.221	7.415	28.46	1.912
	25	5.453	20.16	5.478	28.84	9.125	5.464	28.52	9.173	5.462	27.87	1.863
Sky	15	5.447	24.60	5.478	32.47	7.113	5.475	31.15	6.865	5.485	28.61	1.041
	20	2.954	22.10	2.920	30.84	6.721	2.951	30.41	6.554	2.987	27.25	1.087
	25	1.013	20.16	1.041	28.74	7.034	1.031	28.61	6.483	1.009	26.71	0.754
Peppers	15	12.20	24.60	12.20	32.95	8.091	12.18	32.31	9.023	12.18	28.92	1.553
	20	9.705	22.10	9.721	31.06	8.916	9.704	30.21	7.493	9.692	28.64	1.287
	25	7.791	20.19	7.774	28.82	8.204	7.776	28.47	7.836	7.752	27.83	1.246

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